DEMYSTIFYING THE DIGITAL DIVIDE AND THE ROLE OF INFORMATION AND COMMUNICATION TECHNOLOGIES ON HEALTH AND DISABILITY IN AUSTRALIA

A Thesis Submitted By

Mohammad Afshar Ali

MSS in Economics, BSS in Economics

For the award of
Doctor of Philosophy

2021

Abstract

Information and Communication Technologies (ICTs) today play a pivotal role in almost every sphere of human life. A growing body of literature has reported that ICTs have a substantial positive impact on the individual capabilities, productivity, employment and Gross Domestic Product (GDP) of nations. However, there are also concerns that uneven access to ICTs can exacerbate the extensity of digital inequality which makes policy discussions more complicated. Existing empirical analyses of digital inequality have mostly been conducted at the household, regional or global levels using cross-sectional study designs. In contrast, this thesis is based on state-wide longitudinal and nationally representative household-level cross-sectional and longitudinal survey data which have the potential to produce unbiased results and thus this can provide more empirical detail and reliability. Also, the long-term effect of digital inclusion on the Quality of Life (QoL) at the individual level has not received adequate attention in the existing body of knowledge. Further, existing studies are yet to explore the factors that affect the usage of ICT-enabled health services (particularly eHealth) among Persons with Disabilities (PwD). Given this backdrop, this thesis is aimed at exploring the underlying factors of digital inequality and the impact of digital inclusion on the QoL among PwD.

To attain this broad objective, this thesis applied quantitative research approaches based on panel data estimation framework, causal mediation analysis, and cross-sectional data analysis. As the panel data estimation strategy, several methods have been applied including random effects (RE) model, panel dynamic ordinary least squares (DOLS) model, generalised linear mixed model (GLMM), two-stage instrumental variables (IV-2SLS) method and the full-information maximum likelihood (FIML) method. Besides, for the causal mediation analysis, this thesis applied both parametric causal mediation regression models and parametric mediation effect models. Meanwhile, for cross-sectional data-based analysis, the thesis employed a set of multivariate logistic regression models. These aforementioned quantitative techniques are deployed using several datasets including state-wide longitudinal dataset compiled by the Australian Bureau of Statistics (ABS), household-level longitudinal Household, Income and Labour Dynamics in Australia (HILDA) dataset and cross-sectional Survey of Disability, Ageing and Carers (SDAC).

The thesis is comprised of three major themes of study including ‘understating the predictors of the digital divide’, ‘impact of ICTs on health-related QoL’, and ‘ICT-enabled health service adoption among PwD’ in the Australian context. This thesis is a ‘PhD by publication’ and includes seven studies. These studies correspond to seven sub-themes which fall under three aforementioned broad themes. This thesis is underpinned by four interlinked theories: social exclusion, social capital and cognitive theories, capability theory and theory of digital inequality.

Studies included under broad Theme I (Studies 1–3) explore the determinants and extent of the digital inequality in Australia and its association with socio-demographic inequality, income distribution and remoteness. Study 1 finds that the digital divide is significantly associated with socio-demographic factors and remoteness in Australia. Results of Study 2 reveal that the ICT infrastructure and affordability concentrations are more prevalent in the areas of greater Sydney and greater Melbourne. Findings also indicate that the remoteness of spatial units has a substantial effect on the concentration. Findings of Study 3 reveal that income distribution and socioeconomic inequality have a positive effect on ICT affordability. Theme II (Studies 4–5) of the thesis examines the direct and mediating effect of ICT on QoL. Findings from Study 4 asserts that the association between digital inclusion and QoL is simultaneous. Study 5 evinced that ICT mediates between 61% and 73% of the impact of assistive technology on QoL among PwCD. Theme III (Studies 6–7) investigates the determinants of ICT usage for health care among PwD and elderly PwD. Taken together, results emanating from these studies confirm that age, gender, income, level of education, language proficiency and geographical remoteness are significant predictors of the use of ICT-enabled health care. The results also affirm that technological aspects have a stronger moderating effect on the usage of ICT-enabled health care than behavioural constraints.

The policy implications emanating from the finding of studies included under Theme I are significant and straightforward. The results assert that digital divide is dependent upon several socio-demographic, economic and geo-spatial factors. To shape comprehensive digital inclusion policies, apart from enhancing ICT access by increasing efforts in building and spending on digital infrastructure, policymakers must take the socio-demographic factors of digital exclusion into account. Studies packaged under Theme II, confirm that digital inclusion can significantly contribute

to the enhancement of QoL of general population as well as disadvantaged groups. However, to maximise the impact of digital inclusion on QoL, decision makers should particularly emphasise the improvement of digital abilities and affordability among users from disadvantaged communities including residents living in remote areas, PwD and elderly citizens. Findings from the studies included under Theme III (Studies 6–7) imply that to mitigate the digital disability divide, priority should be given to direct policies and targeted resource allocation to ease technological constraints.

Keywords: Digital divide; information and communication technology; income inequality; quality of life; digital disability divide, eHealth; health care; Australia.

Certification of Thesis

This thesis is the work of Mohammad Afshar Ali except where otherwise acknowledged, with the majority of the authorship of the papers presented as a Thesis by Publication undertaken by the Student. The work is original and has not previously been submitted for any other award, except where acknowledged.

Principal Supervisor: **Professor Khorshed Alam**

Associate Supervisor: **Dr Brad Taylor**

Associate Supervisor: **Dr Shuddhasattwa Rafiq**

Student and supervisors signatures of endorsement are held at the University.

Statement of Contributions

The research articles produced from this study were a joint contribution of the researchers. The following detail is the agreed share of contribution for candidate and co-authors in the presented publications in this thesis.

Study 1:

Mohammad Afshar Ali, Khorshed Alam and Brad Taylor. Do social exclusion and remoteness explain the digital divide in Australia? Evidence from a panel data estimation approach. *Economics of Innovation and New Technology*, DOI: 10.1080/10438599.2019.1664708.

[Journal info: SJR quartile: Q1; H Index: 49; Impact Factor: 1.78; SNIP – 1.496]

The overall contribution of Mohammad Afshar Ali was 75% to the concept development, data extraction, analyses, interpretation, drafting and revising the final submission; Khorshed Alam, and Brad Taylor contributed to the concept development, editing and providing important technical inputs by 15% and 10% respectively.

Study 2:

Mohammad Afshar Ali, Khorshed Alam and Brad Taylor. Measuring the concentration of ICT infrastructure in Australia: Do affordability and remoteness matter? *Socio-Economic Planning Sciences*, 70, 100737, DOI: 10.1016/j.seps.2019.100737.

[Journal info: SJR quartile: Q1; H Index: 47; Impact Factor: 1.163; SNIP – 2.218]

The overall contribution of Mohammad Afshar Ali was 75% to the concept development, data extraction, analyses, interpretation, drafting and revising the final submission; Khorshed Alam, and Brad Taylor contributed to the concept development, editing and providing important technical inputs by 15% and 10% respectively.

Study 3:

Mohammad Afshar Ali, Khorshed Alam, Brad Taylor and Shuddhasattwa Rafiq. Do income distribution and socio-economic inequality affect ICT affordability? Evidence from Australian household panel data. *Economic Analysis and Policy*, 64, 317-328, DOI: 10.1016/j.eap.2019.10.003.

[Journal info: SJR quartile: Q1; H Index: 24; Impact Factor: 1.973; SNIP: 1.252]

The overall contribution of Mohammad Afshar Ali was 70% to the concept development, data extraction, analyses, interpretation, drafting and revising the final submission; Khorshed Alam, Brad Taylor and Shuddhasattwa Rafiq contributed to the concept development, editing and providing important technical inputs by 15%, 10% and 5% respectively.

Study 4:

Mohammad Afshar Ali, Khorshed Alam, Brad Taylor and Shuddhasattwa Rafiq. Does digital inclusion affect quality of life? Evidence from Australian household panel data. *Telematics and Informatics*, 51,101405 DOI: 10.1016/j.tele.2020.101405.
[Journal info: SJR quartile: Q1; H Index: 56; Impact Factor: 4.139; SNIP – 2.566]

The overall contribution of Mohammad Afshar Ali was 70% to the concept development, data extraction, analyses, interpretation, drafting and revising the final submission; Khorshed Alam, Brad Taylor and Shuddhasattwa Rafiq contributed to the concept development, editing and providing important technical inputs by 15%, 10% and 5% respectively.

Study 5:

Mohammad Afshar Ali, Khorshed Alam and Brad Taylor. The mediating effect of information and communication technology usages on the nexus between assistive technology and quality of life among people with communication disability. *Cyberpsychology, Behavior and Social Networking*, 23(5), 338-345, DOI: 10.1089/cyber.2019.0598.

[Journal info: SJR quartile: Q1; H Index: 133; Impact Factor: 2.347; SNIP: 1.296]

The overall contribution of Mohammad Afshar Ali was 75% to the concept development, data extraction, analyses, interpretation, drafting and revising the final submission; Khorshed Alam, and Brad Taylor contributed to the concept development, editing and providing important technical inputs by 15% and 10% respectively.

Study 6:

Mohammad Afshar Ali, Khorshed Alam and Brad Taylor. Determinants of ICT usage for healthcare among people with disabilities: The moderating role of technological and behavioral constraints. *Journal of Biomedical Informatics*, DOI: 10.1016/j.jbi.2020.103480

[Journal info: SJR quartile: Q1; H Index: 91; Impact Factor: 2.95; SNIP: 2.212]

The overall contribution of Mohammad Afshar Ali was 75% to the concept development, data extraction, analyses, interpretation, drafting and revising the final submission; Khorshed Alam, and Brad Taylor contributed to the concept development, editing and providing important technical inputs by 15% and 10% respectively.

Study 7:

Mohammad Afshar Ali, Khorshed Alam and Brad Taylor. Determinants of eHealth use among elderly people with disabilities: The moderating role behavioral constraints. *International Journal of Medical Informatics*, 2021, DOI: 10.1016/j.ijmedinf.2021.104411

[Journal info: SJR quartile: Q1; H Index: 99; Impact Factor: 3.210; SNIP: 1.958]

The overall contribution of Mohammad Afshar Ali was 75% to the concept development, data extraction, analyses, interpretation, drafting and revising the final submission; Khorshed Alam, and Brad Taylor contributed to the concept development, editing and providing important technical inputs by 15% and 10% respectively.

Acknowledgements

To begin with, I would like to acknowledge my utmost gratitude and thanks to the Almighty God who bestowed me with the positive intent to start and finish this challenging work. My PhD journey has come to its endpoint with the academic, financial, and mental support from a number of good souls. Next, I take the opportunity to express utmost gratefulness and profound respect to my principal supervisor, Professor Khorshed Alam for his prudent guidance, insightful comments and cordial mental support throughout the journey. Subsequently, I would like to register my sincere gratitude to my associate supervisor Dr Brad Taylor for his valuable mentorship and continuous guidance. His rigorous inputs and comments enhanced the readability and clarity of the articles published from the thesis. I am extremely indebted to the external supervisor Dr Shuddhasattwa Rafiq for his continuous guidance, which improved the methodological and empirical merit of my published works in reputed journals.

I would like to thank the funding body – University of Southern Queensland (USQ), Australia for its financial support through International Stipend Research Scholarship and International Tuition Fees Scholarship. Without this funding, this research would not be possible. I am also grateful to USQ ICT services for their extended technical support in software installation and assistance other computer-related issues. I also would like to acknowledge the logistic support I received from the USQ Graduate Research Office, USQ Library Services and Faculty of Business, Education, Law and Arts (BELA) Central Operations.

I am also greatly indebted to my whole family as they are an equal partner in this PhD Particularly, I would like to register deep gratitude to my parents, Mohammad Ashraf Ali and Umme Kulsom for their continuous care, sacrifice and support for my studies throughout my entire life. In furtherance, I am incredibly grateful for the support of my brother, Mohammad Kawsar Ali who has taken the responsibility of my parents back in my home while I was snowed under my PhD.

I would like to thank my previous research supervisors and mentor's Dr Md Rakibul Hoque, Dr Debapriya Bhattachrya, Dr Fahmida Khatun and Dr Mahfuz Ashraf for their valuable suggestions during my PhD study and throughout my training and career. Furthermore, I sincerely acknowledge the mental support and academic suggestions that I received from Dr Michael Lane, Dr Aletha Ward, Dr Mohd Mohsin, Mr Rubayyat Hashmi, Dr Wahid Ferdous, and Dr Rashidul Alam Mahumud.

I would further like to thank the head of the Department of Economics of Jagannath University, Professor Md Habibur Rahman for his cordial logistic support while I was in study leave to pursue my PhD. Enormous thanks go to Libby Collett for her professional proofreading service.

I also cordially appreciate the prompt logistic support of Department of Social Services of Australia in authorising my access to use the Household, Income and Labour Dynamics in Australia survey data. In addition, I am also grateful to the Australian Bureau of Statistics who granted my access to their comprehensive database named Survey on Disability, Aging and Caring.

Last but not the least, I am also grateful to the anonymous reviews and editors of the journals where my PhD research articles have been published. Their comments and feedback greatly improved the quality of those papers.

Table of Contents

List of Figures

List of Tables

List of Abbreviations

2SLS	Two Stage Least Squares
ABS	Australian Bureau of Statistics
ACT	Australian Capital Territory
ADF	Augmented Dickey Fuller
AT	Assistive Technology
BIC	Bayesian Information Criterion
CCA	Canonical Correlation Analysis
CI	Confidence Interval
COVID-19	Coronavirus Disease 2019
CURF	Confidentialised Unit Record File
DII	Digital Inclusion Index
DOLS	Dynamic Ordinary Least Squares
DSS	Department of Social Services
FGLS	feasible general least squares
FIML	Full Information Maximum Likelihood
GCCSA	Greater Capital City Area
GDP	Gross Domestic Product
GLMM	Generalized Linear Mixed Model
GMM	Generalized Method of Moments
HAC	Heteroscedasticity and Autocorrelation Consistent
HHm	Herfindahl–Hirschman modified
HILDA	Household, Income and Labour Dynamics in Australia
ICT	Information and Communication Technology
ITU	International Telecommunication Union
IV	Instrumental Variable
LLC	Levine–Lin–Chu
LQ	Location Quotient
NBN	National Broadband Network
NDIA	National Disability Insurance Agency
NDIS	National Disability Insurance Scheme
NSW	New South Wales

OLS	Ordinary Least Squares
PCA	Principal Component Analysis
PP	Phillips Perron
PwCD	People with Communication Disability
PwD	People with Disability
QoL	Quality of Life
RE	Random Effects
RP	Relative Participation
SDAC	Survey of Disability, Ageing and Caring
SEIFA	Socio-Economic Indexes for Areas
UN	United Nations
VIF	Variance Inflation Factor
WHO	World Health Organisation

List of published articles included in the thesis

Study 1:

Mohammad Afshar Ali, Khorshed Alam and Brad Taylor. Do social exclusion and remoteness explain the digital divide in Australia? Evidence from a panel data estimation approach. *Economics of Innovation and New Technology*, 29 (6), 643-659, DOI: 10.1080/10438599.2019.1664708.

[Journal info: SJR quartile: Q1; H Index: 49; Impact Factor: 1.78; SNIP – 1.496]

Study 2:

Mohammad Afshar Ali, Khorshed Alam and Brad Taylor. Measuring the concentration of ICT infrastructure in Australia: Do affordability and remoteness matter? *Socio-Economic Planning Sciences*, 70, 100737, DOI: 10.1016/j.seps.2019.100737.

[Journal info: SJR quartile: Q1; H Index: 47; Impact Factor: 1.163; SNIP – 2.218]

Study 3:

Mohammad Afshar Ali, Khorshed Alam, Brad Taylor and Shuddhasattwa Rafiq. Do income distribution and socio-economic inequality affect ICT affordability? Evidence from Australian household panel data. *Economic Analysis and Policy*, 64, 317-328, DOI: 10.1016/j.eap.2019.10.003.

[Journal info: SJR quartile: Q1; H Index: 24; Impact Factor: 1.973; SNIP: 1.252]

Study 4:

Mohammad Afshar Ali, Khorshed Alam, Brad Taylor and Shuddhasattwa Rafiq. Does digital inclusion affect quality of life? Evidence from Australian household panel data. *Telematics and Informatics*, 51,101405, DOI: 10.1016/j.tele.2020.101405.

[Journal info: SJR quartile: Q1; H Index: 56; Impact Factor: 4.139; SNIP – 2.566]

Study 5:

Mohammad Afshar Ali, Khorshed Alam and Brad Taylor. The mediating effect of information and communication technology usages on the nexus between assistive technology and quality of life among people with communication disability.

Cyberpsychology, Behavior and Social Networking, 23(5), 338-345, DOI: 10.1089/cyber.2019.0598.

[Journal info: SJR quartile: Q1; H Index: 133; Impact Factor: 2.347; SNIP: 1.296]

Study 6:

Mohammad Afshar Ali, Khorshed Alam and Brad Taylor. Determinants of ICT usage for healthcare among people with disabilities: The moderating role of technological and behavioral constraints. *Journal of Biomedical Informatics*, 108, 1034802, DOI: 10.1016/j.jbi.2020.103480

[Journal info: SJR quartile: Q1; H Index: 91; Impact Factor: 2.95; SNIP: 2.212]

Study 7:

Mohammad Afshar Ali, Khorshed Alam and Brad Taylor. Determinants of eHealth use among elderly people with disabilities: The moderating role behavioral constraints. *International Journal of Medical Informatics*, 149, 104411, DOI: 10.1016/j.ijmedinf.2021.104411

[Journal info: SJR quartile: Q1; H Index: 99; Impact Factor: 3.210; SNIP: 1.958]

List of published and under-review articles during the PhD program (not included in the thesis)

Study 1:

Mohammad Afshar Ali, Rakibul Hoque and Khorshed Alam. An empirical investigation of the relationship between e-government development and the digital economy: The case of Asian countries. *Journal of Knowledge Management*, 22 (5), 1176-1200, DOI: 10.1108/JKM-10-2017-0477.

[Journal info: SJR quartile: Q1; H Index: 106; Impact Factor: 7.246; SNIP: 2.714]

Study 2:

Mohammad Afshar Ali, Khorshed Alam, Brad Taylor and Shuddhasattwa Rafiq (2020). Does ICT maturity catalyse economic development? Evidence from a difference-in-difference-in-differences estimation in OECD countries. *Economic Analysis and Policy*, 68 (2020), 163-174, DOI: 10.1016/j.eap.2020.09.003

[Journal info: SJR quartile: Q1; H Index: 24; Impact Factor: 1.973; SNIP: 1.252]

Study 3:

Mohammad Afshar Ali, Khorshed Alam and Brad Taylor. Incorporating affordability, efficiency, and quality in the ICT development index: Implications for index building and ICT policymaking. *The Information Society*, 36(2), 71-96, DOI:10.1080/01972243.2019.1702601

[Journal info: SJR quartile: Q1; H Index: 73; Impact Factor: 2.378; SNIP: 2.086]

Study 4:

Khorshed Alam and **Mohammad Afshar Ali**. Relationship between broadband Internet and income inequality in regional Australia: Addressing endogeneity using the propensity score matching technique, *Information Technology for Development*, (under review, reference number: 07-20-0276-ITD-R).

[Journal info: SJR quartile: Q1; H Index: 33; Impact Factor: 2.600; SNIP: 2.234

Chapter 1: Introduction

1.1 Background

Over the last two decades, the diffusion of Information and Communication Technologies (ICTs) has surged. This swift development in terms of technology adoption has widened the capabilities of individuals by securing greater access to communication, information, and other civic opportunities (Norris 2001; Katz & Rice 2002). However, scholarly works have also evinced that access to ICTs might aggravate existing social disparities if their benefits are not reaped equally by all members of society. This led to the phenomenon of a 'digital divide' or 'digital inequality'. The notion of digital divide has progressed from its narrower version defined as having physical access to the Internet and personal computers (van Dijk 2006) to a wider understanding of encompassing additional aspects of digital inequality including digital skills (van Dijk 2005; Alam & Imran 2015), affordability (Baller, Dutta & Lanvin 2016; Ali, Alam & Taylor 2020) and quality of services (Ali, Alam & Taylor 2020).

The existence of the digital divide remains as one of the major concerns in many regions, including many developed nations like New Zealand and Canada (Ragnedda & Muschert 2013; ITU 2016a). As many remote and regional Australian communities lag behind the rest of the nation in terms of ICT uptake, digital inequality remains an important area of public policy debate in Australia (Alam & Imran 2015; Park 2017). From 1998–2018, the proportion of households with Internet access has risen from 45.0% to 97.1% across Australia (ABS 2018). Although these figures indicate that the digital divide is closing, the pace of digital inclusion is slowing down compared to the past years (Thomas et al. 2020). Specifically, the overall digital inclusion score for Australia has risen from 61.9 in 2019 to 63.0 in 2020, an increase of only 1.1 points. The rate of increase has fallen consequently over the last two years (i.e. in 2018 and 2019). Nevertheless, the scores of several states and territories including Victoria and the Australian Capital Territory (ACT) have remained more or less static over the last couple of years. Undoubtedly, the geographical nature of Australia has played a pivotal role in the digital inclusion landscape as rural and remote areas are still lagging behind when compared to their metropolitan counterparts. For example, in 2020, the digital inclusion scores of Australians living in rural areas (57.4) are substantially lower than their urban counterparts (65.0) (Thomas et al. 2020). Although the degree of digital inclusion in remote areas has increased significantly from 10.0% to 77.1% from 1998 to 2018, the dynamics of digital inclusion in remote areas is not vibrant as compared to the major cities (ABS 2018).

A growing body of literature has explored the association among digital divide, socio-economic factors and socio-spatial locations (De Queiroz Ribeiro et al. 2013; Alam & Imran 2015; Park 2017). While the empirical evidence on the determinants of the digital divide is well-documented, an understanding of its precise nature is pertinent considering the geospatial landscape of Australia. More specifically, the analysis of the concentration of ICT infrastructure at the disaggregated spatial unit of locations is limited. Given this backdrop, the deeper understanding of digital inequality emanating from the thesis can be used to guide digital inclusion strategies in other developed countries with isolated populations and similar geospatial features (Banks 2001; ITU 2016a).

In this modern age, ICTs plays a crucial role in almost every sphere of human life. Though a considerable amount of existing literature has demonstrated that the ICT affects the well-being of nations (Dewan & Kraemer 2000; Dedrick, Kraemer & Shih 2011), the long-term impact of digital inclusion of QoL at the individual level has not been captured adequately (Lissitsa & Chachashvili-Bolotin 2016; Martin 2016; Castellacci & Tveito 2018). In considering the contribution of digital technologies in people's day-to-day life, an empirical examination on the influence on the QoL at the individual level is germane. The knowledge gathered through the empirical exercises embedded in this thesis has the potential to aid policymakers in devising comprehensive digital inclusion policies.

Disability has been identified as one of the barriers to successful adoption of ICT. Research has demonstrated that the degree of digital inequality between people with and without disabilities is quite wide (Brewer, Taber-Doughty & Kubik 2010; Dobransky & Hargittai 2016; Duplaga 2017). This phenomenon has been defined as the 'digital disability divide' in several recent studies (Sachdeva et al. 2015; Dobransky & Hargittai 2016). For example, 84.6% of the Australian population are Internet users (ITU 2016b) while only 64.3% of Australians with disabilities has enjoyed that privilege (ABS 2017b). Although the empirical investigation on underlying factors of the digital divide is well-documented (Dobransky & Hargittai 2006; Sachdeva et al. 2015; Dobransky & Hargittai 2016; Duplaga 2017), the determinants of ICT-enabled health service adoption among PwD are yet to be explored. Given this backdrop, investigation on the predictors of ICT-enabled health care usage among PwD is really useful as it can potentially provide detailed insights to policymakers, regulators and private actors in mitigating the digital inequalities among PwD.

An extensive body of prevailing literature has concluded that ICTs play a pivotal role in augmenting the well-being of PwD by enhancing their capabilities (Vicente & Lopez 2010; Jayakar et al. 2015; Wu , Liu & Yuan 2018). Having said that, it is reported that around 15% population of the globe are affected by some sort of disability, and that figure is expected to rise as the aging population are soaring in many societies (Mcclain-Nhlapo et al. 2018). Access to ICT is regarded as one of the basic human rights according to the Convention on the Rights of Persons with Disabilities (United Nations 2006). Regrettably, several studies have found that PwD are less likely to have Internet access (Sachdeva et al. 2015). Nevertheless, studies evinced that ICTs have significantly uplifted the health-related autonomy of individuals and reduced the limitations caused by their physical and mental impairments. Particularly, ICT-enabled health support care has the potential to rationally allocate medical resources to the vulnerable populations in a health care system that is currently under strain during a pandemic like COVID-19 (Fisk, Livingstone & Pit 2020; Hong et al. 2020; Smith et al. 2020). Eventually, the auspicious outcomes emanating from enhanced penetration of ICTs will result in greater social inclusion and improved QoL among PwD (Mavrou et al. 2017; Papanastasiou et al. 2018). In other respects, PwD is not a homogeneous group and they have diverse needs as they face varied types of barriers (Sachdeva et al. 2015; Mavrou et al. 2017). Therefore, to reap the maximum benefit from the access to technology, the differentiated needs of PwD should be taken into account. The findings from disability-related studies of this thesis can potentially provide some meaningful insights to guide government bodies, business enterprises, and non-government organisations so that the PwD can obtain the maximum return from the usage of ICTs.

To this end, the central aim of this thesis is to investigate the factors underlying the digital divide in Australia and their interplay with other aspects of socio-demographic inequality and socio-spatial heterogeneity. To analyse specific aspects of the digital divide, this thesis investigates the precursors to the adoption of ICT-enabled health services among People with Disabilities (PwD) and the impact of those technologies on health-related Quality of Life (QoL). This thesis aims to design policy recommendations to enable and promote the usage of ICT-enabled health services among PwD which has the potential to assist the National Disability Insurance Agency (NDIA) in achieving its target of securing long-term ICT infrastructure for disadvantaged communities. Moreover, this thesis strives to examine the effect of ICT on the QoL of the Australian population.

The rest of this chapter is structured as follows. Sub-section 1.2 provides a critical review of existing literature; Sub-section 1.3 outlines the research gap, followed by research aim, objectives and research questions in Sub-section 1.4; Sub-section 1.5 describes the scope of the study; Sub-section 1.6 elaborates study design and methodology of the findings; Sub-section 1.8 describes the theoretical underpinning of the study; Sub-section 1.9 concludes this Section 1 by sketching the organisation of the thesis.

1.2 Existing studies

This thesis employed the narrative review method to synthesize the qualitative interpretation of existing knowledge in relevant field. The databases that have been used to extract literature are Scopus, PubMed, Web of Science, EconLit and Google Scholar. The searches for three different broad themes (outlined in the following sections) were conducted using different sets of search words. For Theme I, terms included the following: "digital divide" OR "digital exclusion" OR "digital inclusion" OR "digital inequality" OR "access to technology" OR "ICT usage" OR "adoption of technology". For Theme II, the search term is consisted of ("digital divide" OR "digital exclusion" OR "digital inclusion" OR "digital inequality" OR "access to technology" OR "ICT usage" OR "adoption of technology") AND ("quality of life" OR "health outcome" OR "well-being OR "life satisfaction"). The search term for Theme II contains ("digital inclusion" OR "OR "access to technology" OR "ICT usage" OR "adoption of technology" OR "apps" OR "device") AND ("quality of life" OR "health outcome" OR "well-being" OR "life satisfaction" OR "health care") AND ("disability" OR "impairment"). Articles were also extracted by conducting a backward search using the references of found articles and locating additional articles by executing a forward search utilising the original cited paper.

Three main criteria were utilised to include relevant articles for the review: the language of the article was English, the article was published in peer-reviewed journals after January 1, 1995, and the article for which full text was available. There were two stages of screening – preliminary screening using the title and abstract, and the final reviewing utilising the full-text of the article.

1.2.1 Determinants of the digital divide

The notion of the digital divide has been examined widely in many studies from different perspectives. Several empirical studies have found that the digital divide prevails within countries and between countries due to several socio-economic determinants including income, age and education (Rice & Pearce 2015; Campos, Arrazola & de Hevia 2017; Lindblom & Räsänen 2017; Pratama 2017; Yu, Lin & Liao 2017). A set of studies have found the existence of a gender divide indicating that women are less likely than men to access and use technologies (Pearce & Rice 2013; Alozie & Akpan-Obong 2017; Mumporeze & Prieler 2017). In a cross-country context, a sub-set of the literature has evinced that the divergences in access to and use of technology depend upon the level of national income (Billon, Marco & Lera-Lopez 2009; Rice & Pearce 2015; Ünver 2017). The complex and multi-dimensional facet of the digital divide has motivated scholars to build composite indices to gauge the extent of the digital divide (Hüsing & Selhofer 2002; Vehovar et al. 2006; Albuja et al. 2015).

Over the last two decades, a few studies have explored the extent and nature of the digital divide in Australia. The pioneering work of Curtin (2001) reported that the digital divide persists in rural and regional Australia and it is due to lack of education and income. Another study asserted that inequality in material access, lack of education and affordability are the three key determinants of digital inequality are (Alam & Imran 2015). A group of studies have investigated the determinants of digital divide further with a special focus on regional dimensions. A case study conducted on seven rural local government areas in New South Wales demonstrated that a multi-layered divide exists which is a result of three interlinked aspects – infrastructure, connectivity, and digital engagement (Park et al. 2015). In another case study, conducted on a small town in South Australia confirmed that the digital engagement of elderly citizens is constrained by lack of digital abilities, affordability and lack of organisational capabilities (Hodge et al. 2017). In a seminal work, Park (2017) asserted that proximity to major city centres is one of the strong predictors of Internet connectivity. Moreover, the digital divide was exacerbated by socio-demographic factors including the level of educational attainment and employment status.

A great deal of previous research has examined the association between digital concentration and geospatial landscape. It is well established that the likelihood of having Internet access in urban centres is greater compared to rural and remote areas (ITU 2014; Sujarwoto & Tampubolon 2016). De Queiroz Ribeiro et al. (2013) confirmed that socio-spatial location and socio-economic status are two major determinants of access to computers and the Internet. To date, De Brito et al. (2016) carried out the most detailed study on measuring ICT access in the context of Brazil. Considering access to four types of ICT devices including computers, the Internet, mobile phones, fixed phones access, the authors asserted that a significant divergence exists between the major municipalities and other (remote and rural) regions in ICT infrastructure concentration. Several studies have explored digital concentration in the Australian context. For instance, using geo-cartographical maps an empirical study captured the spatial inequalities across and among local government areas in Sydney (Gibson 2003). Very recently, Thomas et al. (2020) developed composite digital inclusion indices for all states and regions of Australia. They found that digital exclusion is substantially greater in rural areas than their urban counterparts.

1.2.2 ICT and health outcomes

An extensive body of existing literature has examined the nexus between health-related QoL and digital inclusion. Based on a respondent level survey data, a series of studies have asserted that Internet use enhances physical and psychological well-being, facilitates social relationships, and thereby promotes respondents' overall QoL (Campisi et al. 2015; Çikrıkci 2016). Similarly, several studies have found a positive association between ICT use and the psychological aspects of QoL (Çelik & Odacı 2013; Chiao & Chiu 2016). Another strand of literature has asserted that assistive ICTs empowered elderly persons by facilitating greater autonomy in the management of their health-related problems (Chaumon et al. 2014; Nimrod 2017; Siegel & Dorner 2017; Sims, Reed & Carr 2017).

In contrast, another thread of cross-sectional studies has found negative effects of ICT usage. For instance, life satisfaction was found in one study to be inversely associated with problematic Internet use and social media addiction (Gao et al. 2017; Longstreet

& Brooks 2017; Nimrod 2017). Similarly, a group of studies confirmed that smartphone addiction has negative impacts on QoL (Van den Berg et al. 2005; Hayward et al. 2013; Toda et al. 2016). Standing apart from those studies, Arbabisarjou, Allameh and Farhang (2012) reported that no significant relationship exists among QoL and ICT use. Nevertheless, a subset of studies conducted on elderly people asserted that the evidence of the nexus between ICT on QoL is mixed (Hirani et al. 2014; Damant et al. 2016).

A cluster of scholarly works investigating the impact of ICTs on the QoL among PwD asserted that there exists a positive association between those. Particularly, for People with Communication Disabilities (PwCD), ICT-based interventions promote higher levels of health-related autonomy and reduce impairment caused by disabilities. These positive outcomes led to enhanced social inclusion and improved QoL (Lancioni et al. 2013; Mavrou et al. 2017; Papanastasiou et al. 2018; Samuelsson & Ekström 2019). To this end, the use of ICT-based assistive technologies among PwD has drawn considerable research attention (Ashraf et al. 2017; Mavrou et al. 2017). For example, empirical work has found that ICT-based assistive technology enhances QoL among PwCD by lessening the communication and interaction-related deficits (Mavrou et al. 2017; Perelmutter, McGregor & Gordon 2017). However, existing studies cautioned that the transmission of positive effects of ICT-based assistive technology on QoL depends upon the incompatibility of assistive technology with ICT devices and accessibility of compatible ICT devices (Hakobyan et al. 2013; O'Neill et al. 2019). Following this, a group of studies asserted that convergence between ICT and assistive technology minimises digital disability divide by promoting equal opportunities (Hakobyan et al. 2013; Agree 2014; Ashraf et al. 2017).

1.2.3 ICT usage for healthcare among PwD

The digital disability divide is a well-researched topic. A decent number of studies has looked the underlying factors which are responsible for the digital divide among PwD (Dobransky & Hargittai 2006; Raghavendra et al. 2015; Sachdeva et al. 2015; Dobransky & Hargittai 2016; Duplaga 2017). However, literature exclusively focusing on the predictors of ICT-enabled health service adoption among PwD are scarce (Cashen, Dykes & Gerber 2004; Hemsley et al. 2016). Nevertheless, these studies merely reviewed the current state of the art and future strategies to harness ICT-based health information services including telehealth and mobile health care adoption (Cashen, Dykes & Gerber 2004; Hemsley et al. 2016; Jones, Morris & Deruyter 2018). However, a set of factors which shaped the uptake of ICT adoption, in general, has been reflected in the existing empirical studies. Among those factors, the most noticeable and statistically significant factors are age, gender, employment status, socio-economic status, digital skill, ethnicity, disability status, and place of residence (Dobransky & Hargittai 2006; Raghavendra et al. 2015; Sachdeva et al. 2015; Dobransky & Hargittai 2016; Duplaga 2017).

Prevailing literature has evinced that several technological restraints including lack of access, digital ability constraints and poor quality of service are the most noticeable barriers to ICT usage among PwD (Carey 2005; Dobransky & Hargittai 2006, 2016; Šumak et al. 2019). Another strand of studies identified that affordability of the Internet and other ICT equipment appears as another set of prominent barriers (Vicente & Lopez 2010; Jayakar et al. 2015; Lissitsa & Madar 2018). A few studies have also found that incompatibility of ICT devices with assistive technologies as another key impediment (Jayakar et al. 2015; Mavrou et al. 2017).

Apart from these technological constraints, research has revealed that several behavioural or attitudinal constraints substantially impede ICT usage among PwD. To exemplify, studies have asserted that lack of interest, attitudinal restraints, privacy issues and lack of motivation are key reasons for the non-usage of ICTs among PwD (Segrist 2004; Caton & Chapman 2016; Sharpe & Hemsley 2016). A few studies found that other behavioural factors including inadequate support (Carey 2005; Caton & Chapman 2016; Ågren, Kjellberg & Hemmingsson 2018), and time constraints (Wu et al. 2014; Sharpe & Hemsley 2016) are the major barriers in this regard.

1.3 Theoretical framework

The theorising process for the studies included in the thesis was not straightforward. The process involves the reflexive approach and the subsequent theories were chosen based on the considered judgement of the researcher. Rather than a theory-dictated approach, the findings of this thesis are theorised inductively meaning that the analytical investigation was grounded on data. Having said that, every study of the thesis is based on a suitable theoretical framework. For some papers, theoretical discussion was reduced or removed to satisfy reviewers' comments during the peerreview process. The foundation of the thesis is based on four theories: theories of social exclusion, social capital and cognitive theories (Studies 1–3), capability theory (Studies 4–5), and disability and digital divide theory (Studies 6–7). The following sections outline how the selected theories are interlinked with the three broad themes and the designs of the studies included in the thesis.

1.3.1 Theories of social exclusion, social capital and cognitive theories

The notion of the digital divide is not grounded on a particular theoretical framework. Rather, this concept is closely tied with the theories of social exclusion, social capital and cognitive theories (van Dijk & Hacker 2003; Clayton & Macdonald 2013; Ragnedda & Muschert 2013). Digital inequality cannot be studied independently in economic and social terms without taking into account the cognitive factors (Kvasny & Keil 2006). The social cognitive theory is centred on the concept of 'self-efficacy'. This can be accumulated by gathering knowledge using education and advancement of skills through training (Bandura 1986). Besides, economic, social, demographic and educational factors also can potentially impact the probability of having digital access (Tsatsou 2011). Moreover, it is well proven that social inclusion is dependent upon ICT-mediated economic and social networks (Castells 2002; Livingstone & Helsper 2007).

Considering all these facts, it can be argued that enhancement in ICT accessibility has the potential to contribute positively to the social inclusion of individuals in society. This framework hypothesises that a set of social, economic, demographic and cognitive factors play a crucial role in minimising the digital divide and setting the grounds of social inclusion. Studies 1 and 2 of this thesis link these two concepts with the framework of social capital and cognitive theories, using access to ICT as the focal point of digital and social exclusion. The selection of variables for the econometric modelling of the study is embedded in those theories as well as the existing relevant empirical works (see Table A2 of Study 1).

1.3.2 Capability theory

The information and communication technology for development (ICT4D) endeavours people-centred or human development (Forestier, Grace & Kenny 2002; Prakash 2007). Amartya Sen's capability approach is one of the most widely recognised approaches in conceptualising human development. According to this approach, development can be defined as the case when individuals have more freedom or opportunities. A life which is free from poverty, political oppression and inequalities is a good life because it gives individuals the capacity to pursue their goals (Sen 1985, 2010). Social opportunities, economic amenities, political freedoms, transparent societies and security from states are basic components of freedom-oriented development (Sen 2010). Thus, a definition of a good life (life's opportunities) must encompass both the means and outcomes of development.

Study 3 is underpinned on two basic theories, namely, capability theory (Sen 1985) and Engel's law (Engel 1857). Following the theoretical footprints of the capability approach, in an empirical work, Weiss et al. (2015) found that comparatively cheaper ICT-related services promoted digital inclusion where individual capabilities were high. In line with this approach, a strand of studies asserted that inequality in the level of income is a significant predictor of the affordability of telecommunication services (Choudrie et al., 2015; Fuchs, 2009). Meanwhile, Engel's law explains the nature of association between income and household expenditure (Engel 1857). Several works documented that the impact of income distribution on the diffusion of technology is non-linear (Milne 2000; Bohman 2008). More specifically, the impact of income inequality on ICT affordability varies with the level of income and the households from lower quintile in high-income countries spending close to their affordability threshold (Milne 2006). Consequently, as income rises, the proportion of ICT expenditure to household spending falls even though the nominal figure of ICT expenditure rises in absolute terms. Following the proposition of Engel's law, Study 3 presumes ICT service as a necessary good and therefore, hypothesise that in the proportion of income spent on ICT goods falls as income rises.

An extensive body of research in the field of ICT4D has applied the capability approach to various context including investigating the digital exclusion (Zheng & Walsham, 2008), and evaluating the impact of ICT applications on QoL (Ratan & Bailur 2007; Kivunike et al. 2011). These empirical works evidence that ICTs promotes the capabilities of individuals by widening access to information that can be used to avail educational and health services. Following the imitation of the capability approach in relevant studies, Studies 4 and 5 explore the relationship between QoL and digital inclusion (i.e. Internet access) employing a simultaneous equation model (see Section 3.2 of Study 4 for details).

1.3.3 Disability theory and the digital divide

Disability has been regarded as an integral part of the digital divide in a number of scholarly works (Mann et al. 2005). Dobransky and Hargittai (2016) have claimed that disability exacerbates exclusion by amplifying the marginalised status of PwD in several aspects of life including personal identity, health and wealth. To this end, ICT has the potential to make a difference in the daily lives of PwD by facilitating access to a number of avenues including sound health, better education and other civic services (Dobransky & Hargittai 2016). The early critical theory of disability and technology (Roulstone 1998) was influenced by the social model of disability (Barnes & Mercer 2005; Oliver & Barnes 2012). This model is extensively used to evaluate whether access to the Internet can improve social inclusion (Guo, Bricout & Huang 2005). In subsequent periods, Roulstone (2016) developed a complex model of disability and technology which underscored that the social gains and disadvantages of technology could be fully explained by comprehending the unpredictable mix of disability and technology. Following this in recent times, Goggin (2017) coined a novel theory of digital inequality to comprehend the dynamics of access, use and consumption of digital technologies among PwD. Since Studies 6 and 7 aim to trace out the underlying factors of digital exclusion among PwD, they are grounded in broader theories of social exclusion and digital inequality.

The aforementioned theories are linked with three broad themes of this thesis, namely, digital inequality, ICT and health-related QoL and the digital disability divide. A discussion on how these three broad themes are interconnected with each other will ease the understanding of how these four theories and seven sub-themes of this thesis are interlinked with each other. Studies included under Theme I (Studies 1–3) elucidates the underlying reasons for digital inequality among the Australian population. Precisely, these studies investigate the nature and extensity of inequality in digital infrastructure across Australia. By uncovering the geographic localities and Australian communities with digital disadvantage, Theme I (hereby studies included under it), points out growing concerns in ICT for development (ICT4D) research. The second strand of studies (Theme II) elaborates to what extent digital inclusion can augment QoL among Australians in general and PwD in particular. These studies (Studies 4–5) outlines what specific actions need to be undertaken to enhance ICT's positive impact on health-related QoL. To put it differently, these studies narrate the mechanism of reaping the maximum outcome from the digital dividend in terms of health-related outcomes. Theme III (Studies 5–7) continued the momentum established in the preceding studies as these studies investigate the determinants of ICT usage for health care among PwD. In other words, this strand of studies brings along Theme I and II together by studying the dynamics of the digital divide among a disadvantaged cohort of the community within the context of health care utilisation. The logical flow among these three themes is schematically portrayed in Figure 1.

1.4 Research gap

Relevant academic peer-reviewed journal articles and grey literature including reports published by government and international agencies have been used as a guiding protocol to develop the broad themes for the research undertaken this thesis. To this end, several gaps in the existing body of knowledge are yet to be explored which are listed in the following:

1. Existing studies on the digital divide are based on cross-sectional data. Hence, this evidence is not adequate to explain the changing dynamics of the digital divide in present times.
2. Though evidence on geographic digital inequality exists, studies of ICT infrastructure concentration have not been performed at the most disaggregated spatial units available. Besides, there has been a lot of room left in the field of digital inequality as the interlinkages among digital exclusion, affordability and remoteness have not been fully explored.
3. The prevailing body of literature is yet to capture longitudinal dynamics while assessing the impact of digital and social inclusion on QoL. To put it differently, the resultant findings are based on cross-sectional estimation techniques which lacks reliability and accuracy in estimating the nexus between the outcome variable and the predictors.
4. Existing studies investigating the association between the QoL and digital inclusion can be regarded as partial and incomplete as they are yet to cover the simultaneous association between QoL and digital inclusion. Furthermore, a strand of prevailing literature estimated the nexus between those two variables using a single indicator based definition of QoL or subjective well-being which may result in biased estimates.

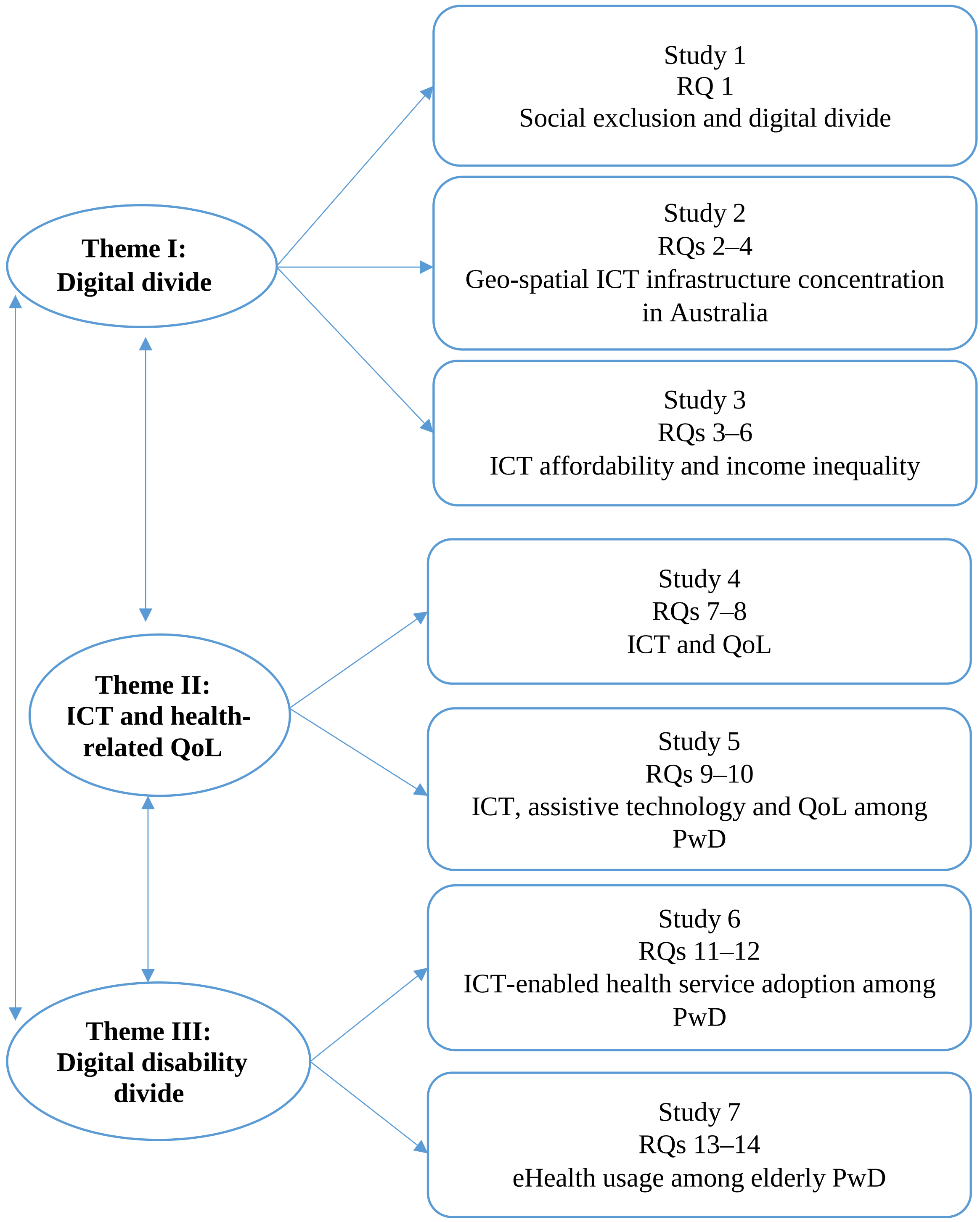

Figure 1. The interlinkages among seven studies of the thesis

5. The existing body of empirical studies is yet to discover the mediating effect of ICT on the association between assistive technology and QoL. Since PwCD have particular need for ICTs and face particular challenges in using

them, the impact of technology is unlikely to be the same as for the general population.

6. There is a high probability that narratives drawn from the digital divide literature, in general, may not be the same for digital disability divide. Because PwD represents a disadvantaged group of people who have special needs.
7. Nevertheless, factors that shape the usage of technology to make health services available among PwD and its consequences on QoL on this group should differ from that for with people with no disability or impairment.

1.5 Research aim, objectives and research questions

The broad aim of this thesis is to explore the effect of socio-demographic inequality and geo-spatial heterogeneity on digital inclusion and the extent to which digital inclusion has been able to augment QoL among general populations and PwD in Australia. To attain the central aim, this thesis sets out the following three specific objectives which corresponds to the three broad themes briefed in Chapters 2–4.

1. Investigate the underlying factors of digital inequality.
2. Examine the effect of ICT on QoL.
3. Explore the factors that promote digital health among PwD.

To achieve these objectives, the seven studies incorporated in this thesis answered the following research questions:

Study 1:

1. Do social exclusion and remoteness explain the digital divide in Australia?

Study 2:

2. Does ICT concentration vary among different spatial units?

3. Is the concentration of ICT infrastructure associated with remoteness?

4. Does the concentration of ICT access and affordability of ICT services have any correlation at the household level?

Study 3:

5. Does income distribution and socio-economic inequality have a significant impact on ICT affordability?

6. Is the effect of income distribution on ICT affordability heterogeneous in nature?

Study 4:

7. Is there any significant simultaneous causal association between digital inclusion and QoL?
8. Does social inclusion have any confounding effect on the simultaneous association between digital inclusion and QoL?

Study 5:

9. Does ICT mediate the causal association between assistive technology and QoL among people with communication disabilities?
10. Does the impact of ICT-based assistive technology on QoL vary with respect to the severity of communication impairment among PwCD?

Study 6:

11. What are the predictors of ICT-enabled health care usage among PwD?
12. Between technological or behavioural aspects, which one moderates ICT-enabled health care usage most significantly?

Study 7:

13. What factors influence eHealth usage among elderly PwD?
14. Do behavioural and attitudinal factors significantly moderate eHealth usage among elderly PwD?

1.6 Scope of the study

The aforementioned research questions are analysed using Australian datasets as the thesis is focused only on Australia. The findings and resultant policy prescriptions emanating from this research can be used as a blueprint for devising digital inclusion policies in advanced ICT user countries with a lower density of population including Australia, New Zealand and Canada. However, these findings should be generalised with great caution as it is possible that institutional, economic, and cultural differences between countries can restrict the applicability of these findings to other developed countries.

Furthermore, in this thesis, the notion of digital inclusion is defined with access to the broadband Internet. However, this may seem a narrow definition as access is only a part of digital inclusion. Several other aspects of digital inclusion including digital skills and affordability can potentially shape the penetration of the Internet. However, information on these variables is not readily available survey datasets that the studies of this thesis have used. Besides, due to the unavailability of data or lack of enough data points, it was not possible to include several relevant control variables in some of the studies included in this thesis.

To investigate the determinants of the health-related digital disability divide and its subsequent impact on QoL, the corresponding econometric exercises (Studies 5–7), grouped all PwD cohort into one group instead of disaggregating by specific disability types. A series of detailed analysis on different subgroups of PwD would provide more effective policy guidance. Apart from this, conclusions are drawn from regression estimates using cross-sectional survey data which may not be suitable to establish causal directions, unlike the longitudinal survey data.

1.7 Study design and methodology

This thesis encompasses seven empirical studies. All these studies are quantitative and based on well-recognised study designs and methodological approaches. These studies are based on advanced econometric methods and statistical techniques. The empirical studies included in this thesis used both household-level data and individual-level survey data compiled by Australians agencies. The thesis is based on three thematic pillars – 'digital divide', 'nexus between ICT and QoL' and 'digital disability divide' in the context of Australia (Figure 1).

Study 1 is based on a macro panel data estimation framework using a publicly accessible state-wide longitudinal data compiled by the ABS. This study extended the existing body of knowledge of digital divide by investigating the impact of social exclusion and remoteness on digital inclusion. Study 2 applied a cross-sectional study design to measure of geospatial distribution and concentration of ICT infrastructure. The design of Studies 3 and 4 is based on longitudinal micro panel data estimation techniques using household-level data (HILDA). Study 5 utilises a counterfactual framework-based causal mediation analysis using the most comprehensive individual level Australian survey data on disability, i.e. SDAC. Using a cross-sectional multivariate logistic regression model, Studies 6 and 7 explore the determinants of digital health usage.

1.8 Data sources and study population

The state-wide data on socio-economic and demographic indicators used in Study 1 were collated from several ABS reports. Particularly, this study used statistical reports including Household Use of Information Technology (ABS 2012, 2016c), Australian Demographic Statistics (ABS 2016b), Education and Work (ABS 2016a), Labour Force Quarterly (ABS 2017a) and Regional Population Growth (ABS 2017c). The dataset consists of 8 cross-sectional units representing eight different states and territories of Australia. These datasets cover the period of 1998–2015 which means that the strongly balanced panel data contains data for 18 reference points (i.e. years). Hence, the total number of observations is 144 (see Section 3 of Study 1 for details).

In Study 2 household level ICT access and expenditure data is used. This study used the data from Wave 15 reported of HILDA Survey Restricted Release 17 (DSS & Melbourne Institute of Applied Economic and Social Research 2017). This restricted dataset is available upon request from the Department of Social Services (DSS). The data on socio-economic advantage and disadvantage, economic resources, education and occupation, and population size of the regions are gathered from the Census of Population and Housing on SEIFA (ABS 2011). Details on the candidate variables used to construct SEIFA is outlined in the technical paper on SEIFA (2011). The data on the remoteness was compiled from the Australian Statistical Geography Standard Remoteness Structure (ABS 2010).

Study 3 of the thesis used the longitudinal data compiled from Wave 11 to Wave 17 of the HILDA Survey Restricted Release 18 (DSS & Melbourne Institute of Applied Economic and Social Research 2018). After merging the dataset, data screening and cleaning process were conducted. These processes include the identification of missing data and outliers. Stata 15 was used for the merging, cleaning and processing of the data. After a rigorous screening and cleaning of the data, the total number of useable observations stand as 38,906. This is a balanced panel of 5,558 persons across seven waves. This study uses individual-level information on age, gender, employment status and personal income. In HILDA, the ICT-related information including household ICT expenditure and access to the Internet are reported at the household level. Information on financial security and benefit were also included in the empirical model to capture the effects of the financial aspects of an individual. The household-level information was converted into individual level by matching the IDs of the households with individual level cross-wave IDs. Study 4 collated the data ranging from Wave 10 to Wave 17 reported in HILDA Survey Restricted Release 18 (DSS & Melbourne Institute of Applied Economic and Social Research 2018). The total number of observation used in that study is 26,248 which is the combination of a balanced panel of 3281 individuals across 8 Waves (see Table 1 of Study 4).

Study 5 used the ABS Microdata – Basic Confidentialised Unit Record Files (CURF)– compiled from the 2015 SDAC (ABS 2017b). The survey was executed across all states and territories encompassing all rural, urban, major cities and remote areas of Australia. The final combined sample consists of 75,211 people, including 23,343 respondents a disability. Among 23,343 PwDs, 10,866 reported that they have difficulty in communicating, and 8,515 stated that they possess at least one relevant medical condition. Thus, a cohort of 6,137 respondents was included as the sample for this study. All of them met both criteria for communication impairment (ABS 2017b). Study 6 used the same dataset. However, in this case, the whole cohort of 23,343 respondents with a disability was used. Finally, as a more updated version of SDAC data has been published, the last study of this thesis used the 2018 SDAC (ABS 2019). In 2018 SDAC, the final sample is composed of 65,487 individuals. The empirical analysis of the Study 7 was conducted using the data of 14,798 individuals who were both elderly (aged 65 years or more) and who reported having at least one disability.

Table 1. Summary facts about different studies objectives, research questions and conceptual issues

Theme	Study	Issues covered	Study design/ perspective	Estimations methods	Sources of data	Outcome variable	Explanatory variables
Theme 1: Digital divide	Study 1	Impact of social exclusion and remoteness on digital divide in Australia	Longitudinal study based on Macro panel data estimation framework	Econometric modelling: • Random effects model • Panel dynamic ordinary least squares (DOLS) model	ABS	Household with access to Internet, and household with access to computer	Age, gender imbalance, education, agricultural dependence, population density, GDP per capita and income inequality.
	Study 2	Concentration of ICT infrastructure and expenditure inequality in the disaggregated spatial unit of various locations in Australia	Cross-sectional study design based on geospatial distribution and concentration measurement	Locational concentration measure: • Location quotient (LQ) • Herfindahl–Hirschman modified (HHm) index • Relative participation (RP)	HILDA	Household ICT variables – telephone and mobile phone access, Internet access and no ICT access, and Expenditure on ICT goods and services	Geo-spatial dimensions (State, rural-urban, and remoteness), Socio-economic indexes for areas (SEIFA), and population.
	Study 3	Impact of income distribution and socio-economic inequality on ICT affordability	Longitudinal study based on micro panel data estimation framework	Econometric modelling: • Generalised linear mixed model (GLMM) • Random effects model	HILDA	Expenditure on ICT services and Index of digital affordability inclusion	Gini coefficient, SEIFA index score, household Internet access, remoteness, rural-urban divide, age, gender, employment, household composition, financial security and income support.
Theme 2: ICT and health-	Study 4	Effect of digital inclusion on QoL	Longitudinal study based on micro panel data	Econometric modelling: • Two-stage least squares (2SLS) method	HILDA	QoL and household Internet access	SEIFA decile, remoteness, rural-urban divide, age, gender, employment, long-term health

Theme	Study	Issues covered	Study design/ perspective	Estimations methods	Sources of data	Outcome variable	Explanatory variables
related QoL			estimation framework	• Full-information maximum likelihood (FIML) method			condition, life style, household composition and expenditure on ICT services.
	Study 5	Mediating Effect of ICT on the nexus between assistive technology and QoL among PwCD	Cross-sectional study based on the counterfactual causal mediation framework	Causal mediation analysis: • Parametric causal mediation regression models • Parametric mediation effects • Interaction effects analysis	SDAC	QoL	Use of assistive technology, use of ICTs for communication purpose, level of impairment, degree of discrimination, income, education, employment status, age, income support and remoteness.
Theme 3: Digital disability divide	Study 6	Predictors of ICT usage for healthcare among PwD	Cross-sectional study	• Econometric modelling: • Multivariate hierarchical regression model	SDAC	ICT-enabled health service usage	Access to ICT, health status, Health care usage, level of impairment, degree of discrimination, marital status, income, education, employment status, age, income support, ethnicity, technological and behavioural constraints.
	Study 7	Determinants of eHealth among elderly PwD	Cross-sectional study	Econometric modelling: • Multivariate logistic regression models	SDAC	eHealth usage	Access to ICT, health status, level of impairment, degree of discrimination, marital status, income, education, employment status, age, ethnicity, assistive technology use and behavioural constraints.

1.9 Structure of the thesis

Chapter one narrates the background of the study, a recap of the existing empirical literature, the gap in the existing body of knowledge, the research objectives and questions, and the theoretical underpinnings of the study.

Chapter two consists of three research papers which look into the first six research questions. The title of the first longitudinal study using ABS data is "Do social exclusion and remoteness explain the digital divide in Australia? Evidence from a panel data estimation approach". This article is published in the journal '*Economics of Innovation and New Technology*'. The second paper of this chapter titled "Measuring the concentration of information and communication technology infrastructure in Australia: Do affordability and remoteness matter?" is a cross-sectional study published in '*Socio-Economic Planning Sciences*'. This chapter ends with the third paper "Do income distribution and socio-economic inequality affect ICT affordability? Evidence from Australian household panel data' which applied a longitudinal study design and published in '*Economic Analysis and Policy*'.

Chapter three of the thesis contains two research articles. These articles correspond with research questions 7–10. The first study included in this chapter is "Does digital inclusion affect quality of life? Evidence from Australian household panel data". This article is published in '*Telematics and Informatics*'. The second article of this chapter titled "The Mediating Effect of Information and Communication Technology Usages on the Nexus Between Assistive Technology and Quality of Life Among People with Communication Disability" is a cross-sectional study and published in '*Cyberpsychology, Behaviour, and Social Networking'*.

Chapter four consists of two articles. The first article of this chapter titled "Determinants of ICT usage for healthcare among people with disabilities: The moderating role of technological and behavioural constraints" is a cohort level study published in '*Journal of Biomedical Informatics*'. The last study of the thesis titled "Examining the determinants of eHealth usage among elderly people with disability: The moderating role of behavioural aspects" is published in '*International Journal of Medical Informatics*'. A part of this study was presented in the *'Digital Health Summit,* held in September 2020 in Brisbane, Australia.

Chapter five concludes by offering concluding remarks bringing the various findings of each study together.

Chapter 2: Introductory note: Relationship between Chapter 1 and Chapter 2

Chapter 1 provided the background and motivation for the thesis, along with the research questions and objectives. Chapter 2 addresses three research gaps identified in Chapter 1, namely: (i) the nature and determinants of the digital divide within a longitudinal study design, (ii) the concentration of ICT infrastructure at the disaggregated spatial unit of locations, and (iii) the undiscovered interlinkages among affordability, socio-economic exclusion and remoteness. Chapter 2 includes three research papers (Studies 1–3), which are published in the journals *'Economics of Innovation and New Technology'*, '*Socio-Economic Planning Sciences*', and '*Economic Analysis and Policy*', respectively.

These papers are edited and formatted following the guidelines prescribed by corresponding journals. Hence, for the remainder of Chapter 2, there are two-page numbers for each page. The first relates to the published journal paper while the second one corresponds to this thesis.

Study 1

ECONOMICS OF INNOVATION AND NEW TECHNOLOGY
https://doi.org/10.1080/10438599.2019.1664708

Do social exclusion and remoteness explain the digital divide in Australia? Evidence from a panel data estimation approach

Mohammad Afshar Ali [a,b], Khorshed Alam [a] and Brad Taylor[c]

[a]School of Commerce, Faculty of Business, Education, Law & Arts, University of Southern Queensland, Toowoomba, Australia; [b]Department of Economics, Jagannath University, Dhaka, Bangladesh; [c]School of Commerce, Faculty of Business, Education, Law & Arts, University of Southern Queensland, Springfield, Australia

ABSTRACT

Despite rapid digital development in the past two decades, the remote parts of Australia still experience disadvantages with the adoption and diffusion of digital technology. As the adoption of information and communication technology continues to increase at a significant rate, investigating the underlying factors of the digital divide in general and also in the context of social exclusion in Australia is pertinent. The current study fills the gap in the existing body of knowledge by exploring the effect of socio-demographic factors and remoteness on the digital divide landscape with a country-specific focus on Australia. Using state-wide longitudinal data covering the 1998–2015 period within the panel data estimation framework, this study finds that digital divide is significantly associated with socio-demographic factors and remoteness in Australia. Moreover, the findings affirm that in addition to telecommunication infrastructure development, policymakers should also underscore socio-demographic factors in shaping digital inclusion strategies.

ARTICLE HISTORY
Received 20 July 2018
Accepted 16 July 2019

KEYWORDS
Digital divide; information and communication technology; panel data; Australia

1. Introduction

Over the past two decades, rapid development of information and communication technologies (ICTs) has led many scholars to celebrate technology's potential to augment individual capabilities by providing greater access to information, communication, and employment opportunities (Katz and Rice 2002; Norris 2001). Others have taken the more cautious view that ICTs exacerbate existing social divisions if their benefits are not shared by all members of society. As access to Internet and mobile phones becomes a pre-requisite for full participation in modern society those left without such access can be materially disadvantaged by uneven ICT development (Zappalà, Parker, and Green 2000). This gives rise to concerns about the persistence of a 'digital divide' in society.

The concept of a digital divide has evolved from a narrow definition based on physical access to the Internet and personal computers (van Dijk 2006) to a broader understanding recognising additional dimensions of digital disadvantage such as the knowledge and skills required to make effective use of ICT (Alam and Imran 2015; van Dijk 2005). This richer understanding of the digital divide complicates policy discussions; if broad physical access is a necessary but not sufficient condition for digital equality, uniformity in access can mask underlying divisions. In this regard, several

CONTACT Mohammad Afshar Ali mohammadafshar.ali@usq.edu.au School of Commerce, Faculty of Business, Education, Law & Arts, University of Southern Queensland, Toowoomba, Queensland 4350, Australia; Department of Economics, Jagannath University, Dhaka-1100, Bangladesh

studies have examined the connection between the digital divide and socio-economic factors in Australia. Park (2017) found that remoteness and high population density are associated with lower levels of Internet use. Another study confirmed that the lower level of educational attainment of many people living in rural areas exacerbates digital disadvantage (Whitacre 2010). Although these studies make important contributions, the factors underlying digital exclusion in Australia have so far only been investigated empirically with regression analysis using cross-sectional data (Curtin 2001; Park 2017; Park et al. 2015; Zappalà, Parker, and Green 2000). As we explain below, such results are potentially biased and provide less empirical traction than more sophisticated methods using panel data (Pradhan et al. 2014; Wooldridge 2010).

Another gap in the literature comes from its focus on the household, regional or global levels. This study looks at the national level using state-wide panel data and thus adds value to place-based strategic development planning (Alam et al. 2018; Alam and Imran 2015). In countries such as Australia, New Zealand and Canada, where the density of population is low, state-level aggregate data is more suitable than a more disaggregated household or regional level data in articulating policies (Baum and Christopher 2006). It is often argued that the sample size may not be representative at more disaggregated regional level (ABS 2017a; Summerfield et al. 2018). Moreover, since ICT infrastructure investment decisions are mostly made at the state and federal levels in Australia, such an analysis has considerable policy relevance in terms of where such investment ought to be directed (Thomas et al. 2016).

The digital divide remains an important area of public policy debate in Australia, as many rural areas and remote communities lag behind the major cities in terms of ICT use (Alam and Imran 2015; Park 2017). Moreover, since the digital divide is a major concern in many parts of the world, including New Zealand and Canada (ITU 2016; Ragnedda and Muschert 2013), the findings of this study will be useful for other developed countries facing similar challenges of dispersed populations and long distances between large population centres and regional cities and communities (Banks 2001; ITU 2016).

The current study investigates the factors underlying the digital divide in Australia and their interaction with other aspects of socio-demographic inequality and remoteness. To the best of the authors' knowledge, this study is the first attempt to explain the association between the digital divide, socio-demographic factors and remoteness using state-wide longitudinal data based on a panel time-series framework in Australia. It thus makes a number of significant contributions to the literature both from the empirical and theoretical point of view. Firstly, to provide a more detailed picture of remoteness, we use data for the proportion of people living in remote areas as a proxy of remoteness. Unlike the dummy variable used by Park (2017) to measure remoteness, this proxy variable is time variant and is capable of providing more detail on remoteness as it is integrated into a standard panel-data econometric framework. This is important and a novel contribution from the empirical viewpoint, since the proportion of population living in remote areas has fallen over time. Among eight states and territories, the sharpest fall has been in the Northern Territory (from 49.13% in 1998 to 41.76% in 2015). For Australia as a whole the proportion dropped from 9.12% to 7.68% over the same period (for further details, see Table A5). Secondly, compared to previous empirical studies, the panel data estimation techniques used here provide a more reliable and accurate estimate of the association between access to the Internet, socio-demographic factors and remoteness. Thirdly, by combining theory of social inclusion and cognitive theories this research also attempts to extend the existing theoretical underpinnings of digital divide research (see Section 2.2 for details).

The paper proceeds as follows: Section 2 provides a critical review of existing literature; Section 3 indicates the data sources and enlists all of the variables used in this study; Section 4 describes the econometric approach; Section 5 reports the empirical results; Section 6 provides a comparative discussion of the findings; and the final section concludes the study by pointing out its limitations, future research directions and policy implications.

2. Review of relevant literature

2.1. Theoretical framework

The concept of a digital divide is not underpinned by any particular theoretical framework. However, the concept is strongly connected to theories of social exclusion, social capital and cognitive theories (Clayton and Macdonald 2013; Ragnedda and Muschert 2013; van Dijk and Hacker 2003). Taking ICT access as the centre-piece of digital and social exclusion, the current research links these two concepts by applying theory of social capital and cognitive theories.

Digital divide cannot be analysed exclusively in economic and social terms without considering the cognitive factors (Kvasny and Keil 2006). 'Self-efficacy' is at the centre of the social cognitive theory which can be achieved by gathering knowledge by means of education and developing skills through training (Bandura 1986). In addition to that, social, demographic, economic and educational factors also have the potential to impact the likelihood of having digital access (Tsatsou 2011). Nevertheless, it is well-established that social inclusion is associated with ICT-mediated economic and social networks (Castells 2002; Livingstone and Helsper 2007). Taking these points on board, it can be claimed that enhanced accessibility to ICT can really contribute positively to the social inclusion of individuals of society. This framework assumes that various social, economic, demographic and cognitive factors play a pivotal role in narrowing the digital divide as well as shaping the foundations of social inclusion.

2.2. The digital divide in a global context

The phenomenon of the digital divide has been studied extensively in many countries from a variety of angles. A number of these studies have investigated the socio-economic determinants of the digital divide within countries and between individuals within countries. For example, studies have found that Internet use is higher among the rich, the young, and the educated (Campos, Arrazola, and de Hevia 2017; Lindblom and Räsänen 2017; Pratama 2017; Rice and Pearce 2015; Yu, Lin, and Liao 2017). Others have found evidence of a gender divide, with women less likely than men to own and use technologies (Alozie and Akpan-Obong 2017; Mumporeze and Prieler 2017; Pearce and Rice 2013). Geographically, rural and remote areas have been found to be at a disadvantage in a variety of developed countries. This disadvantage is expressed in terms of a lack of physical infrastructure, lower levels of ICT skill, and less affordable telecommunication services (Salemink, Strijker, and Bosworth 2017).

In cross-country analyses, a few studies have found that differences in ICT access and use depend on the level of national income or Gross Domestic Product (GDP) (Billon, Marco, and Lera-Lopez 2009, 2017; Rice and Pearce 2015; Ünver 2017). If we consider these socioeconomic, demographic, and geographic determinants of digital disadvantage together, it becomes clear that the digital divide is complex and multi-faceted (Park et al. 2015; Park and Kim 2015). This has motivated scholarly work aimed at building composite measures of digital inclusion, exclusion and concentration. For instance, Hüsing and Selhofer (2002) developed a 'Digital Divide Index.' There are, of course, serious challenges in measuring the digital divide in this way (Vehovar et al. 2006). Several others have proposed simpler measurements such as the Gini coefficient of ICT access and expenditure (Albuja et al. 2015; Vehovar et al. 2006).

2.3. The digital divide in Australia

Relatively few studies have explored the nature and extent of the digital divide in Australia. The first such detailed study comes from Curtin (2001), who demonstrates the digital divide in rural and regional Australia is mediated by individual literacy, education, and income. Alam and Imran (2015) investigated the factors that affect the adoption of ICTs by refugee migrants in Australia and found three key determinants: (i) unevenness in material access to ICTs, (ii) the educational requirements necessary to use ICT effectively, and (iii) the financial capacity to pay for the services.

Several studies with a regional focus have investigated the notion of digital divide in Australia. The case studies conducted by Park et al. (2015) on seven rural local government areas in New South Wales confirmed that rural digital inequality was a consequence of a multi-layered divide consisting of three interconnected dimensions – infrastructure, connectivity and digital engagement. A case study done by Hodge et al. (2017) on a small town in South Australia asserted that the lack of digital skills, as well as organisational and funding restraints, limited the digital engagement of older citizens.

By far, the most influential study of the digital divide in Australia is the seminal work of Park (2017). The author focused in particular on remoteness as an indicator of digital exclusion and investigated its association with socio-economic dimensions of social exclusion. Using secondary data, the author found that proximity to major cities appeared as a strong predictor of home Internet and broadband connectivity. In addition, the digital divide was deepened by other socio-demographic factors, such as differences in education and employment status. Although Park (2017) significantly advances our understanding of the digital divide in Australia, the study has a number of methodological limitations. Firstly, dummy variables for five remote areas are used as proxies for remoteness. These dummies were based on a remoteness index – Accessibility/Remoteness Index of Australia Plus (ARIA+), developed by the Australian Population and Migration Research Centre (ABS 2010). The index ranges from 0 to 15 based on road distance measurements. The five corresponding areas were Major Cities, Inner Regional, Outer Regional, Remote and Very Remote. These dummy variables are time-invariant and thus cannot capture the time dimension of remoteness. A further limitation of Park's (2017) analysis comes from the use of an OLS-based regression model, which can produce misleading estimates because of poor extrapolation properties and sensitivity to outliers. OLS or pooled-OLS estimates based on cross-sectional or time-series data ignore the panel structure of the data when estimating the regression coefficients. Moreover, the standard diagnostic tests (e.g. multicollinearity, heteroscedasticity and auto-correlation) based on those estimates lack validity (Wooldridge 2010). Other studies have for the most part also used OLS or related models based on cross-sectional or time-series data (see Table A1 for an outline of selected empirical studies).

This study, on the other hand, uses panel data. By combining variance over time with variance among individuals, this has several advantages over cross-sectional or time-series data: (i) it accounts for individual heterogeneity by allowing the flexibility to control for variables that are not observed or measured; (ii) in contrast to cross-sectional data, panel data usually possess more degrees of freedom and more sample variability; and (iii) it has the potential to generate more accurate predictions for individual outcomes by pooling the data instead of making predictions using data at the individual level (Hsiao 2007).

3. Variables and sources of data

This study aims to explore a network of relationships at the state level by focusing on five socio-demographic variables (median age, gender imbalance, level of education, agricultural dependence, and population density), two economic variables (GDP per capita and income inequality measured by the Gini coefficient), and one spatial variable (remoteness). Remoteness represents the proportion of people living in Remote and Very Remote areas, which is based on the remoteness index of ARIA+. The selection of the variables was based on the existing literature (see Section 2.2 and Appendix Table A1 for details). The data were collected from several Australian Bureau of Statistics reports for the six states and two mainland territories of Australia from 1998 to 2015. The reports used in this study includes Household Use of Information Technology (ABS 2012, 2016c), Australian Demographic Statistics (ABS 2016a), Education and Work (ABS 2016b), Labour Force Quarterly (ABS 2017b) and Regional Population Growth (ABS 2017c). These datasets contain eight cross-sectional units which represent eight different states and territories of Australia. These datasets span over the period of 1998–2015, that is, the panel data contains data for 18 years for eight states and territories. Thus, the total number of observations is 144, and the panel dataset is strongly balanced.

All variables other than median age, Gini coefficient and GDP per capita are expressed in percentage form so as to exhibit less volatility. Appendix Table A2 provides the summary statistics (in the panel dimension) of the variables used in the study. The descriptive statistics demonstrate that regional disparities emerge in terms of access to the Internet and access to computer at the household level. Specifically, access is notably limited in South Australia and Tasmania, both in terms of Internet and computer access. However, in all cases ICT access has very substantially increased over the study period.

As a part of the diagnostic check, the variance inflation factor has been used to detect multicollinearity. These VIFs are obtained after computing the OLS-based estimations based on Equations (3) and (4). The VIFs of the explanatory variables used in the study ranged from 1.42 to 8.84. The rule of thumb is that multicollinearity among explanatory variable is said to exist if VIF is10 or higher (Hair et al. 1995). In this regard, the correlation matrix using all the variables used in the estimation is presented in Appendix Table A3. These correlation statistics demonstrate that the degree of correlation between explanatory variables is below 0.50, suggesting that the degree of multicollinearity present in current model is not a serious problem.

4. Econometric approach

To investigate causation, several panel data estimation techniques are employed in this study. A major advantage of such methods is that, by considering the country-specific fixed effect, these methods control the individual time series and cross-sectional variations in the data and are able to address the biases related to cross-sectional regressions (Baum and Christopher 2006). The panel data models are estimated by following three systematic steps detailed below.

4.1. Panel data unit root test

An important first step in time-series analysis is to check the stationarity, a key requirement for many time-series methods. A series is stationary if its probability distribution does not change when shifted in time. Any aggregate trend in the series will therefore violate stationarity. The Levine–Lin–Chu (LLC), Breitung, ADF and PP tests are used to investigate whether a series is stationary or not. The justification behind choosing the LLC and Breitung unit root tests is that the panel data used in the analysis are strongly balanced. In addition, ADF and PP unit root tests are commonly used in this regard. The LLC (Levin, Lin, and James Chu 2002) and Breitung methods (Breitung 2000) are used to check the order of integration to detect whether the time series variables attain stationarity. The LLC and Breitung methods are established on the principles of the conventional augmented Dickey–Fuller (ADF) test and are applied by averaging individual ADF t-statistics across the cross-section units. The test is based on the following estimation strategy:

$$\Delta Y_T = \mu_t + \curlyvee_i Y_{it-1} + \sum_{j=1}^{p_i} \beta_{ii} Y_{it-j} + \lambda_i t + \varepsilon_{it} \tag{1}$$

where $i = 1,2 \ldots N$; $t = 1, 2 \ldots T$; Y_{it} denotes the series for state i in the panel over period t; p_i is the number of lags selected for the ADF regression; Δ indicates the first difference filter *(I-L)* and ε_{it} refers to independently and normally distributed random variables for all i and t with zero means and finite heterogeneous variances (σ_i^2).

The LLC test assumes that the coefficients of the auto-regressive term are homogenous across all individual cross-sectional units; hence, $\curlyvee_i = \curlyvee \forall i$. The null hypothesis in the LLC test is assumed as each individual in the panel having an integrated time series, to put it differently, H_0: $\curlyvee_i = \curlyvee = 0\ \forall i$ against the alternative hypothesis: H_A: $\curlyvee_i = \curlyvee < 0\ \forall i$. The LLC test considers pooling the cross-section time-series data. The test is based on the following t-statistic:

$$t_y^* = \frac{\hat{y}}{s.e.\,(\hat{y})} \tag{2}$$

In the LLC test, under the null and alternative hypotheses, $\hat{y}$ is constrained by being kept identical across regions. The LLC test primarily fits a regression model and then adjusts the auto-regressive parameter or its t-statistic to compensate the bias arising from having a dynamic regressor and fixed effects in the model. On the contrary, the Breitung test makes an adjustment in the data prior to fitting a regression model to avoid bias adjustments. In the LLC test, the additional lags of the regression could be incorporated in Equation (1) to control for auto-correlation. However, the Breitung method allows for a pre-whitening of the variables prior to implementing the test. On the basis of the Monte Carlo simulation results, the Breitung test exhibits much higher power than the LLC test in terms of bias-corrected statistics (Breitung 2000). In addition, the Breitung test has good power even in the case of a small sample size.

4.2. Panel data cointegration test

The concept of cointegration, introduced by Granger (1969), is a response to the problem of spurious regression in time-series analysis resulting from non-stationarity. Two non-stationary variables can show statistically significant correlation even when there is no meaningful long-term relationship between them. A cointegration test postulates that, if the variation between two non-stationary series is itself stationary, the two series are cointegrated and there is a long-term relationship at play. Cointegration identifies the extent to which two variables are sensitive to the average value of the same factor over a specific period of time. Thus, if the distance between variables remains constant over time, there is a cointegrating relationship and we conclude that the correlation is genuine. If, on the other hand, variation significantly changes over time there is no cointegrating relationship and we conclude that the correlation is spurious (Engle and Granger 2015). We use the method of Pedroni (2004) to check for cointegration.

4.3. Panel data models

Two estimation techniques have been used to estimate the baseline model: (i) a random effects model and (ii) a panel dynamic ordinary least squares (DOLS) model.

4.3.1. Random effects model

In random effects estimation model, an entity's error term is assumed not to be correlated with the explanatory variables, allowing time-invariant variables (in our case, gender imbalance) to play a role as predictors. The justification for using a random effects model as opposed to a fixed effects model is that the differences across entities are assumed to be random and uncorrelated with the predictor or independent variables included in the model (Greene 2008).

The model of the random effects for our case is as follows:

$$Y_{it} = \alpha + \beta_i X_{it} + u_{it} + \varepsilon_{it} \tag{3}$$

where Y_{it} refers to the ICT access variables, i.e. HHINT (household with access to Internet) and HHCOM (household with access to computer), X_{it} is the 8×1 vector of regressors: FEMALE (% of female population), MEDAGE (median age), BACHELOR (% of population with a bachelor degree), GINI (Gini coefficient of income), AGRI (proportion of population dependent upon agriculture sector), POPDEN (density of population per square kilometre), REMOTE (proportion of population residing in remote areas) and Ln GDPPC (natural logarithm of GDP per capita), u_{it} and ε_{it} are between and within-entity errors, respectively.

4.3.2. Panel DOLS model

OLS is used to estimate the panel cointegration vectors; however, the estimator can potentially be biased and inconsistent. Therefore, the panel dynamic ordinary least squares (DOLS) estimator has been used in this study, which allows the consideration of the autocorrelation and endogeneity of the regressors (Phillips and Moon 1999). The model of the DOLS is as follows:

$$Y_{it} = \alpha + \beta_i X_{it} + u_{it} \tag{4}$$

$$X_{it} = X_{it-1} + v_{it} \tag{5}$$

where Y_{it} is refers to the ICT access variables, i.e. HHINT and HHCOM, X_{it} is the 8×1 vector of regressors – FEMALE, MEDAGE, BACHELOR, GINI, AGRI, POPDEN, REMOTE and Ln GDPPC. u_{it} and v_{it} are the errors in respective equations.

In addition to random effects and panel DOLS, feasible generalised least squares (FGLS) is used to cross check the results obtained from baseline estimations. This is widely used to estimate the coefficients of a regression model holding the zero-conditional mean assumption intact. The FGLS estimator is a special case of the GLS estimation where the errors are unknown (non-i.i.d.). Given that Σ_u is unknown, the estimator is infeasible. FGLS assumes a structure which describes how the errors deviate from i.i.d. errors. With such an assumption, Σ_u can be estimated consistently. Any consistent estimator of Σ_u can be used to convert the data to generate observations with i.i.d. errors. For details, see Baum and Christopher (2006).

5. Empirical results

The empirical results are reported in three stages: the nature of the stationarity of the panel time series variables; the nature of cointegration among them and the evidence of the association between the ICT access, socio-demographic variables, and remoteness.

5.1. Results of the panel unit root tests

The results of the unit root tests at level are reported in Appendix Table A4. All of the variables are stationary at a significance level of 5% according to the LLC statistics at level with intercept and time trend. However, statistics generated by the Breitung, ADF and PP tests indicate that most of them are non-stationary at a significance level of 5%. The initial differences of the series are analysed by the unit root tests to examine whether the series are stationary at the primary level. Table 1 presents the results. As is evident in the table, all of the series become stationary once they are differenced at order 1.

5.2. Results of panel cointegration test

As the results in Appendix Table A4 and Table 1 indicate that all of the series are stationary at order 1, the cointegrating relationships among the series can be analysed. To do so, the Pedroni (2004) panel cointegration analyses is used as this test is the recommended cointegration tests for panel data. Equation (1) is used in the cointegration analysis. In this case, HHINT and HHCOM are the dependent variables measuring the digital divide, whereas FEMALE, MEDAGE, BACHELOR, AGRI, POPDEN, REMOTE and Ln GDPPC are the independent variables. The results of the Pedroni panel cointegration analysis are reported in Table 2.

Taking HHINT and HHCOM as the dependent variables, Panel PP-statistic, Panel ADF-statistic, Group PP-statistic and Group ADF-statistic affirm that all the variables are cointegrated with intercept and trend at a significance level of 5% for both cases. Therefore, these results suggest that a cointegrating relationship exists between the digital divide on one hand and remoteness, income inequality and the socio-demographic variables on the other. The existence of stationarity at order 1, i.e. I(1), and

Table 1. Unit root tests results at first difference.

Variable		LLC		Breitung		ADF		PP	
		Case 1	Case 2	Case 1	Case 2	Case 1	Case 2	Case 1	Case 2
HHINT	Stat.	−4.232*	−2.948*	−3.308*	−5.863*	2.558*	2.574*	10.141*	18.441
	Prob.	0.000	0.002	0.001	0.000	0.005	0.005	0.000	0.000
HHCOM	Stat.	−5.323*	−4.328*	−4.848*	−5.225*	71.745*	46.809*	125.230*	94.168*
	Prob.	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
FEMALE	Stat.	−3.766*	−2.994*	−2.782*	−2.653*	2.460*	2.370*	3.095*	1.358
	Prob.	0.000	0.001	0.002	0.004	0.006	0.007	0.001	0.087***
MEDAGE	Stat.	−2.540*	−1.228*	−1.583**	−1.618	11.434*	3.3062*	2.955*	1.488
	Prob.	0.005	0.109	0.056	0.052***	0.000	0.001	0.002	0.068***
BACHELOR	Stat.	−7.828*	−6.218*	−8.377*	−4.245*	21.238*	16.053*	37.860*	31.245
	Prob.	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
GINI	Stat.	−37.670*	−26.693*	−0.282	−1.629***	120.278*	135.833*	332.279*	341.154*
	Prob.	0.000	0.000	0.389	0.051	0.000	0.000	0.000	0.000
AGRI	Stat.	−4.733*	−3.357*	−5.157*	−4.809*	9.517*	4.555*	32.987*	25.848*
	Prob.	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
POPDEN	Stat.	−2.030**	−2.670*	−1.344***	−2.065	22.545	27.112 ***	1.289***	1.380***
	Prob.	0.021	0.003	0.089	0.019**	0.126	0.040	0.098	0.083
REMOTE	Stat.	−8.928*	3-9.861*	−5.266*	−1.945**	13.374*	12.623*	3.454*	1.742
	Prob.	0.000	0.000	0.000	0.025	0.000	0.000	0.000	0.041
Ln GDPPC	Stat.	−4.013*	−3.565*	−3.222*	−3.122*	50.904*	34.959*	83.893*	67.929*
	Prob.	0.000	0.000	0.001	0.001	0.000	0.004	0.000	0.000

Note 1: LLC: Levin, Lin & Chu adjusted t* statistics; Breitung lambda statistics, ADF: Augmented Dickey-Fuller modified inverse chi-squared Pm statistics; PP: Phillips-Perron modified inverse chi-squared Pm statistics.
Note 2: Case 1: Unit root with intercept only; Case 2: Unit root with both intercept and trend.
Note 3: *, ** and *** denote statistically significant at 1%, 5% and 10% respectively.

Table 2. Results of the Pedroni panel cointegration tests.

	(a) HHINT				(b) HHCOM			
	Case 1		Case 2		Case 1		Case 2	
Test Statistics	Stat.		Prob.		Stat.		Prob.	
Panel v-Statistic	−1.211	0.887	−0.621	0.733	−1.852	0.968	−2.980	0.999
Panel rho-Statistic	1.647	0.950	1.936	0.974	1.452	0.927	2.404	0.992
Panel PP-Statistic	−2.815*	0.002	−7.001*	0.000	−7.895*	0.000	−8.575*	0.000
Panel ADF-Statistic	−2.557*	0.005	−6.114	0.004	−2.031**	0.021	−1.954**	0.025
Group rho-Statistic	2.640	0.996	2.937	0.998	2.790	0.997	3.706	1.000
Group PP-Statistic	−6.914*	0.000	−9.999*	0.000	−11.076*	0.000	−11.078*	0.000
Group ADF-Statistic	−6.904*	0.008	−9.154*	0.009	−2.003**	0.023	−1.780**	0.038

Note 1: Case 1: Cointegration with intercept only; and Case 2: Cointegration with both intercept and trend.
Note 2: *, ** and *** denotes statistically significant at 1%, 5% and 10% respectively.

cointegration of the variables indicate the possibility of non-spurious association among those variables.

5.3. Results of panel data models

5.3.1. Results of baseline estimations

Table 3 exhibits the estimation results based on the baseline panel data models using random effects (RE) and DOLS estimation for both ICT endowment variables.[1] The figures reported in panel (a) indicate the regression coefficient estimates of Equation (3) considering HHINT as the dependent variable, while the estimates reported in panel (b) represent the regression coefficient estimates of Equation (4) taking HHCOM as the dependent variable. The results show that age and educational qualification are statistically significant and positive in both cases. Meanwhile, the share of female population has a negative impact on HHINT and HHCOM. In sum, the demographic composition of different states substantially shapes the extent of digital divide. Further, dependence on the agricultural sector (AGRI) and the density of population are affirmed to be negatively associated with ICT access variables in most of the cases. Moreover, although the coefficients of remoteness and income inequality demonstrate negative signs, these estimates are not statistically significant, except in one case.

5.3.2. Robustness checks

Table 4 exhibits the results of robustness checks. These estimations are based on FGLS using the same baseline models. Two models are estimated, where the first one considers HHINT as the dependent

Table 3. Estimation results of baseline estimation of digital divide.

	(a) HHINT				(b) HHCOM			
	RE		DOLS		RE		DOLS	
Independent variable	Coef.	Robust SE	Coef.	Robust SE	Coef.	Robust SE	Robust Coef.	Robust SE
FEMALE	−12.741**	5.427	−20.022*	4.390	−10.070*	3.364	−18.903*	2.994
MEDAGE	4.472*	1.332	3.215*	1.211	3.356*	0.428	2.634*	0.826
BACHELOR	3.979*	0.382	2.723*	0.532	2.815*	0.188	2.382*	0.363
GINI	7.997	37.476	−38.713	43.361	4.880	23.055	−54.100***	29.577
AGRI	−11.026***	5.864	−7.269	6.286	−8.561*	1.626	−7.476***	4.288
POPDEN	−0.331***	0.101	−0.125	0.213	−0.229*	0.045	−0.015	0.145
REMOTE	−0.201	0.434	−1.472***	1.191	−0.206	0.169	−1.071***	0.812
Ln GDPPC	1.877	2.836	1.041	12.044	1.511	0.950	0.223	8.215
No. of observations	144		144		144		144	
No. of groups	8		8		8		8	
R-squared	0.859		0.916		0.850		0.889	

Note 1:*, ** and *** denote statistically significant at 1%, 5% and 10% respectively.
Note 2: Ceff.: Coefficient, Robust SE: Robust standard error.

Table 4. Robustness checks of digital divide using FGLS.

Independent variable	(a) HHINT Coef.	SE	(b) HHCOM Coef.	SE
FEMALE	−12.741*	4.303	−10.070*	3.257
MEDAGE	4.473*	0.548	3.356*	0.415
BACHELOR	3.979*	0.240	2.815*	0.182
GINI	7.998	29.491	4.880	22.323
AGRI	−11.026*	2.080	−8.561*	1.575
POPDEN	−0.331*	0.058	−0.229*	0.044
REMOTE	−0.201***	0.217	−0.206***	0.164
Ln GDPPC	1.877***	1.215	1.511***	0.919
No. of observations	144		144	
No. of groups	8		8	

Note 1:*, ** and *** denote statistically significant at 1%, 5% and 10% respectively.
Note 2: Ceff.: Coefficient, Robust SE: Robust standard error.

variable and the second one considers HHCOM as a proxy of ICT access. For simplicity, Heteroscedasticity and Autocorrelation Consistent (HAC) FGLS estimates are reported in Table 4. The industry fixed effect model controls potential industry effects. Moreover, the estimations resulting from robust models for both panels reconfirm that socio-demographic factors have a significant impact on ICT access. Akin to the main result, FGLS estimation also shows that dependence on the agricultural sector and remoteness negatively are associated with HHINT and HHCOM. However, the results elucidate that income inequality have no significant association with ICT access in both cases (Table 4).

6. Discussion

The state level panel data analysis conducted here adds to our knowledge of the digital divide in several respects. First, the greater statistical power and robustness of the methods employed in this study provide confirmation that a number of the findings in the existing literature remain true at the state level. Consistent with the findings of Park (2017) and Park et al. (2015) we find that educational attainment positively impacts ICT use. The negative impacts of reliance on agriculture, population density, and remoteness further confirm the results of previous studies. Interestingly, median age has a positive impact on ICT use at the state level, contrary to the findings of Park (2017), Nishijima, Ivanauskas, and Sarti (2017), and Duplaga (2017) at lower levels of geographic disaggregation. There is strong evidence from past studies that older individuals tend to be digitally disadvantaged, but the same cannot be said for states with higher median age.

Although income inequality shows a negative impact on ICT access, this association is statistically insignificant in most cases. Similarly, GDP per capita is also found to have an insignificant impact on both Internet and computer access. Therefore, for both economic variables – income inequality and GDP per capita, these results are inconclusive. At the state level at least, it appear economic factors are less important than demographic and spatial ones. Again, we know based on past research that higher incomes increase ICT access at the individual level, but our results do not materially support the proposition that high-income states have a digital advantage over low-income ones.

Changes in these variables over time are shown in Appendix Table A5. Over the period of 1998–2015, the average values of both dependent variables – access to household Internet and access to computer – across all the states have increased from 45.00% to 97.97% and from 16.00% to 86.63%, respectively. Over the same period of time, average median age across all the states and territories increases from 33.88 to 37.49 and the proportion of population with a bachelor degree rose from and 18.92% to 28.74%. Likewise, the panel data estimates, over-time changes in the proportion of population in agriculture sector have demonstrated a declining trend – dipped from 0.28% in 1998 to 0.13% in 2015. The over-time variations in proportion of population living in remote areas (from 9.12% in 1998 to 7.68% in 2015) are also in accord with the quantitative findings derived from panel data. It is also noticeable that the extensity of digital divide in remote areas has dropped significantly over the period of 1998–2015. To be specific, in remote areas, access to household Internet and access to computer have increased from 10.00% to 79.40% and from 38.00% to 75.20%, respectively (ABS 2016c). However, it is evident from Appendix Table A2 and A5 that the dynamics of digital inclusion in remote areas yet to catch up the national par.

The present investigation is not without limitations. Firstly, the simple and dichotomous measure of ICT access used here – either an individual has access to Internet and computers or not – is relatively crude and does not capture other dimensions such as quality and affordability which we know to be important (Baller, Dutta, and Lanvin 2016; Lyons, Morgenroth, and Tol 2013). However, given that Australia's fixed-line broadband penetration is still one of the lowest among developed countries we know that simple access remains a problem, particularly in rural areas. A related limitation is the focus on fixed-line Internet access only. Australia's fixed-line broadband penetration has not increased as much as mobile broadband penetration. More generally, the digital divide is characterised by differences in the extent and variety of device and Internet usage rather than binary differences in access (Pearce and Rice 2013). Secondly, in some cases, the selection of variables to conduct an econometric analysis is data-driven. Data limitations prevent the inclusion of many other potential control variables, including household income, size of the households, employment status, migration flows, infrastructure quality, mobile Internet usage, and telecommunication policy/market factors. Inclusion of these variables could reduce the explanatory power of some variables. Finally, the highly aggregated nature of state-level data makes it suitable for some policy questions but quite unsuited to others. In this respect the more disaggregated study by Park (2017) provides a more fine-grained picture of digital exclusion in local communities. Since digital technologies advance rapidly it can be difficult for socio-economically disadvantaged or otherwise marginalised groups to keep up the pace with their counterparts. Gender, ethnicity, employment status, and a variety of other factors we cannot adequately capture at the state level are important drivers of digital disadvantage (Alam and Mamun 2017; Alozie and Akpan-Obong 2017; Campos, Arrazola, and de Hevia 2017; Lindblom and Räsänen 2017; Mumporeze and Prieler 2017; Yu, Lin, and Liao 2017). Further research on smaller, targeted disadvantaged groups would be valuable here, as would more disaggregated studies using the more reliable statistical techniques employed in this study. Data availability is the main barrier to further work in this direction.

7. Conclusion

This study investigates the effect of social exclusion and remoteness on the digital divide in Australia. The results of the panel data estimation framework evinced that statistically significant associations exist between socio-demographic variables, remoteness, and the digital divide. States highly dependent on agriculture, with significant remote populations, with a low proportion of university graduates, and with high population density are at a digital disadvantage. However, it appears that state level income per capita and income inequality do not have a significant effect. Many of these findings are consistent with previous work on the digital divide in Australia and elsewhere, but the more robust and detailed statistical methods we employ here add clarity and reliability to these findings. In particular, our measure of remoteness provides greater detail than previous studies, the use of panel data allows us to overcome the shortcomings of OLS-based models, and the cointegration test shows that the relationships we find are not spurious. The relative unimportance of economic factors at the state level is also an interesting finding worthy of further investigation.

The policy implications of these findings are significant and straightforward. The results affirm that a series of associations exist at the state level between Internet access, remoteness, and a variety of demographic variables. The increased penetration of ICT is a necessary condition for shaping digital inclusion strategies, but not a sufficient one. To deal with the digital divide in Australia and other countries facing similar geographic and demographic challenges such as Canada and New Zealand, policymakers must look beyond economic capacity and infrastructure development to consider how the socio-demographic factors explain patterns of digital inclusion and exclusion. Access to ICTs and the skills and knowledge required to make use of them are becoming increasingly important requirements for individuals wishing to fully participate in economic, social, and cultural life. Measures to address the digital divide therefore go well beyond the narrow confines of technology policy and must form an important part of Australia's strategy for regional economic and social development.

Note

1. The Hausman test was conducted to decide whether to use fixed or random effects models. The Chi-square statistics obtained from Hausman test for Equation (5) and (6) are 1.72 and 1.12, respectively. In both cases, the *p*-value is greater than 5% which indicates that the null hypothesis assuming that the difference in coefficients is not systematic, thus it cannot be rejected. Therefore, random effects are preferred over fixed effects.

Acknowledgements

The paper is a part the PhD study of the first author. The PhD program was funded by the University of Southern Queensland, Australia [USQ International Stipend Research Scholarship & USQ International Fees Research Scholarship].

Disclosure statement

No potential conflict of interest was reported by the authors.

ORCID

Mohammad Afshar Ali http://orcid.org/0000-0002-0831-9046
Khorshed Alam http://orcid.org/0000-0003-2232-0745

References

ABS. 2010. *Australian Statistical Geography Standard, Volume 1 – Main Structure and Greater Capital City Statistical Areas.Catalogue Number 1270.0.55.001*. Accessed from Canberra.

ABS. 2012. *Household Use of Information Technology. Catalogue Number 8146.0*.

ABS. 2016a. *Australian Demographic Statistics. Catalogue Number 3101.0*.

ABS. 2016b. *Education and Work. Catalogue Number 6227.0*.

ABS. 2016c. *Household Use of Information Technology. Catalogue Number 8146.0*, Canberra.

ABS. 2017a. *ABS Confidentiality Series, Aug 2017*. https://www.abs.gov.au/AUSSTATS/abs@.nsf/Lookup/1160.0Main+Features1Aug%202017?OpenDocument.

ABS. 2017b. *Labour Force, Australia, Detailed, Quarterly. Catalogue Number 6291.0.55.003*.

ABS. 2017c. *Regional Population Growth. Catalogue Number 3218.0*.

Alam, K., M. O. Erdiaw-Kwasie, M. Shahiduzzaman, and B. Ryan. 2018. "Assessing Regional Digital Competence: Digital Futures and Strategic Planning Implications." *Journal of Rural Studies* 60: 60–69.

Alam, K., and S. Imran. 2015. "The Digital Divide and Social Inclusion among Refugee Migrants." *Information Technology and People* 28 (2): 344–365.

Alam, K., and S. A. K. Mamun. 2017. "Access to Broadband Internet and Labour Force Outcomes: A Case Study of the Western Downs Region, Queensland." *Telematics and Informatics* 34 (4): 73–84.

Albuja, J., A. Navas, D. Paguay, A. Moreno, and P. Nájera. 2015. "Technological GINI: A Study of the Inequality in Ecuador." Paper presented at the 2015 2nd international conference on eDemocracy and eGovernment, Quito, Ecuador, April 2015.

Alozie, N. O., and P. Akpan-Obong. 2017. "The Digital Gender Divide: Confronting Obstacles to Women's Development in Africa." *Development Policy Review* 35 (2): 137–160.

Baller, S., S. Dutta, and B. Lanvin. 2016. "The Global Information Technology Report 2016." Paper presented at the World Economic Forum, Geneva.

Bandura, A. 1986. *Social Foundations of Thought and Action (Vol. 1986)*. Englewood Cliffs, NJ: Prentice-Hall.

Banks, G. 2001. "The Role of ICT in Australia's Economic Performance." https://www.pc.gov.au/news-media/speeches/cs20010926/cs20010926.pdf.

Baum, C. F., and F. Christopher. 2006. *An Introduction to Modern Econometrics Using Stata*. College Station, TX: Stata Press.
Billon, M., R. Marco, and F. Lera-Lopez. 2009. "Disparities in ICT Adoption: A Multidimensional Approach to Study the Cross-Country Digital Divide." *Telecommunications Policy* 33 (10-11): 596–610.
Billon, M., R. Marco, and F. Lera-Lopez. 2017. "Innovation and ICT use by Firms and Households in the EU." *Information Technology & People* 30 (2): 424–448.
Breitung, J. 2000. "The Local Power of Some Unit Root Tests for Panel Data." In *Nonstationary Panels, Panel Cointegration, and Dynamic Panels*, 161–177. Amsterdam: Elsevier.
Campos, R., M. Arrazola, and J. de Hevia. 2017. "Economic Crisis and Benefits of the Internet: Differentiated Internet Usage by Employment Status." *Economics of Innovation and New Technology* 26 (3): 269–294.
Castells, M. 2002. *The Internet Galaxy: Reflections on the Internet, Business, and Society*. Oxford: Oxford University Press.
Clayton, J., and S. J. Macdonald. 2013. "The Limits of Technology." *Information, Communication & Society* 16 (6): 945–966.
Curtin, J. 2001. "A Digital Divide in Rural and Regional Australia." *Information and Research Services*, *Department of the Parliament Library*. (Current issues brief 1).
Duplaga, M. 2017. "Digital Divide among People with Disabilities: Analysis of Data From a Nationwide Study for Determinants of Internet Use and Activities Performed Online." *PLoS ONE* 12 (6): e0179825.
Engle, R. F., and C. W. J. Granger. 2015. "Co-integration and Error Correction: Representation, Estimation, and Testing." *Applied Econometrics* 39 (3): 107–135.
Granger, C. W. J. 1969. "Investigating Causal Relations by Econometric Models and Cross-Spectral Methods." *Econometrica* 37 (3): 424–438.
Greene, W. H. 2008. *Econometric Analysis*. 6th ed. Upper Saddle River, NJ: Prentice Hall.
Hair, J. F. J., R. E. Anderson, R. L. Tatham, and W. C. Black. 1995. *Multivariate Data Analysis*. 3rd ed. New York: Macmillan.
Hodge, H., D. Carson, D. Carson, L. Newman, and J. Garrett. 2017. "Using Internet Technologies in Rural Communities to Access Services: The Views of Older People and Service Providers." *Journal of Rural Studies* 54: 469–478.
Hsiao, C. 2007. "Panel Data Analysis—Advantages and Challenges." *Test* 16 (1): 1–22.
Hüsing, T., and H. Selhofer. 2002. "The Digital Divide Index-A Measure of Social Inequalities in the Adoption of ICT." European Conference on Information Systems 2002, Gdansk, Poland (pp. 1273–1286).
ITU. 2016. *Measuring the Information Society Report 2016*. Geneva, Switzerland. https://www.itu.int/en/ITU-D/Statistics/Documents/publications/misr2016/MISR2016-w4.pdf.
Katz, J. E., and R. E. Rice. 2002. *Social Consequences of Internet use: Access, Involvement, and Interaction*. Cambridge: MIT Press.
Kvasny, L., and M. Keil. 2006. "The Challenges of Redressing the Digital Divide: A Tale of two US Cities." *Information Systems Journal* 16 (1): 23–53.
Levin, A., C.-F. Lin, and C.-S. James Chu. 2002. "Unit Root Tests in Panel Data: Asymptotic and Finite-Sample Properties." *Journal of Econometrics* 108 (1): 1–24.
Lindblom, T., and P. Räsänen. 2017. "Between Class and Status? Examining the Digital Divide in Finland, the United Kingdom, and Greece." *The Information Society* 33 (3): 147–158.
Livingstone, S., and E. Helsper. 2007. "Gradations in Digital Inclusion: Children, Young People and the Digital Divide." *New Media and Society* 9 (4): 671–696.
Lyons, S., E. Morgenroth, and R. S. J. Tol. 2013. "Estimating the Value of Lost Telecoms Connectivity." *Electronic Commerce Research and Applications* 12 (1): 40–51.
Mumporeze, N., and M. Prieler. 2017. "Gender Digital Divide in Rwanda: A Qualitative Analysis of Socioeconomic Factors." *Telematics and Informatics* 34 (7): 1285–1293.
Nishijima, M., T. M. Ivanauskas, and F. M. Sarti. 2017. "Evolution and Determinants of Digital Divide in Brazil (2005–2013)." *Telecommunications Policy* 41 (1): 12–24.
Norris, P. 2001. *Digital Divide: Civic Engagement, Information Poverty, and the Internet Worldwide*. Cambridge: Cambridge University Press.
Park, S. 2017. "Digital Inequalities in Rural Australia: A Double Jeopardy of Remoteness and Social Exclusion." *Journal of Rural Studies* 54: 399–407.
Park, S., J. Freeman, C. Middleton, M. Allen, R. Eckermann, and R. Everson. 2015. "The Multi-layers of Digital Exclusion in Rural Australia." Paper Presented at the Proceedings of the Annual Hawaii International Conference on System Sciences, Hawaii, USA.
Park, S., and G. Kim. 2015. "Same Access, Different Uses, and the Persistent Digital Divide Between Urban and Rural Internet Users." Paper Presented at the TPRC 43rd Research Conference on Communications, Information and Internet Policy, Arlington, VA, USA.
Pearce, K. E., and R. E. Rice. 2013. "Digital Divides From Access to Activities: Comparing Mobile and Personal Computer Internet Users." *Journal of Communication* 63 (4): 721–744.
Pedroni, P. 2004. "Panel Cointegration: Asymptotic and Finite Sample Properties of Pooled Time Series Tests with an Application to the PPP Hypothesis." *Econometric Theory* 20 (3): 597–625.
Phillips, P. C., and H. R. Moon. 1999. "Linear Regression Limit Theory for Nonstationary Panel Data." *Econometrica* 67 (5): 1057–1111.

Pradhan, R. P., M. B. Arvin, N. R. Norman, and S. K. Bele. 2014. "Economic Growth and the Development of Telecommunications Infrastructure in the G-20 Countries: A Panel-VAR Approach." *Telecommunications Policy* 38 (7): 634–649.
Pratama, A. R. 2017. "Cross-country Analysis of ICT and Education Indicators: An Exploratory Study." Paper Presented at the IOP Conference Series: Materials Science and Engineering, Yogyakarta, Indonesia.
Ragnedda, M., and G. W. Muschert. 2013. *The Digital Divide: The Internet and Social Inequality in International Perspective*. London: Routledge.
Rice, R. E., and K. E. Pearce. 2015. "Divide and Diffuse: Comparing Digital Divide and Diffusion of Innovations Perspectives on Mobile Phone Adoption." *Mobile Media & Communication* 3 (3): 401–424.
Salemink, K., D. Strijker, and G. Bosworth. 2017. "Rural Development in the Digital age: A Systematic Literature Review on Unequal ICT Availability, Adoption, and use in Rural Areas." *Journal of Rural Studies* 54: 360–371.
Summerfield, M., S. Freidin, M. Hahn, P. Ittak, N. Li, N. Macalalad, and M. Wooden. 2018. *HILDA User Manual – Release 17. Melbourne Institute of Applied Economic and Social Research*. Vol. 17. University of Melbourne.
Thomas, J., J. Barraket, S. Ewing, T. MacDonald, M. Mundell, and J. Tucker. 2016. *Measuring Australia's Digital Divide: The Australian Digital Inclusion Index 2016*. RMIT University.
Tsatsou, P. 2011. "Digital Divides Revisited: What is new About Divides and Their Research? *Media*." *Culture & Society* 33 (2): 317–331.
Ünver, H. 2017. "Measuring the Global Information Society – Explaining Digital Inequality by Economic Level and Education Standard." Paper Presented at the IOP Conference Series: Materials Science and Engineering, Krasnoyarsk, Russia.
van Dijk, J. A. G. M. 2005. *The Deepening Divide: Inequality in the Information Society*. London: Sage.
van Dijk, J. A. G. M. 2006. "Digital Divide Research, Achievements and Shortcomings." *Poetics* 34 (4-5): 221–235.
van Dijk, J. A. G. M., and K. Hacker. 2003. "The Digital Divide as a Complex and Dynamic Phenomenon." *The Information Society* 19 (4): 315–326.
Vehovar, V., P. Sicherl, T. Hüsing, and V. Dolnicar. 2006. "Methodological Challenges of Digital Divide Measurements." *The Information Society* 22 (5): 279–290.
Whitacre, B. E. 2010. "The Diffusion of Internet Technologies to Rural Communities: A Portrait of Broadband Supply and Demand." *American Behavioral Scientist* 53 (9): 1283–1303.
Wooldridge, J. M. 2010. *Econometric Analysis of Cross Section and Panel Data*. Cambridge, MA: MIT Press.
Yu, T. K., M. L. Lin, and Y. K. Liao. 2017. "Understanding Factors Influencing Information Communication Technology Adoption Behavior: The Moderators of Information Literacy and Digital Skills." *Computers in Human Behavior* 71: 196–208.
Zappalà, G., B. Parker, and V. Green. 2000. *Social Exclusion and Disadvantage in the New Economy*. New South Wales: Research & Advocacy Team, The Smith Family.

Appendix

Table A1. Synopsis of selected existing empirical studies.

S.N.	Author	Variables used	Time frame	Methodology	Major findings
1	Alozie and Akpan-Obong (2017)	Use of Internet, access to cell phone, access to smartphone, gender, age, marital status, employment status, education level, religion, and ICT policy.	2013	Logistic regression	There exits strong gender-wise digital divide.
2	Billon, Marco, and Lera-Lopez (2009)	Access to personal computers, Internet bandwidth, Mobile phone subscribers, and Internet users.	2004	Canonical correlation test and canonical redundancy analysis	The difference in ICT use pattern is due the differences level of economic development of countries.
3	Billon, Marco, and Lera-Lopez (2017)	Household access to Internet, household access to broadband, Research and development (R&D) expenditure in the business sector, GDP per capita, government quality, the number of researchers, and employment by the highest level of education.	2010	Multiple discriminant Analysis and factor analysis	The key variables explaining the disparities in ICT use in the EU regions are R&D expenditure in the business sector, gross domestic product per capita, government quality, the number of researchers, and employment by the highest level of education.
4	Campos, Arrazola, and de Hevia (2017)	Internet use, Internet access, age, education, and employment status.	2007–2011	Bivariate probit model	The likelihood of accessibly to the Internet and its use was higher among employed individuals than the unemployed counterparts.

(*Continued*)

Table A1. Continued.

S.N.	Author	Variables used	Time frame	Methodology	Major findings
5	Duplaga (2017)	Internet use, age, place of residence, level of education, marital status, occupational status, net income, long-term health condition, use of health services, and access to mobile phone.	2013	Multivariate logistic regression models	Educational qualification and age intensifies the digital divide.
6	Lindblom and Räsänen (2017)	Internet access, Internet use, occupational status, social standing, age, gender, level of education, and economic resources.	2013	Logistic regression model	The social class and status had demonstrated substantial impact on Internet access and use.
7	Park (2017)	% of household with broadband connections, % of household with, remoteness, median age, agricultural population, ethnicity, level of education, unemployment, and population density.	2007–2011	OLS regression	Remoteness is a significant predictor of home Internet and broadband connectivity. In addition, digital divide is found to be intensified by other socio-demographic factors, e.g. level of education and employment status.
8	Pratama (2017)	Internet users, broadband subscribers, mobile subscribers.	2011–2014	Ordinary Least Squares-based regression	The digital divide in ICT use and participation gap in due to discrepancies in educational attainment between rich and poor countries.
9	Ünver (2017)	Mobile phone penetration rate, Internet penetration rate, GDP per capita, education index, and adult literacy rate.	2000 and 2013	Multivariate regression analysis	The persistence of a high digital inequality around the globe can be explained by the association between technology penetration rates, level of education and per capita income.
10	Yu, Lin, and Liao (2017)	ICT adoption behaviour, digital skill, digital literacy, social interaction, experience, technostress.	2016	Structural equation modelling	Information literacy and digital skills both had moderating effect on the impact of ICT adoption behaviour.

Table A2. Descriptive statistics in panel dimension.

State	Descriptive statistics	ACSINT	ACSCOM	FEMALE	MEDAGE	BACHELOR	GINI	AGRI	POPDEN	REMOTE	Ln GDPPC
ACT	Mean	70.61	81.05	50.44	34.03	38.64	0.00	0.37	146.86	0.00	13.02
	Median	72.50	82.73	50.45	34.40	38.15	0.00	0.37	143.71	0.00	13.02
	Min	27.00	64.00	50.24	32.30	32.63	0.00	0.36	132.11	0.00	12.80
	Max	94.10	91.00	50.67	35.02	44.40	0.00	0.38	168.22	0.00	13.20
	Std.	19.63	7.76	0.16	0.77	4.33	0.00	0.01	11.58	0.00	0.11
NT	Mean	61.25	72.63	47.67	30.64	21.52	0.03	0.36	0.10	45.65	12.64
	Median	64.00	73.00	47.57	31.00	21.50	0.03	0.37	0.08	45.51	12.66
	Min	16.00	42.00	47.43	28.40	17.59	0.00	0.31	0.07	41.76	12.37
	Max	88.90	99.27	48.10	32.18	27.30	0.06	0.39	0.18	49.14	12.85
	Std.	21.09	15.72	0.23	1.07	2.91	0.02	0.02	0.05	2.13	0.15
NSW	Mean	59.74	71.71	50.38	36.85	25.24	1.46	0.45	8.60	0.58	12.38
	Median	62.00	70.50	50.37	36.85	23.95	1.31	0.45	8.48	0.58	12.43
	Min	18.00	44.00	50.32	35.20	21.15	0.97	0.44	7.87	0.51	12.00
	Max	85.30	99.50	50.48	38.32	30.70	2.06	0.46	9.52	0.66	12.66
	Std.	20.61	16.09	0.05	0.92	3.21	0.33	0.01	0.51	0.05	0.22
QLD	Mean	59.36	71.41	50.11	35.92	19.66	0.02	0.42	4.85	3.22	11.37
	Median	63.00	73.00	50.11	36.15	19.90	0.02	0.42	4.83	3.22	11.37
	Min	15.00	43.00	50.03	34.10	15.48	0.01	0.41	4.05	2.89	11.15
	Max	86.30	98.61	50.22	37.35	24.30	0.03	0.44	5.69	3.56	11.53
	Std.	22.33	16.73	0.05	0.94	2.84	0.01	0.01	0.55	0.21	0.13
SA	Mean	55.42	69.60	50.11	38.66	19.18	0.03	0.41	1.60	3.75	12.01
	Median	56.50	68.00	50.11	38.85	20.00	0.03	0.41	1.59	3.75	12.00
	Min	12.00	41.00	50.03	36.40	13.58	0.02	0.40	1.51	3.58	11.63
	Max	82.40	99.96	50.22	40.43	25.70	0.03	0.42	1.73	3.90	12.44
	Std.	21.60	16.79	0.05	1.15	3.76	0.00	0.00	0.07	0.10	0.26
TAS	Mean	51.49	66.47	50.48	38.97	18.02	0.03	0.38	7.25	2.28	10.11

(*Continued*)

Table A2. Continued.

State	Descriptive statistics	ACSINT	ACSCOM	FEMALE	MEDAGE	BACHELOR	GINI	AGRI	POPDEN	REMOTE	Ln GDPPC
	Median	52.50	63.50	50.63	39.05	17.55	0.03	0.38	7.22	2.29	10.14
	Min	10.00	36.00	50.05	35.70	15.35	0.02	0.38	6.95	2.01	9.93
	Max	81.70	103.74	50.73	41.85	23.20	0.04	0.41	7.58	2.54	10.25
	Std.	21.85	19.47	0.26	1.81	2.11	0.00	0.01	0.24	0.17	0.12
VIC	Mean	59.77	72.35	50.57	36.63	25.47	0.02	0.43	22.84	4.88	9.77
	Median	61.00	71.43	50.53	36.85	25.45	0.01	0.43	22.45	4.88	9.77
	Min	15.00	46.00	50.42	35.00	18.67	0.01	0.40	20.25	4.18	9.42
	Max	86.20	96.73	50.75	37.85	33.00	0.02	0.45	26.52	5.60	10.11
	Std.	21.19	14.18	0.12	0.80	4.67	0.00	0.01	1.97	0.44	0.21
WA	Mean	61.01	73.15	49.70	35.81	21.53	0.02	0.33	0.85	7.05	10.21
	Median	64.00	73.50	49.64	36.20	21.00	0.02	0.32	0.82	7.01	10.21
	Min	15.00	44.00	49.55	33.90	16.89	0.01	0.30	0.72	6.46	9.91
	Max	88.10	97.96	49.95	36.89	27.90	0.03	0.38	1.01	7.57	10.47
	Std.	22.24	15.22	0.13	0.87	3.30	0.00	0.02	0.10	0.31	0.18
Total	Mean	59.83	72.30	49.93	35.94	23.66	0.20	0.39	24.12	8.43	11.44
	Median	62.50	72.00	50.17	36.30	22.05	0.02	0.40	6.32	3.57	11.58
	Min	10.00	36.00	47.43	28.40	13.58	0.00	0.30	0.07	0.00	9.42
	Max	94.10	103.74	50.75	41.85	44.40	2.06	0.46	168.22	49.14	13.20
	Std.	21.43	15.67	0.91	2.72	7.08	0.49	0.04	47.23	14.30	1.20

Note: Med: Median; Max: Maximum; Min: Minimum; Std.: Standard Deviation.

Table A3. Correlation matrix.

Variable	HHINT	HHCOM	FEMALE	MEDAGE	BACHELOR	GINI	AGRI	POPDEN	REMOTE	Ln GDP
HHINT	1									
HHCOM	0.66*	1								
FEMALE	−0.09	−0.08	1							
MEDAGE	0.22***	0.23***	0.44*	1						
BACHELOR	0.61*	0.60*	0.16***	−0.13	1					
GINI	0.03	0.02	0.43*	0.41*	−0.02	1				
AGRI	−0.08	−0.10	0.17**	0.10	0.04	0.48*	1			
POPDEN	0.22*	0.23*	0.28*	−0.22*	0.48*	−0.17**	−0.14	1		
REMOTE	−0.01	−0.03	−0.26*	−0.43*	−0.19**	−0.36*	−0.19*	−0.27*	1	
Ln GDPPC	0.26*	0.26*	−0.35*	−0.41*	0.47*	0.04	0.27*	0.43*	0.27*	1

Note 1:*, ** and *** denote statistically significant at 1%, 5% and 10%, respectively.

Table A4. Unit root test results at level.

		Method							
		LLC		Breitung		ADF		PP	
Variable		Case 1	Case 2	Case 1	Case 2	Case 1	Case 2	Case 1	Case 2
HHINT	Stat.	−9.465*	−7.668*	6.272	3.263	10.544*	6.508*	18.478*	1.873**
	Prob.	0.000	0.000	1.000	0.999	0.000	0.000	0.000	0.031
HHCOM	Stat.	−0.265	−1.632***	7.236	−0.621	7.468	20.602	7.122	26.215***
	Prob.	0.395	0.051	1.000	0.267	0.963	0.1943	0.970	0.051
FEMALE	Stat.	−1.637	−3.383*	0.649	0.512	−0.062	0.953	−1.166	0.878
	Prob.	0.050**	0.000	0.742	0.695	0.525	0.170	−0.400	0.655
MEDAGE	Stat.	−0.650	−3.799*	7.552	1.956	−1.733	1.606***	4.687*	1.644*
	Prob.	0.257	0.000	1.000	0.974	0.958	0.054	0.000	0.050
BACHELOR	Stat.	1.055	−2.880*	4.727	−1.830	−2.550	3.532*	−2.437	4.574*
	Prob.	0.854	0.002	1.000	0.033	0.995	0.000	0.992	0.000
GINI	Stat.	3.423	−37.783*	2.735	1.536	11.235	84.010*	45.835*	155.834*
	Prob.	0.999	0.000	0.996	0.937	0.794	0.000	0.000	0.000
AGRI	Stat.	−1.090	−2.806*	0.064	−2.429*	1.373	2.774*	−1.077	5.310*
	Prob.	0.137	0.003	0.525	0.007	0.915	0.003	0.859	0.000
POPDEN	Stat.	0.737	−2.356*	8.922	4.277	−2.272	−0.747	−2.786	−1.763
	Prob.	0.769	0.009	1.000	1.000	0.988	0.772	0.997	0.961
REMOTE	Stat.	−1.097	−3.865*	8.572	1.070	−2.522	4.565*	−2.395	2.171
	Prob.	0.136	0.000	1.000	0.857	0.994	0.000	0.991	0.985
LN GDPPC	Stat.	−2.543*	−1.111	7.656	2.195	11.490	20.962	20.254	40.981*
	Prob.	0.005	0.133	1.000	0.986	0.778	0.180	0.107	0.006

Note 1: LLC: Levin, Lin & Chu adjusted t* statistics; Breitung lambda statistics, ADF: Augmented Dickey-Fuller modified inverse chi-squared Pm statistics; PP: Phillips-Perron modified inverse chi-squared Pm statistics.
Note 2: Case 1: Unit root with intercept only; Case 2: Unit root with both intercept and trend.
Note 3: *, ** and *** denote statistically significant at 1%, 5% and 10%, respectively.

Table A5. Table A5. Descriptive statistics in time dimension across all states.

Year	Descriptive statistics	ACSINT	ACSCOM	FEMALE	MEDAGE	BACHELOR	GINI	AGRI	POPDEN	REMOTE	Ln GDPPC
1998	Min	36.00	10.00	47.43	28.40	13.58	0.31	0.00	0.07	0.00	9.42
	Max	64.00	27.00	50.69	36.40	32.63	0.44	2.04	132.11	49.14	12.80
	Mean	45.00	16.00	49.92	33.88	18.92	0.39	0.28	21.69	9.12	11.15
1999	Min	40.00	18.00	47.43	28.80	14.08	0.30	0.00	0.07	0.00	9.53
	Max	66.00	34.00	50.72	36.80	33.13	0.44	1.97	133.22	48.70	12.85
	Mean	49.38	23.50	49.96	34.25	19.35	0.39	0.27	21.88	9.03	11.20
2000	Min	45.00	25.00	47.54	29.20	14.60	0.30	0.00	0.07	0.00	9.52
	Max	70.00	46.00	50.74	37.20	33.64	0.44	1.94	134.52	48.26	12.89
	Mean	53.88	33.25	50.01	34.60	19.79	0.39	0.27	22.09	8.95	11.23
2001	Min	50.00	31.00	47.68	29.60	15.14	0.30	0.00	0.07	0.00	9.55
	Max	77.00	60.00	50.75	37.60	34.16	0.44	2.06	136.35	47.83	12.91
	Mean	58.50	41.88	50.07	34.94	20.24	0.39	0.28	22.38	8.86	11.25
2002	Min	51.00	35.00	47.59	30.00	15.70	0.31	0.00	0.07	0.00	9.62
	Max	78.00	60.00	50.73	37.90	34.68	0.44	1.68	137.66	47.40	12.93
	Mean	61.50	46.25	50.04	35.25	20.70	0.39	0.23	22.59	8.78	11.30
2003	Min	57.00	41.00	47.78	30.30	16.28	0.31	0.00	0.07	0.00	9.62
	Max	80.00	66.00	50.69	38.20	35.21	0.44	1.53	138.82	46.98	12.95
	Mean	66.13	52.63	50.05	35.49	21.18	0.39	0.21	22.80	8.70	11.33
2004	Min	60.45	44.00	47.94	30.60	16.88	0.31	0.00	0.07	0.00	9.63
	Max	81.43	66.50	50.71	38.40	35.75	0.44	1.30	139.49	46.56	12.98
	Mean	69.02	54.75	50.04	35.74	21.66	0.39	0.18	22.94	8.61	11.36
2005	Min	61.00	48.00	48.08	30.80	17.20	0.32	0.00	0.07	0.00	9.64
	Max	79.00	67.00	50.70	38.60	36.30	0.45	1.30	140.53	46.14	13.00
	Mean	68.25	56.63	50.04	35.94	22.16	0.39	0.18	23.13	8.53	11.39
2006	Min	60.00	49.00	48.10	31.00	17.90	0.32	0.00	0.07	0.00	9.72
	Max	82.00	72.00	50.70	38.90	37.00	0.45	1.31	142.13	45.73	13.01
	Mean	70.00	59.88	50.01	36.14	23.23	0.39	0.18	23.40	8.45	11.42
2007	Min	66.00	56.00	48.04	31.00	16.70	0.33	0.00	0.08	0.00	9.82
	Max	84.00	73.00	50.60	39.20	39.30	0.45	1.32	145.30	45.29	13.03
	Mean	73.50	63.88	49.98	36.23	23.54	0.39	0.18	23.89	8.36	11.47
2008	Min	67.00	56.00	47.80	31.00	18.50	0.33	0.00	0.08	0.00	9.84
	Max	86.00	80.00	50.47	39.40	40.50	0.45	1.37	147.73	44.87	13.06
	Mean	75.25	66.88	49.91	36.30	24.74	0.39	0.19	24.30	8.28	11.51
2009	Min	71.00	63.00	47.65	31.00	19.20	0.33	0.00	0.08	0.00	9.90
	Max	88.00	82.00	50.42	39.70	43.50	0.45	1.31	150.45	44.56	13.07
	Mean	78.75	72.00	49.84	36.35	25.81	0.39	0.18	24.75	8.21	11.54
2010	Min	75.30	67.00	47.55	31.10	18.60	0.34	0.00	0.08	0.00	9.89
	Max	89.57	85.50	50.46	40.00	41.80	0.45	1.45	153.41	44.37	13.09
	Mean	82.23	75.19	49.83	36.48	25.70	0.40	0.20	25.21	8.16	11.56
2011	Min	76.00	70.30	47.48	31.30	20.70	0.34	0.00	0.08	0.00	9.91
	Max	91.00	88.10	50.50	40.40	44.10	0.45	1.22	156.04	44.18	13.11
	Mean	82.75	78.89	49.83	36.65	26.51	0.40	0.17	25.62	8.12	11.58
2012	Min	83.46	74.50	47.48	31.52	22.10	0.34	0.00	0.18	0.00	9.96
	Max	86.97	88.90	50.49	40.76	44.30	0.45	1.14	159.68	43.90	13.13
	Mean	85.81	80.86	49.82	36.86	28.30	0.40	0.16	26.18	8.06	11.62
2013	Min	84.96	77.90	47.48	31.74	19.40	0.35	0.00	0.18	0.00	10.07
	Max	92.23	89.40	50.48	41.12	42.30	0.45	1.16	162.69	43.37	13.15
	Mean	89.68	83.34	49.81	37.07	27.09	0.40	0.16	26.66	7.96	11.65
2014	Min	86.47	79.50	47.49	31.96	19.60	0.32	0.00	0.18	0.00	10.08
	Max	97.82	91.50	50.47	41.49	44.40	0.46	1.25	165.13	42.63	13.17
	Mean	93.73	84.56	49.81	37.28	28.19	0.40	0.17	27.07	7.82	11.67
2015	Min	88.02	81.70	47.49	32.18	20.50	0.31	0.00	0.18	0.00	10.11
	Max	103.74	94.10	50.45	41.85	42.80	0.46	0.97	168.22	41.76	13.20
	Mean	97.97	86.63	49.80	37.49	28.74	0.40	0.13	27.56	7.68	11.69
Average (1998–2015)	Min	36.00	10.00	47.43	28.40	13.58	0.30	0.00	0.07	0.00	9.42
	Max	103.74	94.10	50.75	41.85	44.40	0.46	2.06	168.22	49.14	13.20
	Mean	72.30	59.83	49.93	35.94	23.66	0.39	0.20	24.12	8.43	11.44

Study 2

Socio-Economic Planning Sciences 70 (2020) 100737

Contents lists available at ScienceDirect

Socio-Economic Planning Sciences

journal homepage: www.elsevier.com/locate/seps

Measuring the concentration of information and communication technology infrastructure in Australia: Do affordability and remoteness matter?

Mohammad Afshar Ali[a,c,*], Khorshed Alam[a], Brad Taylor[b]

[a] School of Commerce, Faculty of Business, Education, Law & Arts, University of Southern Queensland, Toowoomba, Queensland, 4350, Australia
[b] School of Commerce, Faculty of Business, Education, Law & Arts, University of Southern Queensland, Springfield, Queensland, 4300, Australia
[c] Department of Economics, Jagannath University, Dhaka-1100, Bangladesh

A R T I C L E I N F O

Keywords:
Information and communication technology
ICT infrastructure concentration
ICT expenditure
Gini coefficient
Australia

A B S T R A C T

This study measures the concentration of information and communication technology (ICT) infrastructure and expenditure inequality in the disaggregated spatial unit of various locations in Australia. Using survey data from the Household, Income and Labour Dynamics in Australia, a composite concentration index for ICT infrastructure is constructed for urban and rural households. In addition, the Gini coefficient of ICT expenditure is computed to measure the concentration of affordability of ICT services. Findings demonstrate that the concentrations of ICT infrastructure and affordability are profound in the Greater Sydney and Greater Melbourne areas. Nevertheless, results indicate that the remoteness of spatial units has a noteworthy impact on the concentration of ICT infrastructure. In addition, canonical correlation analysis reveals that the association between the concentration of ICT infrastructure and inequality in the affordability of ICT services is statistically significant. These findings imply that policy makers should employ a holistic approach that will not only include technological and economic considerations but also examine place-based context in designing an all-inclusive ICT policy.

1. Introduction

Access to information and communication technology (ICT) greatly differs among and within countries [1]. For example, approximately 49% of the world population still lacks Internet connection [1]. Several studies confirm the existence of a multi-layered divide in Australia involving the three interconnected dimensions of infrastructure, connectivity and digital engagement [2–4]. Specifically, the rural and remote parts of Australia remain at risk of digital disadvantage compared with major cities [4]. Such a difference contributes to the persistent underdevelopment of regional Australia. Following the mining investment boom, which witnessed strong economic growth in remote parts of the country, transitioning to a broad economic base is necessary [5]. A major obstacle to this transition, however, is the lack of sufficient ICT infrastructure.

Although the existence of a geographic digital divide is widely acknowledged, understanding of its precise nature is limited. Studies on the concentration of ICT at the disaggregated spatial unit of locations are scarce, especially those that take the Greater Capital City Area (GCCSA) as the spatial reference unit. In addition, existing studies insufficiently investigated the links among digital exclusion, affordability and remoteness. Given these limitations, an empirical study can assist in devising ICT infrastructure-related public policies not only for Australia but also for countries with similar economic, social and political contexts.

This study constructs a concentration index (CI) for ICT infrastructure in Australia and examines its connections to socio-demographic inequality, affordability and remoteness. This work provides further empirical traction on the digital divide in Australia. To achieve this research objective, we aim to answer three questions:

(i) Do ICT CIs vary among different spatial units?
(ii) Is the concentration of ICT infrastructure associated with remoteness?
(iii) Do concentration of ICT access and affordability of ICT services have any correlation at the household level?

Existing research has yet to capture the potential impacts of socio-spatial heterogeneity and affordability of information and communication technology (ICT) services in measuring the concentration of ICT infrastructure. To the best of our knowledge, this study is the first attempt to measure the concentration of ICT infrastructure at the GCCA.

* Corresponding author.
E-mail addresses: MohammadAfshar.Ali@usq.edu.au (M.A. Ali), Khorshed.Alam@usq.edu.au (K. Alam), Brad.Taylor@usq.edu.au (B. Taylor).

https://doi.org/10.1016/j.seps.2019.100737
Received 1 January 2019; Received in revised form 18 August 2019; Accepted 25 August 2019
Available online 29 August 2019
0038-0121/

This work makes several contributions to the literature. Firstly, this study uses three household ICT variables, namely, telephone and mobile phone access, Internet access and no ICT access, to comprehensively measure the concentration of ICT infrastructure. Using these variables, the study constructs a composite CI for ICT infrastructure, which is composed of the following: (i) location quotient (LQ), (ii) the Herfindahl–Hirschman modified (HHm) index and (iii) relative participation (RP). Secondly, this study examines whether the concentration of ICT infrastructure varies with remoteness. Thirdly, employing the canonical correlation analysis, the study explores the association between ICT access concentration and expenditure inequality, which has received limited attention in the empirical literature.

The remainder of the paper is structured as follows. Section 2 provides a critical review of the existing literature. Section 3 describes the data and methods used. Section 4 presents the results in detail. Section 5 discusses these results. Finally, Section 6 considers the policy implications, study limitations and future research directions.

2. Review of literature

A considerable amount of literature investigates the associations among digital concentration, socio-economic factors and socio-spatial locations. Many studies identify location as one of the major factors of digital inequality. For example, in China, citizens residing in urban areas (62.8%) are more than twice as likely to have Internet access than those who live in rural areas (28.8%) [6]. In another report, 82% of urban households in India have telephone access compared with 54% of rural households [7]. [8] argued that the disparity in Internet access widens across rural–urban countryside–city and highly accessible–remotely located areas.

As digital technologies are reported to yield substantial impacts on economies and societies, ICT statistics are receiving paramount attention from researchers [7]. These ICT statistics not only measure the digital divide within a given country or region [6,9–12] but also reflect international disparity in digital technology adoption and use by reporting the gap between countries [7,13,14]. For instance, ITU's ICT Development Index [7] measures the global digital divide across countries around the world, whereas [11] proposed an index to evaluate the development of ICT at the regional level in Spain.

[15] found that socio-economic status and socio-spatial location are two major determinants of computer ownership and Internet access. According to the authors, the likelihood of having access to the Internet is positively associated with the ownership of material and the presence of intangible resources. Other studies find a similar positive association between digital inclusion and personal income level [7,9,15–17]. Another strand of empirical work investigated the association between digital inclusion and education level [7–9,12,15–17]. These studies report that the level of an individual's digital inclusion varies with the education level attained by such an individual [16]. carried out the most detailed study on measuring ICT access concentration to date. Using four types of classes, namely, computers and Internet access, mobile phones access, fixed phones access and no access, the authors found a substantial spatial disparity between the municipalities of the Amazon and other regions in terms of ICT infrastructure concentration at the household level. In addition, the results demonstrate that rural households are more likely to lack any kind of ICT service than urban households. Although this study meticulously uses the theoretical tools of spatial economics, it overlooks the affordability dimension in measuring the concentration of ICT services. However, affordability is reported to have a crucial impact on access to ICT services [7,18].

A number of studies investigate digital concentration with special reference to Australia. Several of these works report that digital divide in Australia is aggravated by a set of socio-economic and demographic factors, including income, education and employment status, to name a few [2,4,19,20]. [21] provided evidence of spatial inequalities across and among local government areas of Sydney by using geo-cartographical maps. Recently [20], have developed a digital inclusion index for eight states in Australia. They found that the rate of digital exclusion is high for socio-economic groups with low levels of income, education and employment. However, composite measures of the socio-economic divide are required to comprehensively consider the link between digital inclusion and socio-economic status (see Section 3.1 for details). The study also reveals a significant disparity between rural and urban areas in terms of ICT access.

The study, however, has several methodological shortcomings. Firstly, the study vaguely establishes the theoretical basis for selecting the corresponding components for the three sub-indices, namely, access, affordability and digital ability. Secondly, 'headline variables' are computed by applying simple averages which can potentially yield biased and flawed index scores. Thirdly, whether any type of weighting has been applied to estimate the weight of sub-indices and headline variables remains unclear. Fourthly, although existing empirical works provide evidence that remoteness has a huge impact on ICT inclusion or concentration, the study fails to capture any variation in the digital inclusion pattern with regard to remoteness. Finally, many studies reveal that access to ICT goods and services is significantly associated with the affordability of corresponding ICT services [7,18]. However, the current study remains unsuccessful in uncovering whether a significant association exists between digital inclusion and affordability in the context of Australia.

Evidently, a large and growing body of literature has investigated the association among digital concentration, socio-economic factors and socio-spatial locations. However, the extant studies fail to capture the potential impact of socio-spatial differences in the affordability of ICT services on measuring the ICT infrastructure concentration. One of the major concern is that affordability plays a pivotal role in ICT adoption; thus, it constitutes a central part in ICT development [7,18,20]. Previous studies also fail to demonstrate the link between the concentration of ICT and remoteness of spatial units. In addition, the constructed indexes to measure digital inclusion are based on a flawed methodological framework. The current study fills the research gap by incorporating the affordability dimension in constructing the CI for ICT infrastructure and investigating the association among ICT infrastructure concentration, affordability and remoteness.

3. Materials and methods

3.1. Study area and population

The broadest spatial unit used by the Australian Bureau of Statistics is the state/territory. Nine of these spatial units represent six states (New South Wales or NSW, Victoria, Queensland, South Australia, Western Australia and Tasmania), two major territories (Northern Territory and Australian Capital Territory) and an 'other territories' category, which consists of one small administrative territory and external territories [22]. The current study is based on the six states and two major territories, excluding the 'other territories' unit. In 2016, the proportion of populations residing on the eight states/territories were as follows: NSW - 32.0%, Victoria - 25.5%, Queensland - 20.0, South Australia - 7.1%, Western Australia - 10.6%, Tasmania - 2.1%, Northern Territory - 1.0% and Australian Capital Territory - 1.7% [23]. Each state and territory is divided into a 'greater capital city' and a 'rest of state region'. In total, 16 Greater Capital City Statistical Areas (GCCSA) encompass and demarcate the country, specifically, eight Greater Capital City Areas, seven 'rest of state' areas and 'other territories' area (for details, see Fig. 2). The Australian Capital Territory consists of only one statistical area because the greater capital city encompasses the entire territory. Statistical Area Level 4 (SA4s) is the building block of GCCSAs. In total, Australia comprises 87 SA4s [22]. According to recent statistics, 67.1% of the total population of Australia resides in GCCSAs, whilst the remaining 32.9% live in the remaining states/territories [24]. This study uses data from the Household, Income and Labour

Dynamics in Australia (HILDA) Survey Restricted Release 16 [25], which is a survey conducted on 10,837 households. ICT infrastructure (telephone and mobile phone access and Internet access) and expenditure (household expenditure, such as telephone rent, call and Internet charge) in urban and rural households are analysed in conjunction with the socio-economic status and demographic divide. In Australia, 89.8% of the total population of Australia lives in urban areas, whilst the remaining 10.2% reside in rural areas [23]. Unlike the study of [20]; the current research uses Socio-economic Indexes for Areas (SEIFA) to measure the socio-economic advantage and disadvantage (SAD), economic resources (ER), education and occupation (E&O), remoteness and population size (POP) of the regions.

These composite indexes include a number of domains, e.g. household income, education, occupation, employment, housing and other indicators of SAD. These indexes can better measure the spatial socio-economic divide compared with one of the domains in isolation [26].

3.2. Sources of data

The HILDA Survey Restricted Release 16 is used as the source of ICT access and expenditure data at the household level in Australia. This restricted dataset is available upon request from the Department of Social Services. Data accumulation is conducted with respect to (i) the rural–urban decomposition of households, (ii) the existence of telephone and mobile access, (iii) the existence of the Internet, (iv) no ICT access[1] and (v) ICT expenditure. This study uses GCCSA as spatial reference units. The rationale behind selecting GCCSA as the reference unit is that it is the most appropriate disaggregated geographical unit available. According to the terms and conditions of the HILDA Restricted Release, reporting of study findings below this level is not permitted. The data on SAD, ER, E&O and POP are collected from the Census of Population and Housing on SEIFA [26]. Details on the candidate variables used to construct SEIFA can be found in a Technical Paper on SEIFA (2011) [26]. The data on the Accessibility/Remoteness Index of Australia (ARIA) are collected from the Australian Statistical Geography Standard Remoteness Structure [27]. These indicators are then classified into several categories using the ranges of values listed in Table 1.

In each SEIFA index (i.e. SAD, ER and E&O), Australia as a whole is classified into 10 deciles. Deciles 1 and 10 indicate areas with the lowest and highest proportions of corresponding index scores, respectively. In this study, each of the two consecutive deciles is grouped as quintiles for the corresponding indexes. For example, SAD deciles 1 and 2 are grouped as SAD quintile 1. This procedure is reiterated for the remaining deciles and across all SEIFA indexes (i.e. ER and E&O). This study uses ARIA to classify entire Australia into five categories on the basis of the average ARIA index score (Table 1). Finally, to classify the regions on the basis of size/populations, the benchmark range values for each class are computed using the statistical software package 'Stata 14', which applies three equal cut points for three groups, namely, small, medium and low. Table 1 reports the range of values for each group.

3.3. Methods

3.3.1. Conceptual framework

Fig. 1 elaborates the approach undertaken in the study to analyse the concentration of ICT access and expenditure. This process comprises five steps as follows: (i) analysing the ICT infrastructure concentration in urban and rural households at the GCCSA and state levels; (ii) exploring the associations between ICT access status in urban and rural households with indicators for SAD, ER, E&O, remoteness and POP; (iii) analysing the ICT expenditure inequality in urban and rural households at the GCCSA and state levels[2]; (iv) exploring the associations between ICT expenditure inequality in urban and rural households with indicators for SAD, ER, E&O and remoteness; and (v) assessing the association between ICT infrastructure concentration and expenditure inequality. In the first step, the CIs are computed and analysed according to the types of access (telephone and mobile phone, Internet, no ICT) and types of households (rural or urban) in order to identify the ICT infrastructure concentration. In the second step, the association between ICT infrastructure concentration and SAD, ER, E&O, remoteness and POP is investigated by cross-tabulating the ICT infrastructure index score with the SEIFA indexes, remoteness level and size of the spatial unit in terms of population.

3.3.2. Estimation strategy

Measuring the ICT infrastructure CI. In the analysis of ICT infrastructure concentration, six classes are defined for the type of access (Table 2). These classes determine the characteristics of households with respect to the type of household (urban or rural) and access type based on the three kinds of ICT access. Each access type is represented by separate indicators, namely, telephone and mobile phone, Internet and no ICT.

In sequence, a normalised CI is constructed to measure the concentration of ICT infrastructure in each class (telephone & mobile phone, Internet and no ICT) in each spatial unit analysed, i.e. GCCSAs and states. The CI is a composite index that is used to quantify local productive agglomerations. In this study, the methodology developed by [28] is used to calculate ICT infrastructure CI. Moreover, the concept of productive agglomeration is extended with reference to the spatial concentration of households according to the ownership of ICT assets (telephone & mobile phone and Internet). The ICT infrastructure CI comprises three sub-indexes as listed below.

i. LQ is an index that aims to determine whether a GCCSA has a particular specialisation in a specific class. The mathematical expression of LQ is outlined in Equation (1) as follows:

$$LQ_{ij} = \frac{E_{ij}/E_i}{E_i/E} \tag{1}$$

ii. HHm is a modification of the Herfindahl–Hirschman index developed by [28] to capture the weight of a class in GCCSA. This index is defined by Equation (2) as follows:

$$HHm_{ij} = \frac{E_{ij}}{E_i} - \frac{E_j}{E} \tag{2}$$

iii. RP measures the relative participation of the class in the GCCSA in relation to a region. Equation (3) mathematically expresses RP as follows:

$$RP_{ij} = \frac{E_{ij}}{E_i}, \tag{3}$$

where

E_{ij} is the occurrence of class i in GCCSA j,
E_j is the total occurrence in GCCSA j,
E_i is the occurrence of class i considering the entire region under study and
E is the total occurrence considering all classes and entire region under study.

[1] Households without access to any type of ICT services, i.e. telephone, mobile phone or Internet.

[2] This study follows the ABS Section of State (SOS) Structure of the ASGS to define urban and rural areas. Two SOS identifier categories, namely, 'major urban' and 'other urban', are defined as urban areas. The remaining two SOS identifier categories, namely, 'bounded locality' and 'rural balance', are referred to as rural areas [22].

Table 1
Classification of regions based on socio-economic, demographic and spatial indexes.

Indicator/index	Description	Classification of regions	Ranges
SAD	Used to define the relative SAD in terms of people's access to material and social resources and their capability to participate in society.	Quintile 1: highly disadvantaged area	SEIFA SAD deciles 1 & 2
		Quintile 2: disadvantaged area	SEIFA SAD deciles 3 & 4
		Quintile 3: balanced area	SEIFA SAD deciles 5 & 6
		Quintile 4: advantaged area	SEIFA SAD deciles 7 & 8
		Quintile 5: highly advantaged area	SEIFA SAD deciles 9 & 10
ER	Comprised of variables in relation to the financial aspects of relative SAD. It indicates accessibility to ER.	Quintile 1: very low accessible area	SEIFA SAD deciles 1 & 2
		Quintile 2: low accessible area	SEIFA SAD deciles 3 & 4
		Quintile 3: moderate accessible area	SEIFA SAD deciles 5 & 6
		Quintile 4: high accessible area	SEIFA SAD deciles 7 & 8
		Quintile 5: very high accessible area	SEIFA SAD deciles 9 & 10
E&O	This index encompasses variables in relation to the educational and occupational aspects of relative SAD. It emphasises the skills of people in an area in terms of formal qualifications and occupational skills.	Quintile 1: majority are very less skilled and qualified	SEIFA SAD deciles 1 & 2
		Quintile 2: majority are less skilled and qualified	SEIFA SAD deciles 3 & 4
		Quintile 3: majority are moderately skilled and qualified	SEIFA SAD deciles 5 & 6
		Quintile 4: majority are highly skilled and qualified	SEIFA SAD deciles 7 & 8
		Quintile 5: majority are extremely skilled and qualified	SEIFA SAD deciles 9 & 10
ARIA	This index classifies the geographical units of Australia on the basis of remoteness or distance from services.	Extremely remote: very low or no accessible area	Average ARIA index score > 10.53
		Remote: low accessible area	Average ARIA index score 5.92–10.53
		Outer region: moderately accessible area	Average ARIA index score 2.4–5.92
		Inner regional: accessible area	Average ARIA index score 0.2–2.4
		Major cities: highly accessible area	Average ARIA index score < 0.2
POP	Size of regions based on total populations.	Small	Less than 167,080 inhabitants
		Medium	From 167,080 to 273,340 inhabitants
		Low	More than 273,340 inhabitants

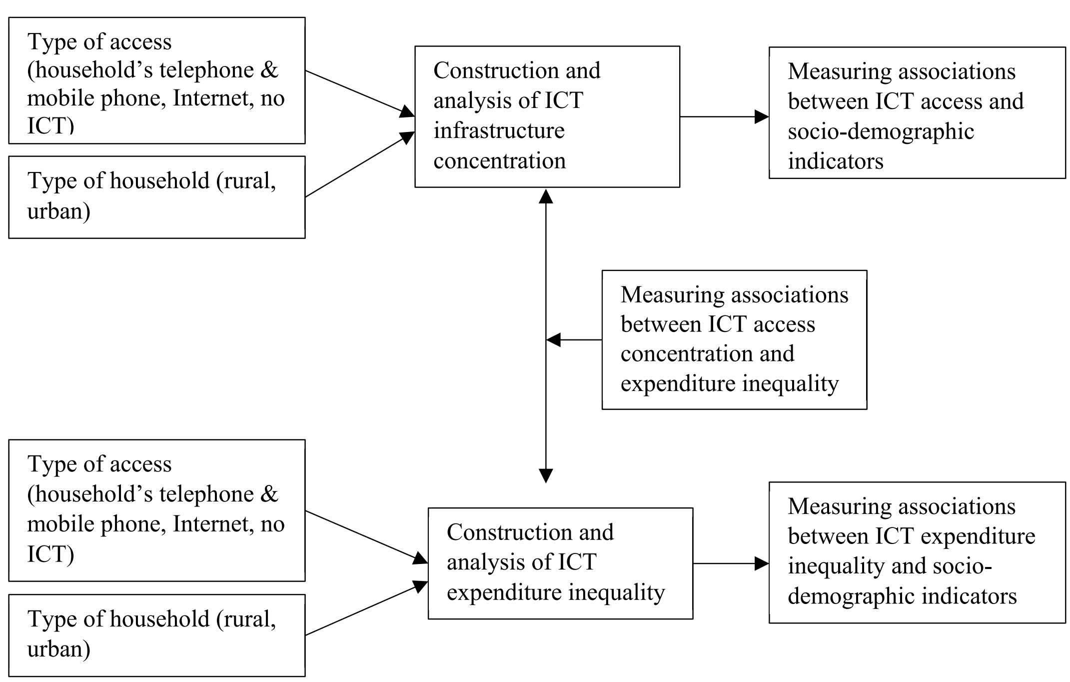

Fig. 1. Approach to analyse the concentration of ICT infrastructure and expenditure.

The three indexes can capture three aspects. LQ demonstrates the concentration of a particular class i in a GCCSA compared with that at the national level. HHm measures the weight of a particular class i in a GCCSA j at the national level compared with the weight of all classes of the GCCSA as the sum of all classes in the nation. RP indicates the importance of class i in a GCCSA in relation to the total of a corresponding class in the nation.

Based on these indexes, the ICT infrastructure CI can be expressed as

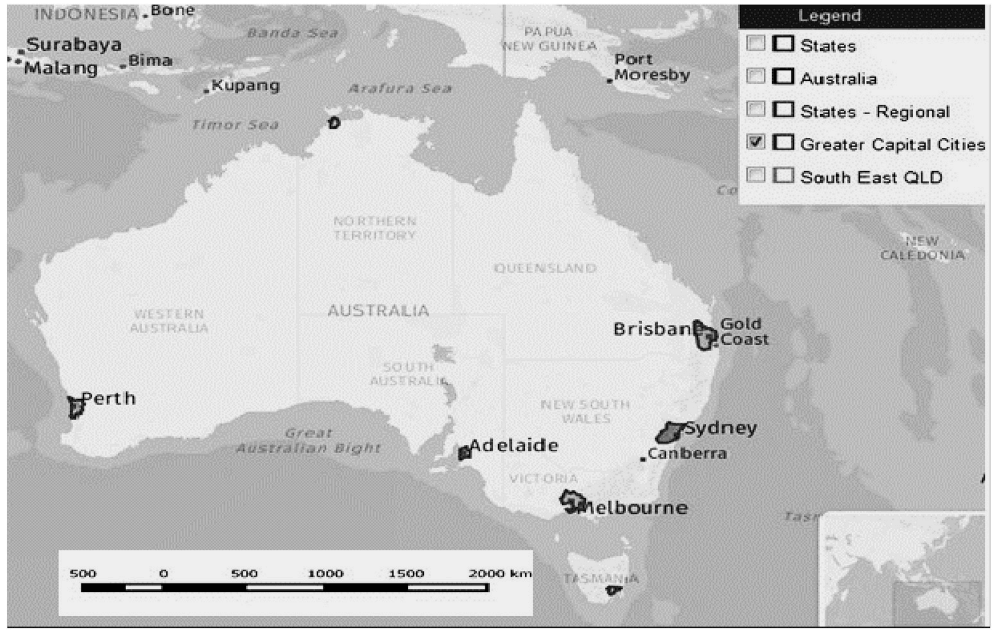

Fig. 2. Greater Capital City and remainder of state areas in Australia.

Table 2
Variable descriptions.

Class	Type of household	Variable for type of access	Description	Possible values
1	Urban	Telephone & mobile phone	Urban households with a telephone (landline or mobile phone)	1 = Yes; 2 = No
2	Urban	Internet	Urban households with Internet	1 = Yes; 2 = No
3	Urban	No ICT	Urban households with no telephone, mobile phone, and Internet	1 = Yes; 2 = No
4	Rural	Telephone & mobile phone	Rural households with a telephone (landline or mobile phone)	1 = Yes; 2 = No
5	Rural	Internet	Rural households with Internet	1 = Yes; 2 = No
6	Rural	No ICT	Rural households with no telephone, mobile phone and Internet	1 = Yes; 2 = No
7	National	Telephone & mobile phone access	Total households with a telephone (landline or mobile phone)	1 = Yes; 2 = No
8	National	Internet	Total households with Internet	1 = Yes; 2 = No
9	National	No ICT	Total households with no telephone, mobile phone, and Internet	1 = Yes; 2 = No

follows:

$$CI_{ij} = \theta_1 LQ_{ij} + \theta_2 HHm_{ij} + \theta_3 RP_{ij}, \tag{4}$$

where θ_1, θ_2 and θ_3 denote the respective weights of each index for each class.

Principal component analysis (PCA) is used to compute the weights. For details on PCA, see [29]. The ICT infrastructure CI is calculated for each class *i* and each GCCSA *j* of Australia. The index scores of telephone and mobile phone, Internet and no ICT access of urban and rural households are then compared between each GCCSA and state. The index contains no maximum or minimum ranges. Therefore, GCCSAs and states with the highest CI scores are regarded as a highly concentrated region in terms of ICT access.

Furthermore, the RP scores of each GCCSA and state are represented in a systematic order to explore the associations among ICT infrastructure concentration, SAD, ER, E&O, remoteness and POP. RP is used to analyse the classes according to socio-economic, spatial and demographic indicators. The rationale for selecting RP is that it shows the percentage of participation, that is, it measures the contribution of a particular GCCSA *j* to class *i*.

Measuring inequality in ICT expenditure. In order to measure inequality in ICT expenditure in each GCCSA, the Gini coefficient for ICT expenditure at the household level for each GCCSA is computed. The Gini coefficient is the standard method in the field of economics research to measure inequality in income and wealth [30]. The Gini coefficient, formulated in 1912 by the Italian statistician and sociologist Corrado Gini [31], is defined as the average of absolute differences between all pairs of individuals. The value of a Gini coefficient ranges between 0 (distribution of a particular variable is most even, i.e. no inequality) to 1 (distribution of that variable is most uneven, i.e. perfect inequality) [32]. In the present study, the Gini coefficient is used to measure inequality in ICT expenditure at the household level with the Jasso–Deaton formula [33,34] as expressed in Equation (5):

$$G = \frac{n+1}{n-1} - \frac{2}{n(n-1)\mu} \sum_{i=1}^{n} P_i X_i, \tag{5}$$

where

μ = mean ICT expenditure of the inhabitants of GCCSA *j*,
P_i = rank of person *i* in GCCSA *j* in terms of ICT expenditure,
X_i = annual ICT expenditure of person *i* and
n = total number of persons living in GCCSA *j*.

To explore the associations among ICT expenditure inequality, SAD, ER, E&O and remoteness, the Gini coefficient scores of ICT expenditure for each GCCSA and state are organised using different tabulations. At the last stage, three maps (one each for telephone and mobile phone access CI, Internet access CI and ICT expenditure inequality) are produced to demonstrate the spatial distribution of ICT infrastructure CI and ICT expenditure Gini. The maps depict the concentrations of ICT

Table 3
Urban and rural households by type of ICT access.

State/Territory	Variable for type of access	Urban households (%)	Rural households (%)	All households (%)
New South Wales	Telephone and mobile phone	99.7	100.0	99.7
	Internet	90.9	88.2	90.6
	No ICT	0.1	0.0	0.1
Victoria	Telephone and mobile phone	99.8	100.0	99.8
	Internet	93.0	86.9	92.3
	No ICT	0.2	0.0	0.2
Queensland	Telephone and mobile phone	99.6	99.7	99.7
	Internet	91.3	92.0	91.4
	No ICT	0.1	0.3	0.2
South Australia	Telephone and mobile phone	99.3	100.0	99.4
	Internet	89.8	84.7	89.2
	No ICT	0.7	0.0	0.7
Western Australia	Telephone and mobile phone	100.0	100.0	100.0
	Internet	93.9	84.9	92.9
	No ICT	0.0	0.0	0.0
Tasmania	Telephone and mobile phone	100.0	100.0	100.0
	Internet	89.6	95.3	91.1
	No ICT	0.0	0.0	0.0
Northern Territory	Telephone and mobile phone	100.0	100.0	100.0
	Internet	97.5	76.9	92.5
	No ICT	0.0	0.0	0.0
Australian Capital Territory	Telephone and mobile phone	100.0	100.0	100.0
	Internet	98.3	100.0	98.3
	No ICT	0.0	0.0	0.0

access and extensity of inequality in ICT expenditure for all households (urban and rural) at the state level.[3]

Measuring the association between ICT infrastructure CI and ICT expenditure inequality. Finally, the canonical correlation analysis (CCA) is applied to explore the potential association between ICT infrastructure CI and ICT expenditure inequality. This analysis enables the investigation of the relationship between two sets of variables (vectors), which are all measured on the same identity [35]. The null hypothesis states that the two sets of variables are not linearly associated. If the test-static (F statistic) is statistically significant (approximately at the 10% level), then the null hypothesis can be rejected. The measures for ICT infrastructure concentration and expenditure inequality are associated with each other. Conversely, the null hypothesis cannot be rejected if test-static (F statistic) is statistically insignificant.

4. Results

4.1. ICT infrastructure concentration

4.1.1. Analysis of ICT infrastructure concentration

With regards telephone and mobile phones in urban households, the state of South Australia has the lowest percentage (99.3%) compared with the eight states and territories studied. For rural households, Queensland has the lowest percentage of households with telephones and mobile phones (99.7%) (see Table 3). Considering all households (urban and rural), South Australia stands last in terms of the percentage of households with telephone and mobile phone access (99.4%). For Internet access, Tasmania (89.6%) and Northern Territory (76.9%) rank last for urban and rural households, respectively. Considering all households (urban and rural), South Australia has the lowest percentage among all households with Internet access (89.2%). South Australia has the highest prevalence of households without any type of ICT access (0.7% for both urban and all households). These results primarily indicate that the probability of no ICT concentration is highest for households in South Australia compared with those in other parts of Australia. As evident from Table 3, there exists an urban–rural divide between households in terms of Internet access. For example, in four states and territories, the proportion of households with Internet access is much higher in urban areas than that in rural areas (greater than 5%). The difference between urban and rural households in terms of Internet access is highest in the Northern Territory (10.6%).

Next, PCA is applied to calculate the weights of LQ, HHm and RP. Table 4 reports the weights for the three sub-indexes, namely, θ_1, θ_2 and θ_3. The table shows that for each type of household, HHm and RP account for approximately 35% of variations in CI for telephone and mobile phone access and Internet access, whilst LQ explains the remaining 30% of variation for these two types of ICT access. Conversely, for no ICT access, LQ, HHm and RP carry nearly equal weights (approximately 33% each) irrespective of household type (i.e. urban or rural).

The weights are used to calculate the CI for each GCCSA for each class analysed. Table 5 reports the CI scores for urban households. Panel A in Table 5 shows that Greater Melbourne has the highest CI scores for telephone and mobile phone (0.3661) and Internet (0.3702) access. Northern Territory has the lowest CI score (0.2906) for telephone and mobile phone access. For Internet access, the Rest of South Australia

Table 4
Weights for LQ, HHm and RP.

Class	Type of household	Variable for type of access	θ_1	θ_2	θ_3
1	Urban	Telephone and mobile phone	0.2963	0.3529	0.3507
2	Urban	Internet	0.2968	0.3527	0.3505
3	Urban	No ICT	0.3261	0.3373	0.3366
4	Rural	Telephone and mobile phone	0.3118	0.3460	0.3421
5	Rural	Internet	0.3125	0.3456	0.3417
6	Rural	No ICT	0.3334	0.3331	0.3334
7	All	Telephone and mobile phone	0.3018	0.3499	0.3481
8	All	Internet	0.3020	0.3498	0.3480
9	All	No ICT	0.3273	0.3364	0.3361

3 The maps at the GCCSA level cannot be produced as the shapefile format is unavailable at that disaggregated geographical level. However, the georeferenced cartographic database of the Australian states and regions is freely available online in shapefile format. These datasets are compiled from the ASGS dataset on the Main Structure and Greater Capital City Statistical Areas published by [43]. QGIS (version 2.12.1- Lyon), a free and open-source geographic information system software (available at http://www.qgis.org), is used to plot all maps in this study.

Table 5
Average CI for urban household classes and GCCSA with highest CI in each class.

Region/GCCSA	State	Urban households		
		Telephone and mobile phone access	Internet access	No ICT access
Panel A				
Greater Sydney	New South Wales	0.3597	0.3632	0.4673
Rest of NSW	New South Wales	0.3422	0.3282	−0.0372
Greater Melbourne	Victoria	**0.3661**	**0.3702**	0.3266
Rest of Victoria	Victoria	0.3217	0.3057	0.6024
Greater Brisbane	Queensland	0.3322	0.3368	0.2853
Rest of Queensland	Queensland	0.3361	0.3281	0.3028
Greater Adelaide	South Australia	0.3234	0.3214	**1.4744**
Rest of South Australia	South Australia	0.3124	0.2891	0.9749
Greater Perth	Western Australia	0.3197	0.3317	−0.0275
Rest of Western Australia	Western Australia	0.3119	0.2892	−0.0041
Tasmania	Tasmania	0.3106	0.3025	−0.0095
Northern Territory	Northern Territory	0.2906	0.3082	−0.0021
Australian Capital Territory	Australian Capital Territory	0.2949	0.3158	−0.0078
Panel B				
New South Wales	Average	**0.3509**	**0.3457**	0.2151
Victoria	Average	0.3439	0.3380	0.4645
Queensland	Average	0.3342	0.3324	0.2941
South Australia	Average	0.3179	0.3053	**1.2246**
Western Australia	Average	0.3158	0.3105	−0.0158
Tasmania	Average	0.3106	0.3025	−0.0095
Northern Territory	Average	0.2906	0.3082	−0.0021
Australian Capital Territory	Average	0.2949	0.3158	−0.0078

Note: Highest values are printed in bold. Figures for Greater Hobart, Rest of Tasmania, Great Darwin and Rest of Northern Territory are unavailable as the relevant indicators are not reported at corresponding GCCSA level in the HILDA data.

region possesses the least concentration (0.2891). Furthermore, the CI scores are comparatively higher in the 'greater capital city' areas compared with the corresponding 'rest of regions' within each state for telephone and mobile phone access and Internet access. Among the eight states (see Panel B), CI scores are highest in NSW for telephone and mobile phone access (0.3509) and Internet access (0.3457). Among all GCCSAs, no ICT access concentration is most prevalent in Greater Adelaide (1.2246) for urban households. At the state level, South Australia has the highest concentration of no ICT access (1.2246). Evidently, as shown in Table 5, the average CI score for no ICT access is highly positive in one case (Greater Adelaide) and negative in a number of other cases. This phenomenon can be explained using the mathematical expression outlined in Equation (2). As for a number of GCSSAs, the number of households with no ICT access is zero ($E_{ij} = 0$), the quotient of the first part of the right-hand side of Equation (2) equals zero. Therefore, the entire output of HHm for those GCCSAs are negative and eventually yield negative CI scores. Following this line of reasoning, the average CI score is highly positive for one GCCSA.

Panels A and B in Table 6 summarise the CI scores for rural households at the GCCSA and state levels, respectively. The Rest of NSW obtained the highest CI scores for telephone and mobile phone access (0.3973). The highest score for Internet access was obtained for Greater Melbourne (0.3702). Northern Territory has the lowest CI score (0.2906) for telephone and mobile phone access, whilst Greater Melbourne has the highest CI (0.3884) for Internet access. Among the eight states, the CI score for telephone and mobile phone access is highest in NSW (0.3570), whilst that for Internet access is highest in Victoria (0.3821). Among all GCCSAs, no ICT access concentration is most prevalent in rural households in the Rest of Queensland (2.3574). Exhibiting a similar trend at the state level, Queensland topped all states in terms of concentration of no ICT access (1.2246) after considering the sample of rural households. As shown in Table 5, the average CI score for no ICT access is highly positive for one GCSSA (Rest of Queensland) and negative for a number of GCSSAs. Similar to the cases described in the preceding paragraph, this phenomenon can be explained through the mathematical properties of Equation (2).

Table 7 provides the CI scores for all households (urban and rural). As can be seen, the results are similar to the corresponding CI scores for urban households. Evidently, the following table shows that for telephone and mobile phone access, the Rest of Victoria has the highest CI score (0.3661), and Greater Melbourne has the highest CI scores for Internet access (0.3819). Among the eight states, CI scores are highest in Victoria (0.4117) for telephone and mobile phone access and in NSW (0.3603) for Internet access. Among all GCCSAs, no ICT access concentration is most prevalent in Greater Adelaide (1.5639) for all households. At the state and territory levels, South Australia ranks first in terms of concentration of no ICT access (1.0349). In a nutshell, Victoria and NSW have the highest concentrations for telephone and Internet access and Internet access, respectively, regardless of the household location (urban or rural) at the state level. The relative participation statistics imply a similar indication. For example, the relative participation for telephone and mobile phone access is highest (30.7%) in Victoria relative to other states. Similarly, for the case of Internet access, households in NSW have the highest relative participation of 29.3% (for mapping, see Figs. 3 and 4). Moreover, South Australia exhibits the highest concentration regardless of household type for no ICT access. The relative participation of South Australia for no ICT access is highest (33.3%) compared with the other states.

4.1.2. Associations among ICT infrastructure concentration, socio-economic divide and remoteness

Table 8 presents the RP scores for telephone and mobile phone, Internet and no ICT access for urban and rural households. To better demonstrate the associations between socio-demographic indicators and ICT infrastructure concentration, the RP scores are represented systematically on the basis of four indicators, namely, (i) SEIFA index on SAD, (ii) SEIFA index on ER, (iii) SEIFA index on E&O and (iv) POP of the region. For the SAD index, the relative participation is highest in quintile 4 for telephone and mobile phone (27.6%) and Internet (30.0%) access. For no ICT access class, the prevalence is persistent in the lower quintiles, namely, quintiles 3 (32.1%) and 2 (24.3%). The results are almost identical when the RP scores are categorised along the quintiles that are arranged on the basis of the indexes of ER and E&O. Taking these results together, the concentration of ICT can be

Table 6
Average CI for rural household classes and GCCSA with highest CI in each class.

Region/GCCSA	State	Rural households		
		Telephone and mobile phone access	Internet access	No ICT access
Panel A				
Greater Sydney	New South Wales	0.3167	0.3441	−0.0171
Rest of NSW	New South Wales	**0.3973**	0.3878	−0.0795
Greater Melbourne	Victoria	0.2721	**0.3884**	−0.0142
Rest of Victoria	Victoria	0.3899	0.3757	−0.0700
Greater Brisbane	Queensland	0.3121	0.3354	−0.0107
Rest of Queensland	Queensland	0.3677	0.3842	**2.3574**
Greater Adelaide	South Australia	0.3155	0.3151	−0.0031
Rest of South Australia	South Australia	0.3467	0.3292	−0.0259
Greater Perth	Western Australia	0.3122	0.3303	−0.0084
Rest of Western Australia	Western Australia	0.3439	0.3144	−0.0176
Tasmania	Tasmania	0.3239	0.3514	−0.0242
Northern Territory	Northern Territory	0.3375	0.2932	−0.0044
Australian Capital Territory	Australian Capital Territory	0.2951	0.3341	−0.0012
Panel B				
New South Wales	Average	**0.3570**	0.3660	−0.0483
Victoria	Average	0.3310	**0.3821**	−0.0421
Queensland	Average	0.3399	0.3598	**1.1734**
South Australia	Average	0.3311	0.3221	−0.0145
Western Australia	Average	0.3281	0.3224	−0.0130
Tasmania	Average	0.3239	0.3514	−0.0242
Northern Territory	Average	0.3375	0.2932	−0.0044
Australian Capital Territory	Average	0.2951	0.3341	−0.0012

Note: Highest values are printed in bold. Figures for Greater Hobart, Rest of Tasmania, Great Darwin and Rest of Northern Territory are unavailable because the relevant indictors are not reported at corresponding GCCSA level in the HILDA data.

concluded to vary depending on socio-economic status, concentration of wealth and levels of education and skills. Specifically, the higher the levels of socio-economic status, wealth and education, the higher the prevalence of ICT infrastructure concentration. The larger-sized regions in terms of population have the highest relative participation rates for telephone and mobile phone (45.1%) and Internet (45.8%) access. Moreover, small and medium-sized GCCSAs comprise the majority of the proportion of households with no ICT access.

Table 9 presents the RP scores in telephone and mobile, Internet and no ICT access according to remoteness structure. The results show that for each type of class (i.e. telephone and mobile phone, Internet and no ICT access), the RP is highest among the households located in major cities, whereas these scores appear to be lower for remote and very remote areas. These findings indicate that spatial distance from the civic service centres crucially affects households' RP in ICT, such that the higher the accessibility of households to the centres, the higher the RP in ICT services and vice versa.

Table 7
Average CI for all household classes and GCCSA with highest CI in each class.

Region/GCCSA	State	Urban and rural households		
		Telephone and mobile phone access	Internet access	No ICT access
Panel A				
Greater Sydney	New South Wales	0.3667	0.3730	0.4864
Rest of NSW	New South Wales	0.3625	0.3476	−0.0423
Greater Melbourne	Victoria	0.3674	**0.3819**	0.3500
Rest of Victoria	Victoria	**0.4561**	0.2258	0.2968
Greater Brisbane	Queensland	0.3426	0.3495	0.2987
Rest of Queensland	Queensland	0.3528	0.3479	0.4099
Greater Adelaide	South Australia	0.3347	0.3344	**1.5639**
Rest of South Australia	South Australia	0.3314	0.3067	0.6260
Greater Perth	Western Australia	0.3313	0.3453	−0.0252
Rest of Western Australia	Western Australia	0.3318	0.3033	−0.0057
Tasmania	Tasmania	0.3246	0.3231	−0.0113
Northern Territory	Northern Territory	0.3132	0.3166	−0.0024
Australian Capital Territory	Australian Capital Territory	0.3082	0.3318	−0.0070
Panel B				
New South Wales	Average	0.3646	**0.3603**	0.2220
Victoria	Average	**0.4117**	0.3039	0.3234
Queensland	Average	0.3477	0.3487	0.3543
South Australia	Average	0.3330	0.3205	**1.0949**
Western Australia	Average	0.3315	0.3243	−0.0154
Tasmania	Average	0.3246	0.3231	−0.0113
Northern Territory	Average	0.3132	0.3166	−0.0024
Australian Capital Territory	Average	0.3082	0.3318	−0.0070

Note: Highest values are in bold. Figures for Greater Hobart, Rest of Tasmania, Great Darwin and Rest of Northern Territory are unavailable because the relevant indictors are not reported at corresponding GCCSA level in the HILDA data.

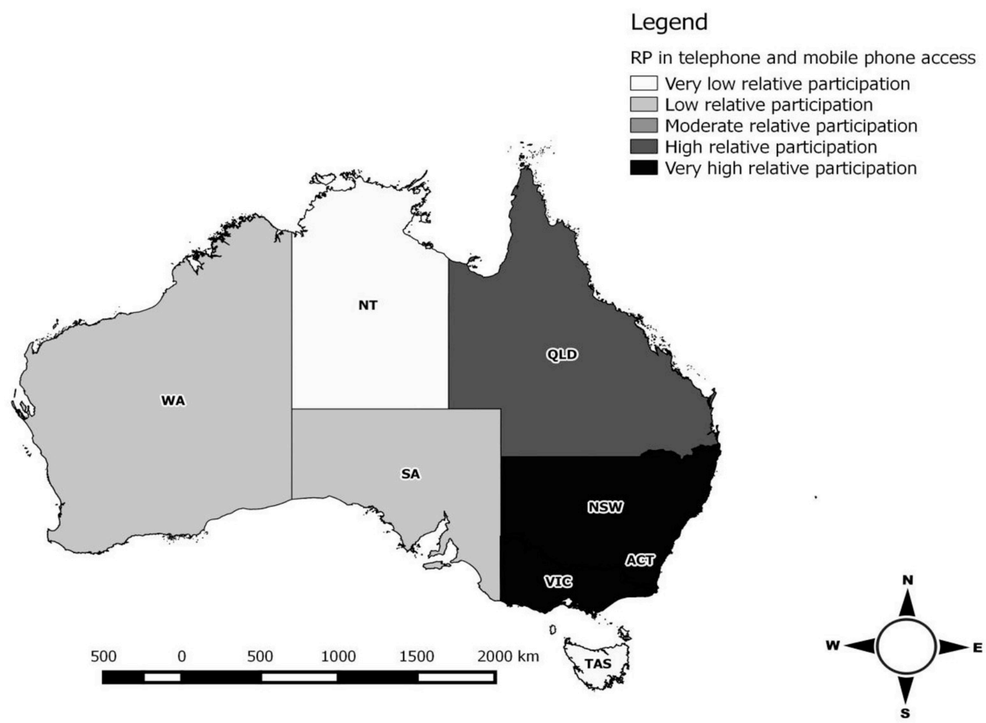

Fig. 3. Relative participation in telephone and mobile phone access in urban and rural households.

4.2. ICT expenditure concentration

4.2.1. Analysis of ICT expenditure concentration

To measure the ICT expenditure concentration, the Gini coefficient is estimated using the household ICT expenditure data. Table 10 reports the results of the Gini coefficient in ICT expenditure for urban and rural households. At the GCCSA level, the incidence of inequality is highest in the Rest of NSW (0.5345) for urban households; the Gini coefficient of ICT expenditure for this GCSSA is much higher than the nationwide value of 0.4404. This result indicates that ICT expenditure in the Rest of NSW areas and the whole of Australia are mostly concentrated within 53.5% and 44.0% of the respondents, respectively. For rural and all

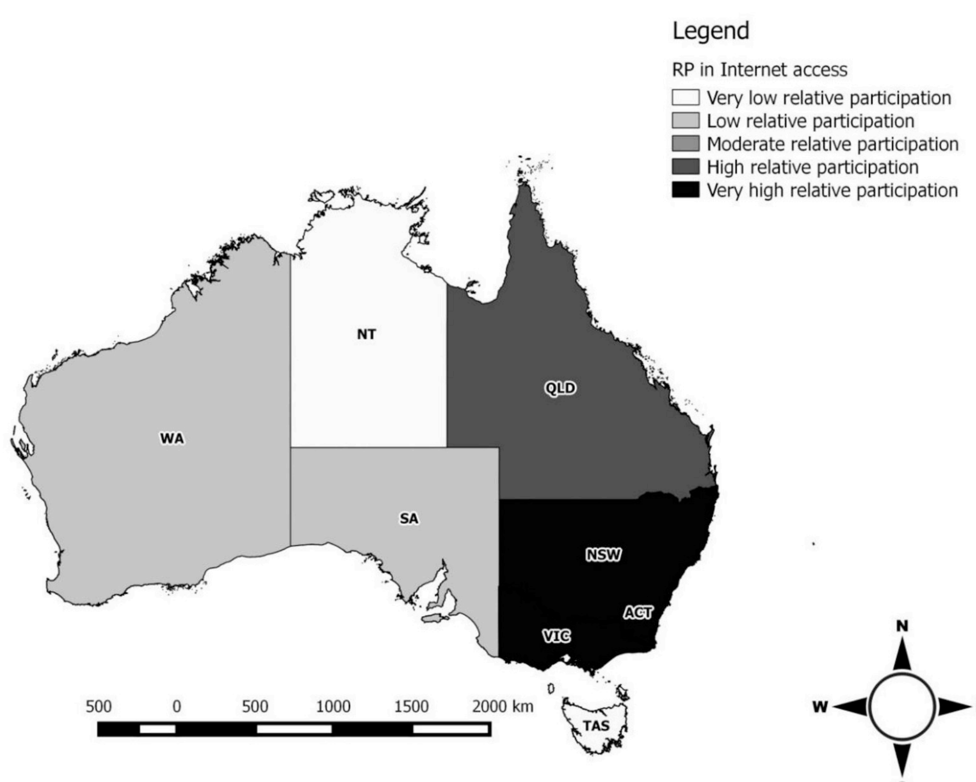

Fig. 4. Relative participation in Internet access in urban and rural households.

Table 8
RP in telephone and mobile, Internet, and no ICT access according to socio-economic and demographic indexes.

Classification of regions	All households (urban and rural)		
	Telephone and mobile phone access	Internet access	No ICT access
SAD			
Quintile 1	0.2321	0.2293	0.1265
Quintile 2	0.1423	0.1385	0.2426
Quintile 3	0.1034	0.1014	**0.3206**
Quintile 4	**0.2757**	**0.2796**	0.2024
Quintile 5	0.2465	0.2512	0.1080
ER			
Quintile 1	0.1883	0.1853	0.0000
Quintile 2	0.2170	0.2169	**0.3857**
Quintile 3	0.0936	0.0907	0.3500
Quintile 4	0.1580	0.1599	0.2644
Quintile 5	**0.3431**	**0.3472**	0.0000
E&O			
Quintile 1	0.1846	0.1816	0.0776
Quintile 2	0.0839	0.0816	0.1900
Quintile 3	0.1810	0.1776	**0.4467**
Quintile 4	**0.3260**	**0.3314**	0.1863
Quintile 5	0.2245	0.2278	0.0994
Size of region			
Small	0.3171	0.3126	0.2999
Medium	0.2316	0.2289	**0.3504**
Large	**0.4513**	**0.4585**	0.3497

Note: Highest values are in bold. Figures for Greater Hobart, Rest of Tasmania, Great Darwin and Rest of Northern Territory are unavailable because the relevant indictors are not reported at corresponding GCCSA level in the HILDA data.

Table 9
RP in telephone and mobile, Internet and no ICT access according to remoteness.

Classification of regions	All households (urban and rural)		
	Telephone and mobile phone access	Internet access	No ICT access
Major city	**0.6711**	**0.6842**	**0.7500**
Inner regional area	0.2159	0.2096	0.2083
Outer regional area	0.1008	0.0950	0.0417
Remote area	0.0101	0.0092	0.0000
Very remote area	0.0021	0.0020	0.0000

Note: Highest values are in bold.

households, the index score is highest for Greater Melbourne (0.5691 and 0.4987, respectively). At the state level, inequality in ICT is highest in NSW (0.5036) for urban household, whereas for rural and all households, Victoria has the highest prevalence of ICT expenditure inequality (see Fig. 5).

4.2.2. Association between ICT expenditure inequality, socio-economic divide and remoteness

Table 11 represents the associations between socio-demographic indicators and ICT expenditure inequality. The Gini coefficient for ICT expenditure is categorically represented based on two indicators, namely, SEIFA indexes on SAD and ER. The results show that ICT expenditure inequality is predominant in quintiles 3 and 4 for both indexes of SAD and ER.

Table 12 lists the Gini coefficient for ICT expenditure according to remoteness structure. The results show that ICT expenditure inequality is most prevalent among households that are located in major cities (0.4783), indicating that ICT expenditure in major city areas is mostly concentrated among 47.8% of respondents. In other words, this high Gini index value indicates higher concentrations in ICT affordability,

Table 10
Average Gini coefficient in ICT expenditure for urban and rural households.

Region/GCCSA	State	Households		
		Urban	Rural	All
Panel A				
Greater Sydney	New South Wales	0.4768	0.3309	0.4578
Rest of NSW	New South Wales	**0.5345**	0.4591	0.4968
Greater Melbourne	Victoria	0.4690	**0.5691**	**0.4987**
Rest of Victoria	Victoria	0.4625	0.4613	0.4619
Greater Brisbane	Queensland	0.4718	0.4922	0.4724
Rest of Queensland	Queensland	0.4777	0.3609	0.4172
Greater Adelaide	South Australia	0.4359	0.2995	0.4072
Rest of South Australia	South Australia	0.4255	0.5200	0.4479
Greater Perth	Western Australia	0.4502	0.3466	0.4140
Rest of Western Australia	Western Australia	0.4201	0.4696	0.4448
Tasmania	Tasmania	0.4681	0.3433	0.3898
Northern Territory	Northern Territory	0.4393	0.3888	0.4140
Australian Capital Territory	Australian Capital Territory	0.4433	0.2538	0.3486
Panel B				
New South Wales	Average	**0.5036**	0.4289	0.4759
Victoria	Average	0.4660	**0.5075**	**0.4814**
Queensland	Average	0.4749	0.4078	0.4434
South Australia	Average	0.4314	0.4097	0.4247
Western Australia	Average	0.4401	0.3993	0.4243
Tasmania	Average	0.4563	0.3562	0.3795
Northern Territory	Average	0.4393	0.3888	0.4140
Australian Capital Territory	Average	0.4433	0.2538	0.3486

Note: Highest values are in bold. Figures for Greater Hobart, Rest of Tasmania, Great Darwin and Rest of Northern Territory are unavailable because the relevant indictors are not reported at corresponding GCCSA level in the HILDA data.

which eventually translate into higher inequality in terms of ICT expenditure. For very remote areas, the coefficient appears to be lower (0.3782), and such a lower level of concentration means lower inequality in ICT expenditure. These findings indicate the link between ICT expenditure inequality and state of the remoteness of households, such that the higher the accessibility of households to city centres, the higher the RP in ICT services and vice versa.

4.3. Association between ICT infrastructure concentration and expenditure inequality

CCA is used to explore the association between ICT infrastructure concentration and expenditure inequality (Table 13). In this analysis, two sets of variables are used. Set 1 comprises ICT infrastructure concentration measures, i.e. CIs for telephone and mobile phone, Internet and no ICT access. Set 2 encompasses ICT expenditure inequality. For variable combination A, the canonical correlation coefficient and Wilks' statistic are 0.7028 and 0.0560, respectively. The corresponding F statistic is 2.9288, which is statistically significant at 10% level. For combination B, the canonical correlation coefficient is statistically significant at 5% level. Therefore, we can reject the null hypothesis that our two sets of variables are not linearly related. This finding indicates that ICT infrastructure concentration and expenditure inequality are statistically associated with each other.

5. Discussion

This study finds that the concentration of telephone and mobile and Internet access is higher in Greater Sydney and Greater Melbourne at the GCCSA level. Following this trend, Victoria and NSW secure the top spots in terms of ICT infrastructure concentration at the state level. These findings are consistent with those of [20]; who reported that the two aforementioned states have the highest relevance of digital concentration in Australia. In turn, these results indicate that ICT

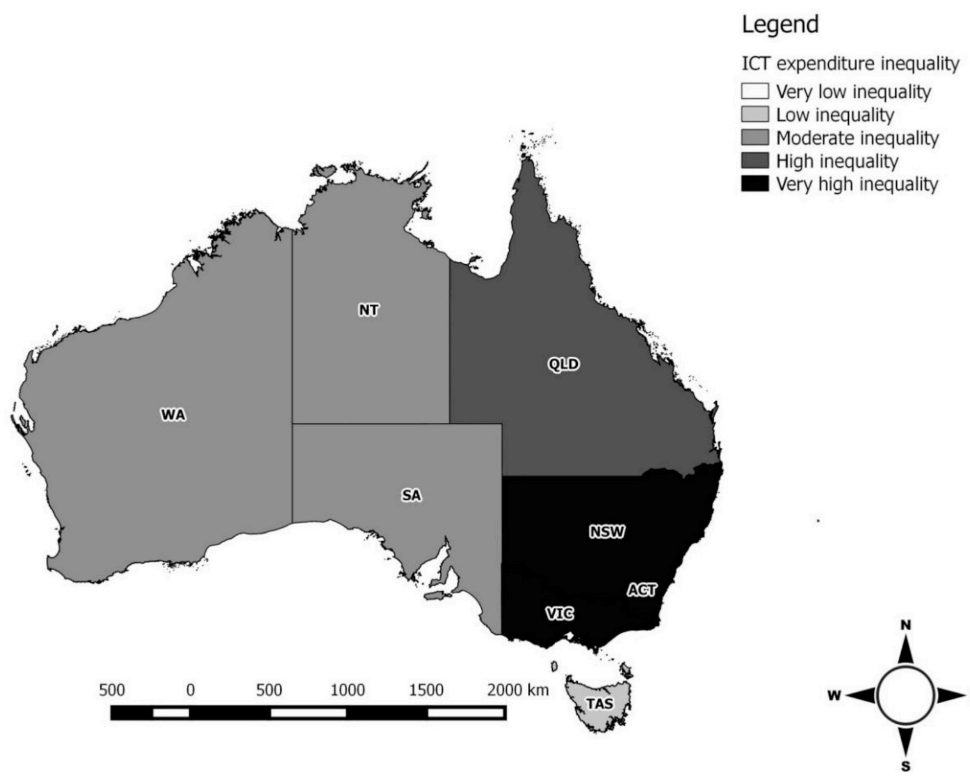

Fig. 5. Inequality in ICT expenditure in urban and rural households.

Table 11
Average Gini coefficient for ICT expenditure according to socio-economic classification of regions.

Classification of regions	All households (urban and rural)
SAD quintile	
Quintile 1	0.4507
Quintile 2	0.4636
Quintile 3	**0.4744**
Quintile 4	0.4624
Quintile 5	0.4146
ER quintile	
Quintile 1	0.4754
Quintile 2	0.4464
Quintile 3	**0.4783**
Quintile 4	0.4575
Quintile 5	0.3782

Note: Highest values are printed in bold.

Table 12
Average Gini coefficient for ICT expenditure according to remoteness.

Classification of regions	All households (urban and rural)
Major city	**0.4783**
Inner regional area	0.4464
Outer regional area	0.4754
Remote area	0.4575
Very remote area	0.3782

Note: Highest values are printed in bold.

infrastructure is highly concentrated in the largest economic hubs of Australia, namely, the urban centres in Sydney and Melbourne. The reason behind this phenomenon is that economic activity in Australia is concentrated most heavily in the cities [36]. The concentration of highly productive business enterprises and proximity to suppliers, customers and partners are the main reasons behind the consolidation of major economic activities in Sydney and Melbourne [36].

Aligning these numerical results with the entire population of Australia might aid in articulating the discussion of the results from a policy perspective. This comparative discussion can help identify those groups reaping benefits from the current distribution of ICT infrastructure. For all household classes, telephone and mobile phone access are highly concentrated in Rest of Victoria, which constitutes 6.0% of the total population (approximately 1.4 million people) [24]. The CI score for Internet access is highest in the Greater Melbourne region representing 19.5% of the total population (around 4.7 million people) [24]. No ICT access is most extensively concentrated in 5.5% of the population who are largely residing in the Greater Adelaide region [24]. In comparison, the CI scores for telephone and mobile phone access is lowest among 1.7% of people (0.4 million) living in the Australian Capital Territory [24]. For Internet access, 2.1% of the total population (0.5 million people belonging from Rest of Western Australia) have the lowest CI scores [24]. These figures indicate that digital exclusion is less prominent in Australian Capital Territory and the Rest of Western Australia region compared to that of the Rest of Victoria and Greater Melbourne regions.

Another important finding is that the degree of ICT infrastructure concentration varies with the level of income, educational qualification and employment status. This finding is in accordance with those of existing empirical studies [2,12,15–17]. Consistent with the literature, the current research finds that the digital divide broadens across rural–urban and regional–capital city households [6,8,20]. The findings of the current study extend those of [20] by representing ICT concentration with remoteness. Furthermore, the results of the current study indicate that ICT infrastructure concentration is predominant in households that are located in major cities compared with those in remote and very remote areas. Precisely, this study finds that about two-thirds of the respondents who reported having access to telephone and mobile phone as well as the Internet are located in major city areas. In turn, this implies that nearly about 17.3 million people (71.6% of the total population) reported demonstrating high concentration in terms of ICT access. These results are also consistent with existing empirical

Table 13
Canonical correlation between ICT infrastructure concentration and expenditure inequality.

Variable combination	Set 1 (ICT infrastructure concentration)	Set 2 (ICT expenditure inequality)	Canonical correlation	Wilks' statistic	F statistic
A	CIs for telephone and mobile phone, Internet, and no ICT access	ICT expenditure inequality	0.7028	0.5060	2.9288**
B	CIs for telephone and mobile phone and Internet access	ICT expenditure inequality	0.6977	0.5132	7.7437*

Note: * and ** denote statistical significance at the 5 and 10% levels, respectively.

studies [8], reinforcing the challenges faced by regional Australia during its transition to a broad-based economy as well as the geographic dimension of the digital divide [4,5].

The current study also extends the empirical contribution of [20] by investigating the association between digital inclusion and affordability in the Australian context. The concentration patterns of ICT infrastructure and expenditure inequality are comparatively high in Victoria and NSW. Inequality in ICT expenditure is found to be prevalent in households that are located in major cities. Nonetheless, a significant association exists between ICT infrastructure concentration and expenditure inequality. Specifically, the concentration of ICT expenditure is predominant in areas where the concentration of ICT infrastructure is high, indicating that ICT expenditure is a notable catalyst in ICT development because it plays a substantial role in explaining the pattern of ICT infrastructure concentration. These results corroborate the claim of previous seminal studies [7,18].

6. Conclusion

This study measures the concentration of ICT infrastructure and examines its association with various indicators, including socio-demographic inequality, affordability and remoteness in Australia. Constructing a composite CI for ICT infrastructure, the study finds that ICT infrastructure is highly concentrated in large economic hubs in Australia, i.e. Sydney and Melbourne. The results for ICT expenditure inequality demonstrate a similar trend. Employing CCA, the study also finds that the association between ICT infrastructure concentration and ICT expenditure inequality are statistically significant.

This research offers several practical implications. Most importantly, the research provides a comprehensive picture of the digital divide in Australia. A crucial first step towards narrowing the digital divide is accurately mapping the geographic patterns of disadvantage and this study extends the existing knowledge in this area. For example, according to the findings of this study, ICT infrastructure concentration is predominant in major cities compared to those in remote and very remote areas. This knowledge can be used by policy makers to inform the prioritisation of spatial and regional development strategies for digital infrastructure as it provides a compact guideline regarding the location of people without access. Furthermore, all dimensions of the digital divide should be taken together in devising ICT policies. The interplay between the first layer of the digital divide (i.e. access) should be holistically analysed with the second layer of the digital divide (i.e. affordability and digital literacy). In this regard, the nationwide National Broadband Network (NBN) rollout plan has been playing a major role in delivering quality broadband service to all Australians. This study provides support for this initiative and, in particular, for the provision of reliable high-speed Internet to regional and remote areas. Following different scenarios of cost-benefit analysis of broadband provision projected by the independent panel of experts and NBN Co, the total costs of continued NBN roll-out using fibre to the premises across Australia is estimated at AU$32.7 billion for the period of 2019–2024 (Department of Communication and the Arts, 2014; NBN Co, 2013). According to these projections, by 2024 about 13.06 million premises across Australia would potentially benefit from this nationwide NBN roll-out (Department of Communication and the Arts, 2014). Moreover, to deal with the divide in ICT infrastructure in socio-economically disadvantaged areas, regional and remote areas should be provided with increased reliable high-speed Internet connections. If the demand and willingness among a particular regional or remote community are sufficient, then the federal government can contribute towards the establishment of fibreoptic network connections. In this regard, the government-owned NBN Co and major telecommunications providers, such as Telstra and Optus, should work with local governments to identify critical infrastructure priorities and challenges. Consulting with the Ministry of Communication and Arts and the Ministry of Finance to allocate budget to encourage technological as well as service, institutional and market innovations in the telecommunication sector to facilitate last-mile connectivity would also further the goal of regional ICT development.

Digital literacy is another important aspect of the digital divide. Improved ICT infrastructure will mean little to disadvantaged individuals in remote communities without the appropriate skills and knowledge. In some ways, this is a catch-22 situation. Without ICT access individuals have no reason to develop ICT skills, and without ICT skills the practical impact of ICT access will be weak. Therefore, digital literacy must be considered alongside efforts to increase access, such as the NBN. For example, the Department of Local Government and Communities and the Department of Training and Workforce Development can provide assistance to communities in targeting ICT training programmes for vulnerable and disadvantaged groups in regional Australia. In both rural and urban areas, the digital divide is intertwined with other dimensions of social exclusion. For this reason, digital inclusion policy makers should take the systemic approach of looking beyond technological and narrowly economic factors to consider place-based context. In this regard, NBN Co can gather local community input and advice on the network roll-out by considering local communities as reference groups.

In the development and delivery of ICT infrastructure, the private sector can contribute significantly by bringing new technologies, innovation, experience and efficiency as well as better management. The development of public–private partnerships (PPPs) is a key avenue for mobilising resources from the private sector in the delivery of digital infrastructure. In particular, in addition to measures taken by the government, private telecommunication service providers can also play a major role in enhancing and expanding connectivity in regional and rural area through the network infrastructure. In this regard, Optus–the second largest telecommunication service provider in Australia–has invested AU$6 billion in infrastructure development. In addition, they have built a number of towers across 1000 + regional towns and upgraded existing ones [37]. They have also committed to investing AU$1 billion to improve and expand mobile coverage in regional and remote sites across Western Australia, South Australia and the Northern Territory [37]. Coordination among different departments of government and private telecommunication service provider play a substantial role in ensuring equitable access to ICT infrastructure and services. For example, Telstra–the largest telecommunication service provider of Australia–has a Universal Service Obligation (USO) to warrant standard telephone services and payphones are reasonably accessible to all people in Australia on an equitable basis regardless of where they work or live. On behalf of the Australian Government, the Department of Communications and Arts administers Telstra's USO Performance Agreement [38].

The current study also finds that a significant association exists between the digital divide and ICT expenditure inequality. As affordability is an important dimension of the digital divide, NBN co and the Department of Communications and Arts should work with various telecommunications companies in order to ensure that a range of technologies and services can be profitably provided in a way that is appropriate for all Australians. For example, issues of affordability are relevant to the choice between competing technologies in the NBN rollout, as the technologically superior solution of using fibreoptic technology in these premises may not be the best choice once the effect on the government budget and retail prices are taken into account [39,40]. Competition policy is also highly relevant here, and the Australian Competition and Consumer Commission must look at competition not only at the national level, but also in specific regional communities that are more vulnerable to monopoly, and often less able to deal with the cost thereof, than thicker urban markets [41].

This study is not free from limitations. Firstly, to yield meaningful results, the construction and reporting of a concentration measure should be conducted at the most disaggregated geographical level. Many studies are conducted to measure the concentration of ICT up to a considerable level of disaggregated geographical units in the context of USA, Brazil and China [12,16,42]. For the current study, the construction of the ICT CI at the SA4 geographical levels is impossible due to the terms and conditions of using the HILDA Restricted Release database. Geographical mapping in terms of ICT concentration at a disaggregated spatial unit like SA4 would have rendered better insights for the policy makers. Given the circumstances, the provisions and clauses of data reporting should be more flexible and user-friendly. Secondly, the concentration measure estimated in the current study is a static one. In the future, a dynamic assessment of ICT concentration can be conducted to gain better insights into whether the concentration of ICT in a particular spatial unit has changed over time. Finally, this study measures the concentration of ICT in terms of access and affordability. Further research can be conducted by incorporating various service quality dimensions (e.g. speed of Internet connection, network coverage and call drops) in measuring the concentration of ICT services.

Acknowledgements

The paper is a part of the PhD study of the first author. The PhD program was funded by the University of Southern Queensland, Australia [USQ International Stipend Research Scholarship & USQ International Fees Research Scholarship].

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.seps.2019.100737.

References

[1] ITU. Measuring the information society report 2017 Retrieved from https://www.itu.int/en/ITU-D/Statistics/Documents/publications/misr2017/MISR2017_Volume1.pdf 2017.
[2] Alam K, Imran S. The digital divide and social inclusion among refugee migrants: a case in regional Australia. Inf Technol People 2015;28(2):344–65.
[3] Hodge H, Carson D, Carson D, Newman L, Garrett J. Using Internet technologies in rural communities to access services: the views of older people and service providers. J Rural Stud 2016;54:469–78.
[4] Park S. Digital inequalities in rural Australia: a double jeopardy of remoteness and social exclusion. J Rural Stud 2017;54:399–407.
[5] Productivity Commission. Ransitioning regional economies, study report. T. 2017. December 2017. Retrieved from https://www.pc.gov.au/inquiries/completed/transitioning-regions#report.
[6] CINIC. The 35th Statistical report on internet development in China Retrieved from https://cnnic.com.cn/IDR/ReportDownloads/201507/P020150720486421654597.pdf 2015.
[7] ITU. Measuring the information society report 2014 Retrieved from https://www.itu.int/en/ITU-D/Statistics/Documents/publications/mis2014/MIS2014_without_Annex_4.pdf 2014.
[8] Sujarwoto S, Tampubolon G. Spatial inequality and the Internet divide in Indonesia 2010–2012. Telecommun Policy 2016;40(7):602–16.
[9] Martin SP, Robinson JP. The income digital divide: trends and predictions for levels of internet use. Soc Probl 2007;54(1):1–22.
[10] Mutula SM, van Brakel P. An evaluation of e-readiness assessment tools with respect to information access: towards an integrated information rich tool. Int J Inf Manag 2006;26(3):212–23.
[11] Novo-Corti I, Barreiro-Gen M. Public policies based on social networks for the introduction of technology at home: demographic and socioeconomic profiles of households. Comput Hum Behav 2015;51:1216–28.
[12] Pick JB, Sarkar A, Johnson J. United States digital divide: state level analysis of spatial clustering and multivariate determinants of ICT utilization. Soc Econ Plan Sci 2015;49:16–32.
[13] Ayanso A, Cho DI, Lertwachara K. Information and communications technology development and the digital divide: a global and regional assessment. Inf Technol Dev 2014;20(1):60–77.
[14] Dobrota M, Martic M, Bulajic M, Jeremic V. Two-phased composite I-distance indicator approach for evaluation of countries' information development. Telecommun Policy 2015;39(5):406–20.
[15] De Queiroz Ribeiro LC, Salata A, Costa L, Gomes Ribeiro M. Digital inequalities: internet access and use, social-economic position, and spatial segmentation in the Brazilian metropolitan areas. Análise Soc 2013;48(207):288–320.
[16] De Brito SR, Silva ADSD, Cruz AG, De Monteiro MA, Vijaykumar NL, Silva MSD, Francês CRL. Concentration of access to information and communication technologies in the municipalities of the brazilian legal amazon. PLoS One 2016;11(4).
[17] Mendonça S, Crespo N, Simões N. Inequality in the network society: an integrated approach to ICT access, basic skills, and complex capabilities. Telecommun Policy 2015;39(3):192–207.
[18] Raghupathi W, Wu SJ. The relationship between information and communication technologies and country governance: an exploratory study. CAIS 2011;28:12.
[19] Holloway D. The digital divide in Sydney. Inf. Commun Soc 2005;8(2):168–93.
[20] Thomas J, Barraket J, Ewing S, MacDonald T, Mundell M, Tucker J. Measuring Australia's digital divide: the Australian digital inclusion index 2016 Retrieved from https://researchbank.rmit.edu.au/view/rmit:42462; 2016.
[21] Gibson C. Digital Divides in New South Wales: a research note on socio-spatial inequality using 2001 Census data on computer and Internet technology. Aust Geogr 2003;34(2):239–57.
[22] ABS. Australian standard geographical classification (ASGC) 2011, ABS catalogue No. 1216.0 Retrieved from http://www.abs.gov.au/AUSSTATS/abs@.nsf/DetailsPage/1216.0July%202011?OpenDocument 2011.
[23] ABS. Australian historical population statistics 2016. Retrieved from Canberra https://www.abs.gov.au/AUSSTATS/abs@.nsf/DetailsPage/3105.0.65.0012016?OpenDocument; 2016.
[24] ABS. Australia Regional population growth. 2016. p. 2016–7. Retrieved from Canberra https://www.abs.gov.au/AUSSTATS/abs@.nsf/DetailsPage/3218.02016-17?OpenDocument.
[25] DSS, Melbourne Institute of Applied Economic and Social Research. The household, income and Labour dynamics in Australia (HILDA) survey RESTRICTED RELEASE 16 (Waves 1-16) (Publication no. doi/10.4225/87/QFUIBM). from ADA Dataverse. https://doi.org/10.4225/87/QFUIBM; 2017.
[26] ABS. Census of population and housing: socio-economic indexes for areas (SEIFA), ABS catalogue no. 2033.0.55.001 Retrieved from Canberra http://www.abs.gov.au/AUSSTATS/abs@.nsf/DetailsPage/2033.0.55.0012016?OpenDocument; 2011.
[27] ABS. Australian statistical Geography standard (ASGS): volume 5 - remoteness structure July 2011. Retrieved from http://www.abs.gov.au/AUSSTATS/abs@.nsf/DetailsPage/1270.0.55.005July%202011?OpenDocument; 2011.
[28] Crocco MA, Galinari R, Santos F, Lemos MB, Simões R. Metodologia de identificação de aglomerações produtivas locais. Nova Econ 2006;16(2):211–41.
[29] Hosseini HM, Kaneko S. Dynamic sustainability assessment of countries at the macro level: a principal component analysis. Ecol Indicat 2011;11(3):811–23.
[30] Cowell F. Measuring inequality, LSE perspectives in economic analysis. Oxford, UK: Oxford University Press; 2008.
[31] Gini C. Variabilità e mutabilità (Variability and Mutability). Reprinted in Memorie di metodologica statistica [Bologna]. In: Pizetti E, Salvemini T, editors. Rome: Libreria Eredi Virgilio Veschi1912. *1955*.
[32] Stuart A, Ord K. Kendall's advanced theory of statistics: distribution theory vol. 2. London: Edward Arnold; 1994.
[33] Deaton A. The analysis of household surveys: a microeconometric approach to development policy. Washington, D.C.: The World Bank; 1997.
[34] Jasso G. On Gini's mean difference and Gini's index of concentration. Am Sociol Rev 1979;44(5):867–70.
[35] Härdle W, Simar L. Canonical correlation analysis *applied multivariate statistical analysis* vol. 22007. Springer; 2007. p. 321–30.
[36] Kelly J-F, Donegan P, Chisholm C, Oberklaid M. Mapping Australia's economy: cities as engines of prosperity Grattan Institute Report No. 2014-9 Retrieved from https://grattan.edu.au/wp-content/uploads/2014/07/814-mapping-australia-economy1.pdf; 2014.
[37] Optus. Connecting regional-'yes' Retrieved from https://www.optus.com.au/about/network/regional-coverage/news/coverage-investment/connecting-regional-yes 2018.
[38] Department of Communications and Arts. Universal service obligation Retrieved from https://www.communications.gov.au/what-we-do/phone/phone-services/universal-service-obligation 2017.
[39] de Ridder J, James B. Affordable retail pricing on the NBN. Aust J Telecommun Digit Econ 2013;1(1):5.
[40] Eckermann R. Getting some reality into debates about NBN FTTP. Aust J Telecommun Digit Econ 2013;1(1).
[41] Grubesic TH, Murray AT. Waiting for broadband: local competition and the spatial distribution of advanced telecommunication services in the United States. Growth

Chang 2004;35(2):139–65.
[42] Lin J, Yu Z, Wei YD, Wang M. Internet access, spillover and regional development in China. Sustainability 2017;9(6):946.
[43] ABS. Australian statistical Geography standard (ASGS): volume 1 - main structure and greater capital city statistical areas July 2011 http://www.abs.gov.au/AUSSTATS/abs@.nsf/DetailsPage/1270.0.55.001July%202011?OpenDocument; 2011.

Mr. Mohammad Afshar Ali received Masters of Social Science in Economics from Jagannath University, Bangladesh. Currently he is undertaking his Ph.D. in information economics at the University of Southern Queensland. His areas of research interest include information economics and policy, digitisation, health informatics, sustainable development issues and ICT4D. He has published a number of research articles in peer-reviewed journals.

Dr. Khorshed Alam is a Professor of Economics in the School of Commerce at the University of Southern Queensland, Australia. He holds a PhD in Environmental and Resource Economics from Murdoch University, Australia and a Masters in Economics from the Institute of Social Studies of Erasmus University Rotterdam in the Netherlands. His research interests include environmental, resource and agricultural economic issues, economics of water-energy-climate change, sustainability, health economics and policy, digital economy and adoption and use of digital technologies.

Dr. Brad Taylor is a Lecturer in Economics and Political Economy at the University of Southern Queensland. His primary areas of research are public choice theory and analytic political theory. His work has been published in journals such as Kyklos and Constitutional Political Economy. He has a PhD in political science from the Australian National University.

Study 3

Economic Analysis and Policy 64 (2019) 317–328

Contents lists available at ScienceDirect

Economic Analysis and Policy

journal homepage: www.elsevier.com/locate/eap

Full length article

Do income distribution and socio-economic inequality affect ICT affordability? Evidence from Australian household panel data

Mohammad Afshar Ali [a,d,*], Khorshed Alam [a], Brad Taylor [b], Shuddha Rafiq [c]

[a] School of Commerce, Faculty of Business, Education, Law & Arts, University of Southern Queensland, Toowoomba, Queensland 4350, Australia
[b] School of Commerce, Faculty of Business, Education, Law & Arts, University of Southern Queensland, Springfield, Queensland 4300, Australia
[c] School of Commerce, Faculty of Business and Law, BL Deakin Business School, Deakin University, Melbourne Burwood Campus, Australia
[d] Department of Economics, Jagannath University, Dhaka-1100, Bangladesh

ARTICLE INFO

Article history:
Received 4 August 2019
Received in revised form 13 October 2019
Accepted 14 October 2019
Available online 19 October 2019

JEL classification:
D63
O15
O33

Keywords:
Information and communication technology
Affordability
Income distribution
Socio-economic inequality
Panel data

ABSTRACT

The impact of information and communication technology (ICT) on human development depends on the distribution of income and affordability of ICT services. This study explores the responsiveness of ICT affordability to income distribution and socio-economic inequality. Applying a generalised linear mixed model and a random effects model based on Australian household panel data covering 2011–2017, this study finds that gross ICT affordability is positively associated with income distribution and socio-economic inequality. Interestingly, for low-income subgroups, inequality reveals to have a positive impact on ICT affordability, whereas for high-income household, the impact is reversed. These findings provide insights that are useful in the design of policies and strategies to promote ICT affordability and penetration.

1. Introduction

A country's state of information and communication technology (ICT) development can be predicted based on its present and past ICT affordability information (Ayanso and Lertwachara, 2015; Choudrie et al., 2015). Previous research has established that affordability plays a pivotal role in bridging the 'digital divide' resulting from socio-economic inequality within and between developed and developing nations (Choudrie et al., 2015; Grosso, 2006; Lee, 2008). Several studies have suggested that ICT accessibility is significantly influenced by the distribution of income (Hilbert, 2010; Prieger, 2003, 2015). In the presence of income inequality, ICT services may not be affordable, and thus fail to contribute to developmental outcomes (United Nations, 2010; van Dijk, 2005). This concern has been most pressing on developing countries, but affordability remains an issue for developed countries, such as Australia (Thomas et al., 2016). Expenditure on Internet services has increased faster than household income in Australia in recent years, reducing

* Corresponding author.
E-mail addresses: MohammadAfshar.Ali@usq.edu.au (M.A. Ali), khorshed.alam@usq.edu.au (K. Alam), Brad.Taylor@usq.edu.au (B. Taylor), srafiq@deakin.edu.au (S. Rafiq).

https://doi.org/10.1016/j.eap.2019.10.003
0313-5926/

affordability particularly to low-income households (Thomas et al., 2016). Looking at how ICT affordability varies with income distribution and socio-economic inequality is a useful exercise for developed and developing countries.

Conceptualisation on accessibility to affordable ICT in terms of the capability approach developed by Sen (1985) is useful. ICT increases individuals' substantive freedom to pursue their goals by allowing them to find employment opportunities, maintain social relationships and seek information. Technology has become extremely central to modern life that a lack of affordable ICT access is a major disadvantage (Johnstone, 2007; Sen, 2010; Wresch, 2009). Following the capability approach, Weiss et al. (2015) found that inexpensive ICT-related services aided digital inclusion where individual capabilities were high. In line with this theory, a number of cross-country empirical studies showed that disparity in personal income is a significant predictor of the affordability of telecommunication services (Choudrie et al., 2015; Fuchs, 2009; Weiss et al., 2015). Cross-sectional studies confirmed that the global-level income inequality and per capita income shape the affordability of mobile broadband services (Fuchs, 2009; Weiss et al., 2015). In another cross-national study in a developing country context, Choudrie et al. (2015) found that after controlling for the effects of wealth, education and other factors, the Gini coefficient of income significantly determines the mobile broadband price basket.

Existing empirical studies reveal that the effect of income distribution on ICT diffusion is non-linear in nature (Bohman, 2008; Milne, 2000). Specifically, ICT diffusion is negatively impacted by income inequality in low-income countries. This finding implies that only a small proportion of the population can afford ICT services. In high-income countries, income inequality is associated with high levels of ICT diffusion (Bohman, 2008; Milne, 2000). Furthermore, the impact of income on ICT affordability also varies with the level of income and with the lowest quintile in high-income countries spending near their affordability threshold (Milne, 2006). In addition, ICT expenditure of the high-income group is approximately 2–4 times higher than that of the low-income group (Milne, 2006). As a result, as income increases, household expenditure on ICT rises in absolute terms, but falls in proportion to total expenditure. If ICT service is considered as a necessity in developed countries, then this assumption provides evidence for Engel's law, which states that the proportion of income spent on necessary goods falls as income rises (Engel, 1857).

The current study contributes to the existing literature in four ways. Firstly, this study is the first attempt to examine the responsiveness of ICT affordability to changes in income distribution using a household level longitudinal dataset. Secondly, this study examines the effect of social exclusion on the affordability of ICT services. Unlike previous studies, a composite index score is used to measure social exclusion, namely, socio-economic advantage and disadvantage index. These indexes measure the relative socio-economic advantages and disadvantages of individuals in terms of their access to material and social resources and their ability to participate in society (ABS, 2011). Lastly, by exploring the non-linearity in the effect of income distribution on ICT affordability, the current study provides deep insights for policy makers regarding the connection between income distribution and ICT affordability.

Therefore, the current research attempts to explore the nature of responsiveness of income distribution and socio-economic inequality on the affordability of ICT services. By doing so, two research questions are posed: (i) Do income distribution and socio-economic inequality have a significant impact on ICT affordability? (ii) Is the effect of income distribution on ICT affordability heterogeneous in nature? The rest of the study is structured as follows. Section 2 describes the data and estimation methods. Section 3 presents the empirical results. Section 4 provides a comparative discussion of the findings. Section 5 concludes by pointing out policy implications.

2. Materials and methods

2.1. Data and variables

This study uses the longitudinal data compiled from wave 11 to wave 17 of the Household, Income and Labour Dynamics in Australia (HILDA) Survey-Restricted Release. The survey methodology is thoroughly explained by Wooden et al. (2002). In wave 1, a total of 7683 representatives of all in-scope households were interviewed. The total sample eligible for interviews were 15,127 persons who were 15 years old and above. A total of 13,969 individuals were successfully interviewed in wave 1. Every year, subsequent interviews are conducted for later waves. Each person completing a personal interview was also given a self-completion questionnaire. To make the longitudinal dataset balanced, the Stata program developed by Sun et al. (2016) was used in the study. After merging the dataset, data screening and cleaning process were conducted. These processes include checking for missing data and finding out outliers. Stata 15 was used for the merging, cleaning and processing of the data. The total number of useable observations are 38,906, which is a balanced panel of 5558 individuals across seven waves, that is, from wave 11 to wave 17.

The HILDA survey contained detailed demographic and economic information on each individual, including age, gender, employment status and personal income. ICT-related information used in this study included household ICT expenditure and access to the Internet. Information on financial security and benefit were also included to capture the financial aspects of an individual. However, for a few variables, data were reported at the household level, such as, distribution of household income (measured by the Gini coefficient), socio-economic advantage and disadvantage index score, Internet access, remoteness, urbanisation, household composition and household annual ICT expenditure. Using the IDs of the households, information on those variables were then matched at the individual level using cross-wave IDs.

Table 1 provides the definitions of the variables included in the models along with their means and standard deviations across seven waves. The classification of the variables also reflects on the model specifications. The variables listed in panel

Table 1
Variable descriptions and summary statistics.

Variable name	Definition of variable	Mean	SD
A. Dependent variables			
hhICTexp	Household annual expenditure on telephone rent, calls and internet charges (measured in AU$).	1953.9950	2544.2540
DII_afford[a]	A composite index that measures two key aspects or dimensions of digital affordability inclusion. It is composed of the share of household income spent on Internet access and total Internet data allowance per dollar of expenditure. The index score ranges from 0 to 100.	54.0786	6.4017
B. Independent variables			
Gini_hh_inc[b]	Household income distribution measured by Gini coefficient. The index score ranges from 0 to 1.	0.3339	0.0606
sad	Socio-economic advantage and disadvantage index score measured by ABS (2011). It is used to define the relative socio-economic advantage and disadvantage in terms of people's access to material and social resources, and their capability to participate in society.	1010.5950	92.0925
hhInt_accss	A dummy variable indicating whether or not a respondent person has access to the Internet at home (1 = has access to the Internet at home, 0 = otherwise).	0.9132	0.2815
major_city	A dummy variable indicating whether a respondent person lives in a major city or not (1 = resident of the major city, 0 = otherwise). This variable is created on the basis of the Australian Statistical Geography Standard (ASGS) geographical classification which used Remoteness Structure as building blocks (ABS, 2011). ABS surveys defines remote areas on the basis of this classification.	0.6565	0.4749
urban_area	A dummy variable indicating whether a respondent person lives in an urban area or not (1 = resident of an urban area, 0 = otherwise). This variable is created on the basis of the ASGS geographical classification which used Section of State Structures as building blocks (ABS, 2011). ABS surveys defines rural and urban areas on the basis of this classification.	0.8628	0.3441
C. Control variables			
age	Age of the respondent (years).	52.8426	15.3504
gender	A dummy variable indicating the gender of the respondent (1 = male, 0 = female).	1.5432	0.4981
employment_status	A dummy variable indicating the employment status of the respondent (1 = employed, 0 = otherwise).	0.6281	0.4833
hhwtchild	A dummy variable indicating whether or not there is a child aged 14 or less in the respondent person's house (1 = has children aged 14 or less, 0 = otherwise).	0.2680	0.4429
FS_composite	A composite index to measure the financial security of a respondent.	1.0843	0.3505
benefit_govt	Annual payments received ($) as Australian Government income support	4054.3410	7903.7300
Number of persons		5 558	
Number of observations (balanced panel for 2011–2017)		38 906	

[a]This variable is available for data points for the period of 2014–2017. For details, see Thomas et al. (2016).
[b]It is a measure of inequality, can be defined as the mean of absolute differences between all pairs of persons for some measure. For details, Cowell (2008).

A are the dependent variables used in two different sets of estimations, whereas those included in panel B are independent variables; and those in panel C are control variables in baseline and robust estimations.

The Gini coefficient of household income is computed to measure its inequality and is also used as a summary measure for income inequality (Cowell, 2008). Fifty-seven state-wide geographical regions are used as the aggregation unit to compute the Gini coefficient of household income. The formation of geographical aggregation units (i.e. regions) are conducted following the state-wide regional clustering piloted by Thomas et al. (2016).

The basic mathematical expression of Gini coefficient can be expressed by the following equation:

$$G = \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} |x_i - x_j|}{2n^2\overline{x}}, \tag{1}$$

where x is an observed value, n is the number of values observed and $\overline{x}$ is the mean value.

If the values of x are arranged in ascending order, such that each x has rank i, then the expression can be rewritten as:

$$G = \frac{2}{2n^2\overline{x}} \sum_{i=1}^{n} i(x_i - \overline{x}), \tag{2}$$

where x is an observed value, n is the number of values observed , i is the rank of values arranged in ascending order, and $\overline{x}$is the mean value.

The composite index to measure financial security (*FS_composite*) is composed of three indicators: (i) whether the individual asked for financial help from family or friends, (ii) self-assessed status of financial satisfaction and (iii) whether the individual faced difficulties in raising emergency fund. The value of *FS_composite* ranged from 0 to 1. An *FS_composite* score of 0 indicates an extremely low level of financial security, whereas 1 specifies the exact level of financial security. This index is constructed by using Principal Component Analysis (PCA) with the weights of each indicator computed to constitute *FS_composite*. PCA is a multivariate statistical estimation technique that analyses a data table by presenting observations described by a set of variables which are assumed to be intercorrelated (Hosseini and Kaneko, 2011). The objective of PCA is to construct new variables (P_{i}) from a set of variables, X_j ($j = 1, 2, \ldots., n$). These variables are referred to as principal components, which are linear combinations of *Xs*. The following equation is used to construct the composite index, *FS_composite*:

$$FS_{composite} = \sum_{i=1}^{3} a_{ij} \frac{X_{ij}}{Sd\,(X)_i}, \tag{3}$$

where *FS_composite* is the composite index of financial security of each individual, *Sd* is the standard deviation, X_{ij} is the ith variable in the jth year and a_{ij} is the factor loading derived through PCA.

2.2. Model specification

This study deploys a set of panel data estimation models to explore the relationship between ICT affordability and access to the Internet. The selection of variables is determined by two facts. Firstly, the theoretical foundation of the current study is based on two basic theories, namely, Engel's law (Engel, 1857) and capability theory (Sen, 1985). Engel's law postulates the relationship between income and household expenditure. Following Sen's capability approach, the idea that affordable ICT services aid digital inclusion by augmenting individual capabilities is argued. In addition, guided by the argument rooted in capability theory, several studies reported that personal income and socio-economic inequality are two major determinants of ICT affordability (Choudrie et al., 2015; Weiss et al., 2015). A few studies also found that ICT affordability is dependent upon the provision or availability of telecommunication services (Milne, 2000, 2006; Moonesinghe et al., 2006). These previous studies used access to the Internet as an alternate indicator in the provision of telecommunication services. Moreover, the evidence that a number of socio-demographic factors and location-specific variables can influence the affordability of ICT services remains (Barrantes and Galperin, 2008; Choudrie et al., 2015; Prieger, 2003; Weiss et al., 2015). For instance, from the context of a developing country, Choudrie et al. (2015) found that the level of education is a significant predictor of mobile broadband affordability. Empirical work also indicated that age, gender, employment status and location significantly impact ICT affordability (Prieger, 2003; Weiss et al., 2015). Finally, studies also reported that employment status significantly explains the affordability of ICT services (Barrantes and Galperin, 2008; Prieger, 2003). Therefore, a baseline model and an additional model for robustness measurement is hypothesised in this study. These models are outlined in Eqs. (4) and (5), respectively.

The following equation specifies the determination of ICT affordability using annual household ICT expenditure as a proxy of ICT affordability:

$$hhICTexp_{it} = \alpha_i + \beta_1 Gini\_hh\_inc_{it} + \beta_2 sad\_decile_{it} + \beta_3 hhInt\_accss_{it} + \Lambda X_{it} + u_i + \eta_t + \varepsilon_{it}, \tag{4}$$

where i stands for an individual and t represents the year. $hhICTexp_{it}$ represents yearly ICT expenditure of person i in year t. The model also controls for observed time-varying covariates X_{it}. *major_city, urban_area, age, gender, employment_status, FS_composite* and *benefit_govt* are the control variables. u_i represents the individual fixed effect, η_t stands for the time effect and ε_{it} is the error term. α_i, β_1, β_2, β_3 and the vector λ are the parameters to be estimated. β_1, β_2 and β_3 estimates represent the average effect of income distribution (*Gini_hh_inc*), socio-economic position (*sad_decile*) of an individual and household access to the Internet (*Gini_hh_inc*) on household ICT expenditure (*hhICTexp*), respectively.

In addition to the baseline model, taking digital affordability inclusion index score *(DII_afford)* as a substitute for ICT affordability, the estimation specification is presented as:

$$DII\_afford_{it} = \alpha_i + \beta_1 Gini\_hh\_inc_{it} + \beta_2 sad\_decile_{it} + \beta_3 hhInt\_accss_{it} + \Lambda X_{it} + u_i + \eta_t + \varepsilon_{it}, \tag{5}$$

where *DII_afford* $_{it}$ indicates the digital affordability index scores of a person residing in a particular region. This model has the same set of independent and control variables as the previous model (Eq. (4)).

2.3. Estimation methods

To examine the responsiveness of ICT affordability in income distribution and socio-economic inequality, two different estimation methods have been used, namely, generalised linear mixed model (GLMM) and random effects with Mundlak corrections (RE-Mundlak). Both estimation techniques provide consistent parameter estimates by capturing the unobserved heterogeneity amongst individuals.

2.3.1. Generalised linear mixed model

The GLMM is an extension of the generalised linear model (GLM). This model incorporates the random effects with usual fixed effects. This inclusion of random effects in the linear predictor provides the option to account for natural heterogeneity across clusters in the regression coefficients. Given that differences between groups can be modelled as a random effect, GLMM provides a wide range of analysis of grouped data including longitudinal data (Fitzmaurice et al., 2012).

One of the major limitations of GLM is the assumption that responses of different i units are independent given the x_i covariates. However, this assumption is not realistic as most of the time data are multilevel in nature with unit i nested in clusters j. As a result, unobserved heterogeneity at the cluster level may be present indicating that confounders are missed out either because they cannot be measured or their existence is unknown (Skrondal and Rabe-Hesketh, 2003).

By including random effects $eta_{mj}^{(2)}$ in the linear predictor, the combined effect of all unobserved cluster-level covariates are modelled. These covariates take on the same value for all units within the same cluster.

$$g\mu_{ij} = \nu_{ij} = x'_{ij}\beta + \sum_{m=0}^{M-1} \eta_{mj}^{(2)} z_{mj}^{(2)}, \tag{6}$$

where $\mu_{ij} \equiv E[y_{ij}|x_{ij}, z_{mj}^{(2)}\eta_{mj}^{(2)}]$, $\eta_j^{(2)} = (\eta_{0j}^{(2)}, \eta_{M-1,j}^{(2)})'$ are random effects varying at level 2 and $z_{ij}^{(2)}$ corresponding variates. The first and second part of the right hand side of Eq. (4) is the fixed and random components, respectively.

2.3.2. Random effects model with Mundlak (1978) corrections

To relax the assumption in random effects estimation that the observed variables are uncorrelated with the unobserved variables, Mundlak (1978) estimated random effects regression models by adding group means of variables in which independent variables vary within groups. Considering the linear regression of y_{it} on k time-varying covariates (x_{it}) and g time-invariant *(z_{it})* covariates, the following is obtained:

$$y_{it} = x'_{it}\beta + z'_{it}\gamma + \varepsilon_{it}, \tag{7}$$

where *i=1, …..,N; t=1, ….,T* and

$$\varepsilon_{it} = \alpha_i + u_{it}, \tag{8}$$

where u_i is the group residual, and

$$\alpha_{it} = x'_{i1}\lambda_1 + x'_{i2}\lambda_2 + \cdots + x'_{iT}\lambda_T + \eta_i. \tag{9}$$

Eq. (7) indicates that as α_i is correlated with x_{it} in the structural form, all the leads and lags of x_{it} (x'_{i1} … … x'_{iT}) are included in the regression. The first component of Eq. (9) ($x'_{i1}\lambda_1 + x'_{i2}\lambda_2 + \cdots + x'_{iT}\lambda_T$) is correlated with the observable covariates; the second random effect component, η_i, is uncorrelated with the covariates. The projection coefficient, λ_i, indicates the extensity of the correlation between α_i and x_{it}.

Mundlak (1978) assumed the restrictive specification that $\lambda_1 = \lambda_2 = \lambda_T = \lambda$ using Eq. (7) can be rewritten as

$$\alpha_i = (T\overline{X_i})' + \eta_i. \tag{10}$$

Replacing the value of ε_i in Eq. (5) derived from Eq. (6), the following specification is obtained

$$y_{it} = x'_{ij}\beta + Z'_{ij}\gamma + \alpha_i + u_{it}. \tag{11}$$

Substituting the value of α_i obtained from Eq. (8) into Eq. (9), the equations stand as:

$$y_{it} = x'_{ij}\beta + Z'_{ij}\gamma + (T\overline{X_i})' + \eta_i + u_{it}. \tag{12}$$

Some crucial aspects of causality need to be considered. Although a number of theoretical and empirical works have analysed the causal effects of income distribution on ICT affordability, other studies focus on the causality running from the other way around (Calderón and Servén, 2004; Card and DiNardo, 2002; Lee and Wie, 2015; Mallick and Sousa, 2017; Vivarelli, 2014). These studies are theoretically grounded on the skill-based technological change argument (SBTC), which suggests that technology has increased returns to skills in the labour market and income inequality. To account for this possibility, we have conducted baseline estimations using lagged explanatory variables as instruments. This approach has been used to deal with causality issues in past empirical research on related topics (Bohman, 2008). As the estimates using the lagged variables do not significantly differ from the baseline results, these results are reported in the Appendix (Table A.1).

Table 2
Estimation results of ICT affordability using GLMM and RE-Mundlak corrections.

Variables	GLMM				RE-Mundlak	
	(1)		(2)		(3)	
	Coefficient	SE	Coefficient	SE	Coefficient	SE
gini_hh_inc	531.3072**	212.9078	431.1531**	215.1057	1233.76**	506.9860
sad	0.8874*	0.1577	0.8996*	0.1577	1.1400**	0.4760
hhInt_accss	661.6898*	49.0284	648.5447*	49.1591	540.7770*	114.9600
major_city	14.0997***	32.9900	15.5907***	32.9860	134.2490***	122.1500
urban_area	53.5937***	42.5165	53.6768***	42.5078	−284.8450***	125.1550
age	−1.1346	1.1480	−1.5758	1.1538	−15.0660	6.4440
gender	22.5334	26.0046	21.9268	25.9997	25.7790	35.4880
employment_status	118.4028*	34.2535	115.9233*	34.2527	119.7270	79.5640
hhwtchild	148.8796*	32.6869	147.1229*	32.6840	220.328**	80.1500
FS_composite	−206.3284*	39.4726	−211.0440*	39.4943	−358.7420*	90.7230
benefit_govt	−0.0084*	0.0021	−0.0086*	0.0021	−0.0240*	0.0050
constant	499.6347*	186.5167	504.9904*	187.7796	182.1790	286.3760
Log-likelihood	−359678.7400		−359670.6100			
R-squared					0.6010	
Time FE	No		Yes		No	
Number of persons	5 558		5 558		5 558	
Number of observations	38 906		38 906		38 906	

*Denote statistically significant at 1%.
**Denote statistically significant at 5%.
***Denote statistically significant at 10%.

3. Empirical results

3.1. Main results

Table 2 reports he estimation results obtained from the baseline models of *hhICTexp* as a substitute of ICT affordability. The figures in panels 1 and 2 indicate the GLMM estimates of Eq. (4) using regression specifications without and with time fixed effects, respectively. Figures in panel 3 represents the RE-Mundlak estimates of Eq. (4). Table 2 presents evidence that the main variable of interest–*gini_hh_inc* (Gini coefficient of household income) is statistically significant and positive in both specifications using GLMM. Findings indicate that when income inequality is high, so is ICT affordability. The other variable of interest, the SAD index score is revealed to have a positive association with the outcome variable, *hhICTexp*, across all specifications. These results signify that the ICT affordability of a person is positively associated with socio-economic position. ICT affordability of individuals significantly vary with the location of households as estimates of location-specific variables, such as *major_cites* and *urban_areas*, are statistically significant.

Demographic factors, such as age and gender, have no significant impact on ICT affordability. However, ICT affordability of employed persons is significantly higher than unemployed cohorts. From a financial perspective, financial security and benefits from the government tend to have a negative impact on household ICT expenditure. The results using the RE-Mundlak corrections method produce similar estimates similar to the GLMM. The results in panel 3 of Table 2 revalidate that household income inequality and position in terms of socio-economic advantage positively shape ICT affordability.

3.2. Robustness checks

A battery of robustness checks is conducted to cross-examine the results found using baseline models. In this case, the digital affordability inclusion index score *(DII_afford)* is the dependent variable across all corresponding regression specifications. Table 3 reports the regression estimates of Eq. (5) using GLMM and RE-Mundlak corrections. The figures in panels 1 and 2 indicate the regression coefficient estimates of Eq. (5) using GLMM for regression specification without and with time fixed effects, respectively. The estimates reported in panel 3 represent the regression coefficient estimates of Eq. (5) using RE-Mundlak corrections method. Table 3 supports the evidence that *gini_hh_inc* and *sad* are positively associated with *DII_access* across all specifications (panels 1, 2 and 3). These findings support the baseline results indicating that ICT affordability is positively related to income inequality and socio-economic advantage.

3.3. Heterogeneity analysis

To conduct the heterogeneity analysis, Fig. 1 (see Table A.2) represents the estimates for the subsample according to income brackets. Total respondents are divided into five quantiles based on the annual household disposable income. Statistical package Stata 15 is used to generate these quantiles. The mean household disposable income for five quantiles are AU$ 26,152, AU$ 51,824, AU$ 79,593, AU$ 111,904 and AU$ 206,639. For low- and middle-income brackets (Q1 to Q4),

Table 3
Robustness checks of ICT affordability using GLMM and RE-Mundlak corrections.

Variables	GLMM				RE-Mundlak	
	(1)		(2)		(3)	
	Coefficient	SE	Coefficient	SE	Coefficient	SE
gini_hh_inc	20.4597*	0.6399	19.4689*	0.6293	39.0900*	1.4790
sad	0.0136*	0.0004	0.0136*	0.0004	0.0070*	0.0010
hhInt_accss	0.0221	0.1270	0.0005	0.1243	0.0040	0.2880
major_city	6.7841*	0.0819	6.7900*	0.0802	0.6540**	0.3090
urban_area	1.3651*	0.1055	1.3696*	0.1032	1.1120*	0.3150
age	−0.0053***	0.0030	−0.0041	0.0029	−0.0130*	0.0050
gender	0.0285	0.0647	0.0286	0.0633	0.0330	0.0970
employment_status	0.2704*	0.0860	0.2660*	0.0841	0.4030*	0.1950
hhwtchild	−0.0170	0.0840	−0.0066	0.0822	−0.4130*	0.2130
FS_composite	−0.0742	0.1010	−0.0427	0.0989	0.4150***	0.2250
benefit_govt	<-0.0001*	0.0000	<-0.0001***	0.0000	<-0.0001	0.0000
constant	28.2987*	0.4812	29.58486*	0.4732	23.1470*	0.7920
Log-likelihood	−66107.2180		−65627.5570			
R-squared					0.6030	
Time FE	No		Yes		No	
Number of persons	5 558		5 558		5 558	
Number of observations	22 232		22 232		22 232	

*Denote statistically significant at 1%.
**Denote statistically significant at 5%.
***Denote statistically significant at 10%.

income inequality has a positive impact on household ICT affordability. The direction of association remains the same if respondents from these four income brackets are considered a separate aggregated unit of study.

For households in the high-income bracket (Q5), the effect of income inequality on ICT affordability is reversed. The minimum household income of the high-income bracket (Q5) is AU$ 133,070. This finding indicates that income inequality has a positive impact on ICT affordability for Q1–Q4 households if their income is below AU$ 133,070. Conversely, if the household income is AU$ 133,070 and above and when the distribution of income is uneven, then the level of ICT affordability becomes low. These findings corroborate the proposition of Engel's law which states that the proportion of income spent on necessary goods falls as income rises (Engel, 1857). Specifically, the proportion of income spent on ICT (i.e. expenditure on ICT as a proportion of total expenditure) falls as household income rises.

Results from the different subsamples of income groups confirm that the hypothesis of non-linearity, that is, for low-income brackets, income inequality has a positive impact on ICT affordability. For high-income brackets, income inequality has a negative income on ICT affordability. On the one hand, for households in low-income brackets, a one-unit increase in the Gini coefficient can increase the household ICT expenditure by AU$ 907. On the other hand, for the high-income bracket, a one-unit increase in income inequality reduces ICT affordability by AU$ 670 (see Table A.2). One plausible explanation behind non-linearity in the estimates is that household ICT affordability rises with the level of income, whereas it falls as a proportion of total expenditure. These results indicate that low-income bands can spend much if affordability is perceived. However, for the high-income bracket, ICT affordability declines as the distribution of income becomes concentrated. These results can be tied with the claims of Engel's law (Engel, 1857).

4. Discussion

The key finding from the analysis is that an aggregate income inequality has a positive impact on ICT affordability across all the econometric specifications used in the study. The nexus between ICT affordability and income distribution is tested by using different statistical methods, and the findings appear robust. These results reflect those of existing empirical findings (Thomas et al., 2016). The results indicating the positive nexus between income inequality and ICT affordability seem to be consistent with other research that revealed that ICT diffusion is positively influenced by income inequality in high-income countries (Bohman, 2008; Milne, 2000). Furthermore, several studies indicate that diffusion of ICT is dependent on the affordability of ICT services. A high level of affordability denotes high diffusion of ICT (Choudrie and Dwivedi, 2006; Feng, 2015; Flamm and Chaudhuri, 2007; Kiiski and Pohjola, 2002). These results suggest that ICT affordability can potentially play a mediating role in translating the impact of income inequality on ICT diffusion. In high-income countries, a highly skewed distribution of income enhances ICT affordability, which in turn promotes ICT diffusion. These findings can be justified by the fact that a highly skewed distribution of income may infer high headcount and may lead to high ICT penetration (Bohman, 2008). Further research may be carried out to explore whether or not ICT affordability plays a mediating role in translating the impact of income inequality on ICT diffusion.

However, using subsamples from different income brackets, the estimates indicate that the effect of income distribution is non-linear. For low-income brackets, income inequality seems to enhance affordability, whereas for the high-income

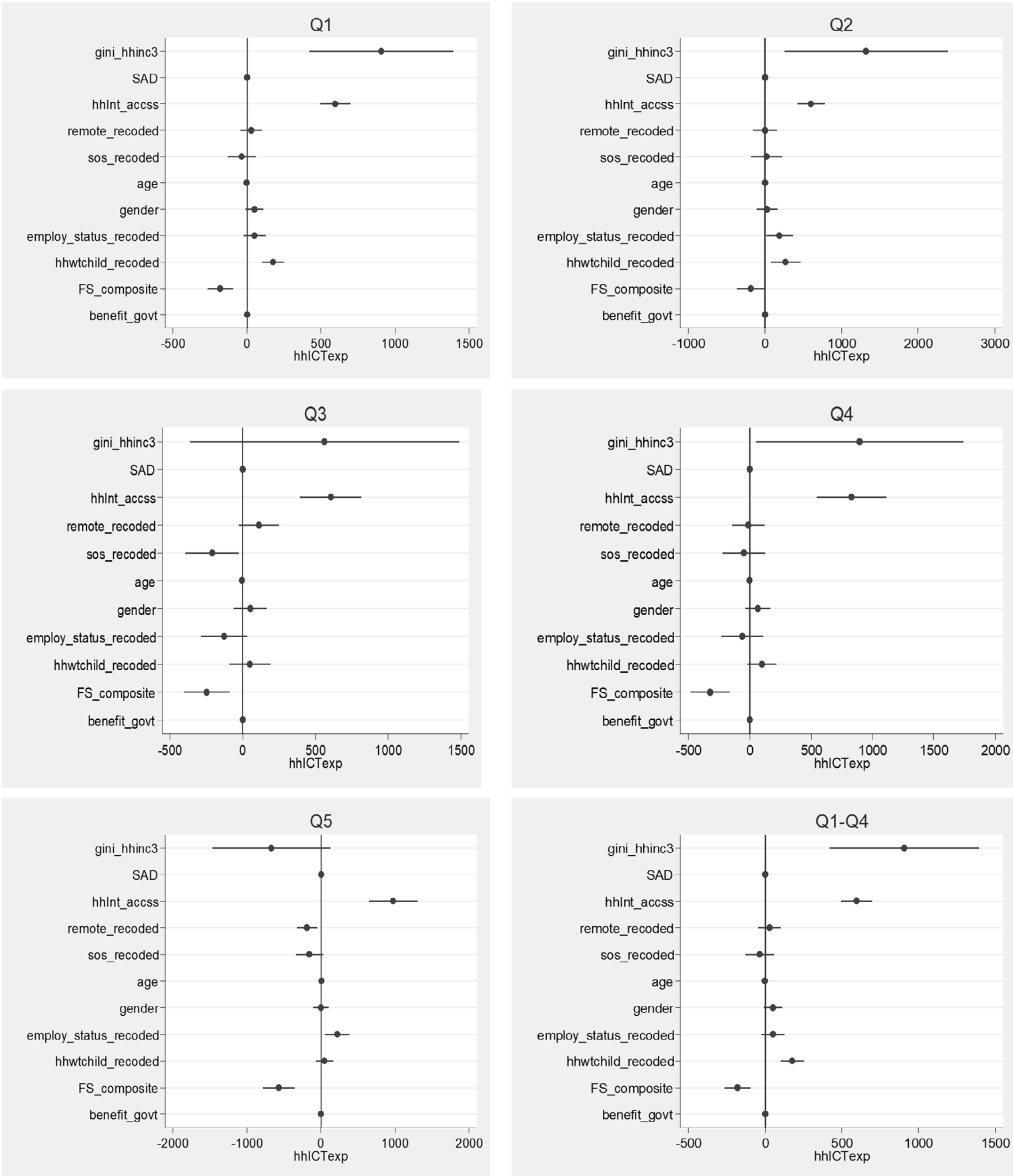

Fig. 1. Quantile-wise heterogeneous impact of income distribution of ICT affordability.

bracket, this effect completely reverses. For a low-income bracket, an uneven distribution of income may be conducive as it implies that the subgroup has enough resources to afford ICT services. However, with an even distribution, almost no one can afford ICT services. For a high-income bracket, the effect of distribution is reversed. An equal distribution of income infers that large middle-income households may afford ICT services, whereas an uneven income distribution may leave many people below the threshold level of income; therefore, their affordability declines. These results match with those observed in earlier studies (Bohman, 2008). Non-linearity in the estimates of ICT affordability can be explained by the fact that the household expenditure on ICT rises with the level of income and falls as a proportion of total expenditure at the

Table A.1
Estimation results of ICT affordability using GLMM with lagged explanatory variable.

Variables	Dependent variable: hhICTexp				Dependent variable: DII_afford			
	(1)		(2)		(1)		(2)	
	Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE
gini_hh_inc	741.4807*	255.7095	706.3661*	257.2522	10.1096*	0.6207	6.3075*	0.5970
sad	0.9133*	0.1732	0.9207*	0.1732	0.0079*	0.0004	0.0075*	0.0004
hhInt_accss	643.8043*	54.8689	635.4681*	54.9354	0.0556***	0.1218	0.0201***	0.1157
major_city	−12.4364	36.2053	−13.4054	36.2015	4.0137*	0.0879	3.7003*	0.0840
urban_area	−56.4748	46.6609	−56.4532	46.6535	0.6581*	0.1009	0.6279*	0.0959
age	−0.3057	1.2740	−0.6413	1.2789	0.0049***	0.0029	0.0002	0.0027
gender	19.7318	28.5484	19.2862	28.5442	0.0540	0.0618	0.0435	0.0587
employment_status	152.5721*	37.6605	150.6859*	37.6597	−0.1565***	0.0829	−0.1700**	0.0787
hhwtchild	150.9685*	36.2918	149.4284*	36.2905	−0.0402	0.0811	−0.0725	0.0771
FS_composite	−191.2439*	43.8242	−193.9107	43.8354	−0.0062*	0.0984	−0.0243	0.0935
benefit_govt	−0.0065*	0.0022	−0.0066	0.0022	< 0.0000*	< 0.0000	< 0.0000***	< 0.0000
l1.gini_hh_inc	138.4725	252.8670	98.2343	253.7698				
l1.DII_afford					0.5007	0.0061	0.5476*	0.0060
constant	301.4314	209.3535	404.9903**	214.1518	11.8996	0.4911	11.8996*	0.4911
Log-likelihood	−308770.6300		−308765.2700		−46432.5520		−45581.1720	
Time FE	No		Yes		No		Yes	
Number of persons	4758		4758		2378		2378	
Number of observations	33306		33306		16646		16646	

*Denote statistically significant at 1%.
**Denote statistically significant at 5%.
***Denote statistically significant at 10%.

same time. These results indicate that low-income households can spend much if affordability is perceived. However, for the high-income bracket, ICT affordability declines as the distribution of income becomes concentrated. These features of ICT affordability can be tied to Engel's law (Engel, 1857).

The current study also found that affordability of ICT services varies with regard to wealth, age and employment status. Particularly, socio-economic advantage translates into a digital advantage by impacting affordability. With great socio-economic advantage that a household poses, great household ICT affordability can be attained. In addition, affordability has a negative relationship with age. Based on the findings, the employed segment of respondents can afford to spend more on ICT services than unemployed counterparts. Therefore, these findings conform with the previous observational study conducted by Thomas et al. (2016), which reported that employed participants who are wealthy and young enjoy great digital inclusion in terms of affordability. This study merits further investigation in the future.

The results of the current study confirm that geography plays a critical role in explaining ICT affordability at the household level. Being a resident of a household in a major city and an urban area enhances ICT affordability. These results accord with the findings of Thomas et al. (2016) who argued that 'major city–remote area gap' and 'capital–country gap' substantially influence digital affordability. The current research also demonstrates that respondents with a higher level of financial security have a lower level of affordability than their counterparts. Several studies reported that financial investment in ICTs is significant predictors of mobile broadband affordability (Choudrie et al., 2015; Yates et al., 2010). These findings imply that respondents who want to ensure financial security at the household level are likely to prioritise investment in other necessary goods over paying on ICT-related services. In contrast, respondents with a high level of ICT expenditure (i.e. investments) tend to have a high level of affordability.

5. Conclusion

This study aims to examine the effect of income distribution and socio-economic inequality on the affordability of ICT services in Australia. The findings clearly indicate that income distribution and socio-economic inequality have positive and significant impacts on ICT affordability. ICT affordability is also positively associated with income inequality in low-income bracket households. However, the effect of income inequality on ICT affordability is reversed in high-income households. The effect of income distribution on ICT affordability can be described as non-linear.

The principal implication of the findings from the study is that low quintile households in high-income countries spend nearly close to their affordability threshold to avail ICT services, whereas ICT expenditure by high-income households is much greater than that of low-income counterparts. As a result, as income increases, household expenditure on telecommunications rises in absolute terms but falls as a proportion of total expenditure at the same time. In light of Engel's law, this finding suggests that ICT services can be considered a necessity good in economic terms. Combining this finding with the argument that access to affordable ICT services enhances individual capabilities may provide impetus for policy measures to narrow the digital divide.

These findings can help in devising policy tools to ease the affordability of telecommunication services, and thus promote ICT penetration. On the one hand, regions with equal distribution of income can be best served by policy

Table A.2
Heterogeneity analysis using quantile-wise regression.

Variables	Q1		Q2		Q3		Q4		Q5		Q1-Q4	
	Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE
gini_hh_inc	899.8644***	552.0262	1320.9430**	542.6915	562.6915	472.4151	895.7668**	431.0119	−669.7296***	406.4936	906.8436*	248.5469
sad	0.7388***	0.3947	0.5022	0.3744	0.2694	0.3470	0.4892	0.3289	1.8975*	0.3393	0.5121106*	0.1796
hhInt_accss	514.9899*	104.2860	600.3623*	90.7895	605.6363*	107.4663	829.6086*	144.8989	975.2635*	167.8011	595.5275*	52.0197
major_city	1.9876	82.4140	1.7345	79.2018	112.5263	69.9114	−12.3743	67.2355	−189.9873*	71.0986	27.9888	37.2415
urban_area	50.7286	98.2338	19.7437	103.6689	−209.8156**	93.3011	−49.3346	89.3703	−158.0726***	92.4346	−35.0942	47.9088
age	−3.3614	2.6115	0.9598	2.9032	−5.9807**	2.4505	−2.7500	2.4527	7.7092*	2.7921	−2.6262**	1.2720
gender	46.2069	71.1588	23.1876	69.3595	52.9333	58.3311	65.4579	52.1826	−0.8130	53.8368	51.1505***	30.4932
employment_status	98.9637	83.9992	189.6192**	90.8879	−127.1859	81.8489	−62.3135	87.5434	219.5677*	85.7917	50.7649	38.3011
hhwtchild	357.9339*	92.1811	269.2531*	99.1168	47.8211	72.3420	98.3915	61.0450	48.2222	60.9919	176.9113*	38.8183
FS_composite	0.5866	94.3189	−182.2951***	93.5492	−246.4604*	81.1041	−323.8869	81.2782	−572.4131*	107.8563	−180.4631*	43.3435
benefit_govt	−0.0097***	0.0054	−0.0029	0.0046	−0.0209*	0.0046	−0.0146	0.0051	0.0341*	0.0056	−0.0121*	0.0023
constant	363.7440	453.7054	279.3690	454.0909	1687.9410*	414.3092	911.2837	410.3910	−178.7482	445.8547	790.8623	211.4806
Log-likelihood	−66068.3060		−68827.4820		−69912.7830		−74371.1040		−80197.3230		−279356.1700	
Time FE	No		No		No		No		No		No	
Number of persons	1012		1052		1083		1159		1248		4305	
Number of observations	7084		7364		7581		8113		8736		30135	

*Denote statistically significant at 1%.
**Denote statistically significant at 5%.
***Denote statistically significant at 10%.

initiatives designed to enhance affordability for a critical mass of the population. On the other hand, for regions characterised with uneven income distribution, universal access initiatives can be effectively placed for low-income bracket households. In either case, access to reliable public Internet and online government services should be ensured for remote communities because issues related to ICT affordability cause these communities to lag behind in terms of social and economic development.

The present study is not free from pitfalls. Firstly, to measure ICT affordability, the current study used household ICT expenditure data. In the future, research can be conducted using national-level ICT price basket data that are regularly reported by the International Telecommunication Union. These data consists of mobile-cellular sub-basket, fixed-broadband sub-basket and mobile-broadband sub-basket. However, these information are not readily available and not reported at a household level, which prevents the current study from incorporating these variables into the analytical framework. ICT price basket can serve as a better alternative instead of annual ICT expenditure because the former is conceptually more comprehensive. Secondly, the use of respondent-level affordability information instead of household affordability measures can provide more accurate results than household-level data. Thirdly, the current study focuses on the direction of causality running from income inequality to ICT affordability. However, studies also reveal that the causality running from the other way around (ICT concentration to income inequality) is also an important possibility. In addition, the current study exclusively focuses on the demand-side factors in analysing the nexus between ICT affordability and income distribution. Such considerations are beyond the scope of this study. However, depending on data availability, future research on supply-side effects, as well as further investigation of the direction and mechanisms of causality can be worthwhile. Fourthly, this study fails to control for the structure and regulations in the telecommunication market due to the unavailability of data. However, both factors can potentially impact the cost of availing and using ICT services. Lastly, research focusing on the determinants of ICT affordability of socio-economically disadvantaged groups, for example, indigenous community or disabled population, can be an avenue for research.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

The paper is a part of the PhD study of the first author. The PhD program was funded by the University of Southern Queensland, Australia [USQ International Stipend Research Scholarship & USQ International Fees Research Scholarship].

Appendix

See Tables A.1 and A.2.

References

ABS, 2011. Census of Population and Housing: Socio-Economic Indexes for Areas (SEIFA), ABS Catalogue no. 2033055001 Retrieved from Canberra: http://www.abs.gov.au/AUSSTATS/abs@nsf/DetailsPage/20330550012016?OpenDocument.
Ayanso, A., Lertwachara, K., 2015. An analytics approach to exploring the link between ICT development and affordability. Gov. Inf. Q. 32 (4), 389–398.
Barrantes, R., Galperin, H., 2008. Can the poor afford mobile telephony? evidence from latin america. Telecommun. Policy 32 (8), 521–530.
Bohman, H., 2008. Income distribution and the diffusion of networks: An empirical study of Brazilian telecommunications. Telecommun. Policy 32 (9), 600–614.
Calderón, C., Servén, L., 2004. The effects of infrastructure development on growth and income distribution. Central Bank of Chile Working Papers.
Card, D., DiNardo, J.E., 2002. Skill-biased technological change and rising wage inequality: Some problems and puzzles. J. Labor Econ. 20 (4), 733–783.
Choudrie, J., David, J.Y., Gulati, G.J.J., 2015. Investigating mobile broadband affordability in developing countries: a cross-national comparison. In: Paper presented at the Proceedings of the Seventh International Conference on Information and Communication Technologies and Development, Singapore, Singapore.
Choudrie, J., Dwivedi, Y.K., 2006. Investigating factors influencing adoption of broadband in the household. J. Comput. Inf. Syst. 46 (4), 25–34.
Cowell, F., 2008. Measuring Inequality, LSE Perspectives in Economic Analysis. Oxford University Press, Oxford, UK.
Engel, E., 1857. The productions and consumptions of the kingdom of saxony. J. Stat. Bur. R. Saxon Minist. Inter. 8, 1–54.
Feng, G.C., 2015. Factors affecting internet diffusion in China: A multivariate time series analysis. Telemat. Inform. 32 (4), 681–693.
Fitzmaurice, G.M., Laird, N.M., Ware, J.H., 2012. Applied Longitudinal Analysis, Vol. 998. John Wiley & Sons.
Flamm, K., Chaudhuri, A., 2007. An analysis of the determinants of broadband access. Telecommun. Policy 31 (6), 312–326.
Fuchs, C., 2009. The role of income inequality in a multivariate cross-national analysis of the digital divide. Soc. Sci. Comput. Rev. 27 (1), 41–58.
Grosso, M., 2006. Determinants of Broadband Penetration in OECD Nations. Australian Communications Policy and Research Forum.
Hilbert, M., 2010. Cheap enough to bridge the digital divide? modeling income related structural challenges of technology diffusion in latin america. World Dev. 38 (5), 756–770.
Hosseini, H.M., Kaneko, S., 2011. Dynamic sustainability assessment of countries at the macro level: A principal component analysis. Ecol. Indic. 11 (3), 811–823.
Johnstone, J., 2007. Technology as empowerment: A capability approach to computer ethics. Ethics Inf. Technol. 9 (1), 73–87.
Kiiski, S., Pohjola, M., 2002. Cross-country diffusion of the internet. Inf. Econ. Policy 14 (2), 297–310.
Lee, S., 2008. A Cross-Country Analysis of Ubiquitous Broadband Deployment: Examination of Adoption Factors. University of Florida, Gainsville, FL.
Lee, J.W., Wie, D., 2015. Technological change, skill demand, and wage inequality: Evidence from Indonesia. World Dev. 67, 238–250.

Mallick, S.K., Sousa, R.M., 2017. The skill premium effect of technological change: New evidence from United States manufacturing. Int. Labour Rev. 156 (1), 113–131.

Milne, C., 2000. Affordability of basic telephone service: an income distribution approach. Telecommun. Policy 24 (10), 907–927.

Milne, C., 2006. Telecoms demand: measures for improving affordability in developing countries. Retrieved from http://www.ruralict.ftml.net/publications/TD_main_report.pdf.

Moonesinghe, A., Silva, N.S., Abeysuriya, A., 2006. Telecom use on a shoestring: Expenditure and perceptions of costs amongst the financially constrained. p. 610, World Dialogue on Regulation Discussion Paper.

Mundlak, Y., 1978. On the pooling of time series and cross section data. Econometrica 46 (1), 69–85.

Prieger, J.E., 2003. The supply side of the digital divide: Is there equal availability in the broadband internet access market? Econ. Inq..

Prieger, J.E., 2015. The broadband digital divide and the benefits of mobile broadband for minorities. J. Econ. Inequal. 13 (3), 373–400.

Sen, A., 1985. Commodities and Capabilities. North-Holland, Amsterdam.

Sen, A., 2010. The mobile and the world. Inf. Technol. Int. Dev. 6 (Special Issue), 1–3.

Skrondal, A., Rabe-Hesketh, S., 2003. Some applications of generalized linear latent and mixed models in epidemiology: repeated measures, measurement error and multilevel modeling. Nor. Epidemiol. 13 (2), 265–278.

Sun, C., Watson, N., Hahn, M., 2016. Program 10 (Stata). Melbourne Melbourne Institute of Applied Economic and Social Research.

Thomas, J., Barraket, J., Ewing, S., MacDonald, T., Mundell, M., Tucker, J., 2016. Measuring Australia's digital divide: The Australian digital inclusion index 2016. Retrieved from https://researchbank.rmit.edu.au/view/rmit:42462.

United Nations, 2010. Human development report 2010 — 20th anniversary edition. Retrieved from New York, NY: http://hdr.undp.org/sites/default/files/reports/270/hdr_2010_en_complete_reprint.pdf.

van Dijk, J., 2005. The Deepening Divide: Inequality in the Information Society. Sage Publications, London, U.K..

Vivarelli, M., 2014. Innovation, employment and skills in advanced and developing countries: A survey of economic literature. J. Econ. Issues 48 (1), 123–154.

Weiss, J.W., Gulati, G.J., Yates, D.J., Yates, L. E., 2015. Mobile broadband affordability and the global digital divide - An information ethics perspective. In: Paper presented at the 2015 48th Hawaii International Conference on System Sciences, Kauai, HI, USA, 5-8 Jan. 2015.

Wooden, M., Freidin, S., Watson, N., 2002. The household, income and labour dynamics in Australia (HILDA) survey: Wave 1. Aust. Econ. Rev. 35 (3), 339–348.

Wresch, W., 2009. Progress on the global digital divide: an ethical perspective based on Amartya Sen's capabilities model. Ethics Inf. Technol. 11 (4), 255.

Yates, D.J., Weiss, J.W., Gulati, G.J., 2010. Universal broadband: An analysis of global stakeholders and the pursuit of the common good. Int. J. Innov. Digit. Econ. 1 (2), 25–43.

Chapter 3: **Introductory note: Relationship between Chapter 2 and Chapter 3**

The previous chapter traced out several key facilitators and inhibitors of digital inclusion in the context of Australia. It is well-documented in the literature that access to and use of ICTs promotes individual capabilities and thus enhances their overall quality of life (see Section 1.8.2 of Chapter 1 for details). Following this line of investigation, the two studies included Chapter 3 investigate how and to what extent digital inclusion improves QoL. Particularly, Study 5 points out the mediating role of ICT in translating the impact of assistive technology on QoL among PwD. Study 4 and Study 5 have been published in the journals '*Telematics and Informatics*' and '*Cyberpsychology, Behaviour, and Social Networking'*.

These papers are edited and formatted following the guidelines prescribed by corresponding journals. Hence, for the remainder of Chapter 3, there are two-page numbers for each page. The first relates to the published journal paper while the second one corresponds to this thesis.

Telematics and Informatics 51 (2020) 101405

Contents lists available at ScienceDirect

Telematics and Informatics

journal homepage: www.elsevier.com/locate/tele

Does digital inclusion affect quality of life? Evidence from Australian household panel data

Mohammad Afshar Ali[a,b,c,*], Khorshed Alam[a,b], Brad Taylor[d], Shuddhasattwa Rafiq[e]

[a] School of Commerce, University of Southern Queensland, Toowoomba, Queensland 4350, Australia
[b] Centre for Health Research, University of Southern Queensland, Toowoomba, QLD 4350, Australia
[c] Department of Economics, Jagannath University, Dhaka 1100, Bangladesh
[d] School of Commerce, University of Southern Queensland, Springfield, Queensland 4300, Australia
[e] School of Business, Deakin University, Burwood, Victoria, Australia

A R T I C L E I N F O

Keywords:
Digital inclusion
Information and communication technology
Quality of life
Simultaneous equation model
Australia

A B S T R A C T

The evidence on the role of information and communication technology (ICT) in enhancing quality of life (QoL) is mixed and the precise nature of this relationship is not yet fully understood. Existing single equation-based empirical works have provided a number of specific insights, but there remains a gap in our understanding of the association between digital inclusion and QoL. The current study seeks to fill this gap by capturing the simultaneous association between digital inclusion and QoL. This study employs simultaneous equation models based on a two-stage and full-information likelihood method using a household-level longitudinal dataset of Australia to explore the relationship between QoL and digital inclusion. This research confirms that digital inclusion significantly predicts QoL and vice versa. Socio-economic advantages, remoteness, rural-urban divide and lifestyle also appear to be significant determinants of the QoL. Findings from the study imply that to promote digital inclusion, policymakers should emphasise not only supply-side issues but also demand-side strategies including the enhancement of digital skills and affordability for the users.

1. Introduction

At present, almost every aspect of human life is affected by information and communication technologies (ICTs). A considerable body of literature has focused on the effects of ICT on the productivity and gross domestic product (GDP) of nations (Dedrick et al., 2011; Dewan and Kraemer, 2000; Mowery et al., 2011). However, the long-term effect of digital inclusion on the quality of life (QoL) at the individual level has been largely overlooked (Castellacci and Tveito, 2018; Lissitsa and Chachashvili-Bolotin, 2016; Martin, 2016). Considering the increasingly prominent role of digital technologies in people's daily life, an examination of the influence of digital inclusion on an individual's QoL is crucial. Existing empirical works have identified several major determinants of the QoL, including lifestyle, access to digital technologies, social and community environment, physical and mental health conditions, and social inclusion and demographic factors.

The impact of ICT on QoL can be understood conceptually through the capabilities approach (Sen, 1985; Sen, 2010). On this view, the well-being of individuals is ultimately determined by their capabilities – that is, their real capacity to pursue their various objectives. ICTs such as internet access augments human capabilities by acting as a general purpose tool for communication and

* Corresponding author.
E-mail address: MohammadAfshar.Ali@usq.edu.au (M.A. Ali).

https://doi.org/10.1016/j.tele.2020.101405
Received 17 May 2019; Received in revised form 11 March 2020; Accepted 29 March 2020
Available online 31 March 2020

information acquisition. Following this approach, a number of empirical studies found that Internet access is generally beneficial for human health and wellness, and has a positive effect on QoL (Campisi et al., 2015; Çelik and Odacı, 2013; Chiao and Chiu, 2016; Çikrıkci, 2016; Gianchandani, 2011). A number of studies have also demonstrated that the adoption of ICTs contributes to the QoL of physically disabled people (Gao et al., 2017; Rosner and Perlman, 2018; Siegel and Dorner, 2017). Moreover, long-term health conditions, ICT access, lifestyle, access to material and social resources, community participation are reported to have a direct effect on an individual's QoL (Binder and Buenstorf, 2018; Ganju et al., 2016; Rotondi et al., 2017). However, the link between individuals' QoL and access to digital technologies at the household level is yet to be unveiled.

Existing studies on the link between QoL and digital inclusion nexus are based on a single equation estimation framework; thus, they do not consider the simultaneous nature of the association between QoL and digital inclusion. Moreover, the endogeneity of QoL has also not been taken into consideration in the existing studies. For instance, some aspects of the QoL are predetermined at birth as endowments. More specifically, the QoL is not exogenous to an individual's age, educational attainment, number of children and household income (Habibov and Afandi, 2016). Given this backdrop, using the simultaneous equation approach, both the endogeneity of QoL originating from unobserved heterogeneity and the reverse causality running from digital inclusion to QoL can be estimated (Cai, 2010). In furtherance, use of panel data allows better control for unobserved heterogeneity over cross-sectional data (Cai, 2010).

Based on this motivation and following the conceptual framework rooted in the capability approach (Sen, 2010) outlined above, the present study aims to investigate the simultaneous association between digital inclusion[1] and QoL. To achieve this research objective, two precise research questions are posed: (i) whether any significant simultaneous causal association exists between digital inclusion and QoL, and (ii) whether social inclusion has any confounding effect on the simultaneous association between digital inclusion and QoL. To the best of the authors' knowledge, this study is the first ever attempt to explain the simultaneous link between digital inclusion and QoL in a single-country setting using a household-level longitudinal dataset. This study makes a number of noteworthy contributions to the literature. First, it constructs a composite index to measure the QoL following the World Health Organisation's Quality of Life Scale Abbreviated Version (WHOQoL-BREF) (WHO, 1996). Using that composite index, the research investigates the association between digital inclusion and QoL which constructed the composite QoL using an indicator from each distinctive domains – physical health, psychological, and environment (see Section 3.1 for details). Second, to check for potential endogeneity problems that arise from QoL and digital inclusion, it employs simultaneous equation models using an instrumental variable technique based on a two-stage estimation framework. Third, unlike existing studies, the current study uses panel data to blend the inter-individual differences and intra-individual dynamics. This approach has several advantages over cross-sectional data such as (i) it accounts for individual heterogeneity by allowing the flexibility to control for variables which are not observed or measured; (ii) in contrast to cross-sectional data, panel data usually possess more degrees of freedom and more sample variability, and (iii) it has the potential to generate more accurate predictions for individual outcomes by pooling the data instead of making predictions using the data at the individual level (Hsiao, 2007). Fourth, the study sheds light on the potential confounding effects of socio-economic, spatial and demographic factors predicting QoL and digital exclusion. Findings from the current study are expected to be significant to policymakers and practitioners because the study is a single country analysis based on longitudinal household data as well as a stronger methodological foundation than previous empirical work.

The remainder of this paper proceeds as follows: Section 2 provides a critical review of the relevant literature. Section 3 specifies the methodology of the study, including a description of the source of data and empirical strategies. Section 4 discusses the empirical results in detail. Section 5 provides a discussion on the results, and the final section concludes the study by pointing out its limitations, future research directions and policy implications.

2. Review of existing literature

A great deal of previous research has investigated the determinants of QoL or well-being using individual, household and country-level data. Using survey data at the respondent level, a number of studies have found that the Internet use promoted the overall QoL by enhancing physical and psychological well-being, promoting self-esteem and facilitating social relationships (Campisi et al., 2015; Çikrıkci, 2016). Similarly, studies have investigated the relationship between ICT and the social and psychological aspects of the QoL among elementary students and confirmed the existence of a positive association between them (Çelik and Odacı, 2013; Chiao and Chiu, 2016). Another considerable segment of literature has focused on the determinants of the QoL among elderly people (Chaumon et al., 2014; Nimrod, 2017; Siegel and Dorner, 2017; Sims et al., 2017). These studies reported that assistive ICTs (e.g. mobile apps, robots and smart home solutions) empowered them by providing more autonomy in managing their health-related problems and overcoming other functional disabilities. However, several studies claim that the effects of the Internet on well-being are mediated by a set of personal characteristics, such as psychological functioning, digital ability, personal economic condition and culture (Bartikowski et al., 2018; Castellacci and Tveito, 2018).

A number of cross-sectional studies investigated the effects of assistive ICTs on the QoL of physically disabled people or people with long-term health conditions (Gao et al., 2017; Rosner and Perlman, 2018; Siegel and Dorner, 2017). The findings from these studies suggest that assistive ICTs can contribute significantly to all dimensions of the QoL of such individuals. Several studies have

[1] Access to broadband Internet access is chosen as the proxy of digital inclusion. This is consistent with prior studies (e.g. Çikrıkci, 2016; Gianchandani, 2011). Since this is an incomplete definition of digital inclusion, the current study also uses a broader definition of digital inclusion by developing a composite index consisting of digital access, ability and affordability (see Table 1).

also explored the effects of ICT on the work and personal lives of employees (De Wet et al., 2016; Gopinathan and Raman, 2016). These empirical works demonstrate that the use of ICTs in the workplace enhanced the QoL of employees. A number of cross-country analysis reported that Internet access is a significant determinant of life satisfaction and well-being of residents of a country (Bartikowski et al., 2018; Ganju et al., 2016). These studies confirm that perceived personal economic condition mediates the relationship between Internet access and life satisfaction. The authors have reported that access to the Internet has a heterogeneous effect on life satisfaction. Specifically, the positive effects of mobile Internet are weaker for ethnic minorities than for the majority of consumers (Bartikowski et al., 2018).

In contrast to abovementioned research, a number of cross-sectional studies have obtained counterintuitive findings. For example, studies claim that life satisfaction is inversely related with problematic Internet use in the form of Internet addiction or social media addiction (Gao et al., 2017; Lachmann et al., 2016; Longstreet and Brooks, 2017; Nimrod, 2017). In addition, studies also report that smartphone addiction has mediating effects on the QoL (Hayward et al., 2013; Toda et al., 2016; Van den Berg et al., 2005). Chern and Huang (2018) reveal that college students with Internet access are reported to have significantly lower QoL in terms of physical, psychological, social and environmental contexts. In addition, the findings of Arbabisarjou et al. (2012) demonstrate the absence of a significant relationship between ICT use and QoL among university faculty members. Nevertheless, the evidence on the impact of ICT on QoL of elderly people is mixed (Damant et al., 2016; Hirani et al., 2014).

Few studies explored the determinants of ICT adoption in the Australian context. In this regard, the pioneering work of Curtin (2001) point out that access to ICT is dependent upon literacy, level of education and income of the users. Alam and Imran (2015) have investigated the factors affecting the adoption of ICT by refugee migrants in Australia and found that ICT access among refugee migrant depends on the digital ability and the financial capacity of the users. Several studies have investigated determinants of ICT diffusion in regional Australia. A case study conducted by Park (2017) concludes that remoteness, level of education, employment status, socio-economic inclusion, demographic factors are strong predictors of home Internet adoption and broadband connectivity in rural and regional Australia. A case study by Hodge et al. (2017) on a small town in South Australia find that the lack of internal digital skills, as well as funding restraints, limit the digital engagement of older citizens.

Another strand of literature explains the role of geography in the interplay between Internet connectivity and QoL. Several cross-sectional studies found that the penetration of Internet and broadband is substantially lower in regional and remote parts of Australia (Park, 2017). In a recent study, Ali et al. (2019) found further evidence of the negative association between digital inclusion and remoteness in Australia using state–wide panel data. Moreover, a few studies have reported that the burden of diseases associated with long–term health conditions are larger for people in rural and remote Australia compared to those in metropolitan areas (Alston et al., 2017; Pateman et al., 2018). One way of explaining this phenomena is that people residing in rural and remote Australia might have limited access to digital health care services compared to metropolitan counterparts (Alam et al., 2019; Alston et al., 2017). However, the existing literature has not yet found compelling evidence that there is a significant difference in QoL outcomes between metropolitan and regional–remote Australian populations (Allen et al., 2013; Pateman et al., 2018).

In summary, a number of studies have investigated the association between the QoL and digital inclusion. However, these investigations can be seen as incomplete analyses because they are based on single equation estimation frameworks and thus do not capture the simultaneous association between the QoL and digital inclusion. Given this backdrop, the current study fills the gap in the literature by investigating the simultaneous link between QoL and digital inclusion and assessing the confounding impact of social inclusion in explaining the simultaneous association for an Australian household-level panel dataset. One of the noteworthy advantages of panel data is that it controls the individual time series and cross-sectional variations in the data and addresses the biases related to cross-sectional regressions by taking into consideration the country-specific fixed effect (Baum and Christopher, 2006). Furthermore, most of the previous studies used a single indicator based general or mental health outcome to define QoL or subjective well-being. However, single indicator-based analyses may yield a biased measurement of QoL. Given these limitations, a composite index provides an overall measure of QoL (Böhringer and Jochem, 2007; Ding et al., 2015; Mahuteau and Zhu, 2016). To be precise, a composite index eliminates the bias of a single indicator-based analysis by applying a weighing mechanism based on Principal Component Analysis (PCA) to the individual variables (See Section 3.1 for details). This study corrects the flaw by adopting a more holistic approach in defining the QoL. In other words, in measuring the QoL, this study develops a composite index consisting of educational qualification and standard of living along with health-related indicators.

3. Data, variables, model specifications and estimation methods

3.1. Data and variables

The current study used longitudinal data compiled from wave 10 to wave 17 of the Household, Income and Labour Dynamics in Australia (HILDA) Survey Restricted Release. Details of the survey methodology can be found in Wooden et al. (2002). In wave 1, 7683 households representing all in-scope households were interviewed. The total sample eligible to be interviewed were 15,127 people who were 15 years and above. A total of 13,969 individuals were interviewed successfully in wave 1. Every year, subsequent interviews were conducted for later waves. Each person completing a personal interview was also given a self-completion questionnaire. To balance the longitudinal dataset, the Stata program developed by Sun et al. (2016) was used in the study. After merging the dataset, the data screening and cleaning processes were conducted to check missing data and outliers. Stata 15 was used to merge, clean and process the data. The total number of observations used in the study was 26,248, representing a balanced panel of 3281 individuals across eight waves, i.e. from waves 10 to 17. All enumerations were adjusted for the effect of sampling by applying a weighting index provided by the HILDA as a supplement of the original data set.

Table 1
Variable descriptions and summary statistics.

Variable name	Definition of variable	Mean	SD
A. Endogenous variables			
QoL	A composite index to measure the QoL following the WHOQoL-BREF module. This includes indicators from each domains - (i) self-assessed physical health (physical health domain), (ii) self-assessed mental health (psychological health domain), (iii) level of education achieved (environment domain – a proxy for skills or capability), and (iv) personal annual disposable income (environment domain – a proxy for financial resources)	3.13	0.77
hhInt_accss	A dummy variable indicating whether or not the respondent has access to broadband Internet at home (1 = has access, 0 = otherwise)	0.91	0.28
B. Variables included in both equations			
sad_decile	Socio-economic advantage and disadvantage decile defined by SEIFA (2011). It is used to define the relative socio-economic advantage and disadvantage in terms of people's access to material and social resources, and their capability to participate in the society	5.78	2.84
major_city[1]	A dummy variable indicating whether the respondent lives in a major city (1 = resident of a major city, 0 = otherwise)	0.64	0.48
regional_city[1]	A dummy variable indicating whether the respondent lives in an inner or outer regional city (1 = resident of a regional city, 0 = otherwise)	0.35	0.48
remote_area[1]	A dummy variable indicating whether the respondent lives in a remote or very remote area (1 = resident of a remote area, 0 = otherwise)	0.01	0.11
urban_area[2]	A dummy variable indicating whether the respondent live in an urban area or not (1 = resident of an urban area, 0 = otherwise)	0.84	0.36
age55p	A dummy variable indicating whether the respondent is aged over 55 years or not (1 = aged over 55, 0 = otherwise). This cut off was selected on the basis that is the median age for all respondents.	0.49	0.50
community_part	A dummy variable indicating whether or not the respondent participates in community activities, defined as currently being an active member of a sporting/hobby/ community-based club or association (1 = actively participates in community activities, 0 = otherwise)	0.41	0.49
C. Variables included exclusively in the QoL equation			
health_con	A dummy variable indicating whether or not the respondent has a long-term health condition, disability or impairment (1 = has long-term health condition, disability or impairment, 0 = otherwise)	0.27	0.44
heavy_drinker	A dummy variable indicating whether or not the respondent is a heavy drinker, defined as drinking more than 6 standard drinks per day (1 = heavy drinker, 0 = otherwise)	0.12	0.32
D. Variables included exclusively in the Internet access equation			
hhwtchild	A dummy variable indicating whether or not there is a child aged 14 or under in the respondent's house (1 = has children aged 14 or under, 0 = otherwise)	1.74	0.44
hhICTexp	Household annual expenditure on telephone rent, calls and internet charges	1990.32	2387.98
DII_accss[3]	A composite index that measures three key aspects or dimensions of inclusion of digital access. It is composed of availability of Internet access points, access to digital devices & Internet technology, and availability of Internet data allowance. The index score ranges from 0 to 100	65.67	5.90
DII[3]	A composite index that measures three key aspects or dimensions of digital inclusion including Internet access, affordability of Internet data services, and ability to use ICT devices. The index score ranges from 0 to 100	55.11	5.16
Number of persons		3281	
Number of observations (balanced panel data for 2010–2017)		26,246	

Note: 1) These variables indicate different degrees of remoteness of geographical areas, based on the remoteness index of Accessibility/Remoteness Index of Australia (ARIA+). ARIA+ categorises geographical areas of Australia into five categories – major city, inner regional, outer regional, remote, and very remote (ABS, 2011). 2) On the basis of population ranges, the ABS Section of State (SOS) Structure of the Australian Statistical Geography Standard (ASGS) defines Urban and Rural areas. Urban area is defined as the combination of all Urban Centres with a population between 1000 and 100,000 or more. Rural area represents the remainder of State/Territory (ABS, 2011). 3) Indicates that this variable is available for data points for the period of 2014–2017. For details about the construction of this index see Thomas et al. (2016).

The HILDA survey contains detailed information on each individual's key demographic information and economic activity. From the personal interviews and self-completion questionnaires, the health-related information of individuals has been collated. Demographic information at the individual level includes age, level of education and personal income. Health-related information used in this study includes self-assessed general and mental health and long-term health condition. To capture the lifestyle of an individual, drinking habit was also included. However, for several variables, data are reported at the household level including socio-economic advantage and disadvantage index decile, Internet access, remoteness, urbanization, household composition and annual ICT expenditure. Using the household IDs, information on those variables were then matched at the individual level using cross-wave IDs.

Table 1 provides the definitions of the variables included in the models along with their means and standard deviations across seven waves. The classification of the variables also reflects the model specifications. The variables in panel B are variables included in both QoL and Internet access equation. Variables listed in panel C are included exclusively in the QoL equation in addition to variables listed in panel B. On the other hand, those in panel D are included only in the Internet access equation along with the variables listed in panel B. Incorporation of all these variables in respective models are supported by relevant literature as outlined in Section 2.

The composite index to measure the QoL is composed of four indicators: (i) self-assessed physical health, (ii) self-assessed psychological health, (iii) level of education attained (a proxy for skills or capability), and (iv) personal annual disposable income (a proxy for financial resources). The empirical basis for selecting these indicators for QoL is rooted in the WHOQoL-BREF proposed by WHO (WHO, 1996). The value of QoL ranges from 0 to 1. A QoL score of 0 indicates a very low QoL, whereas 1 specifies a very high QoL.

PCA is used to construct a composite index of QoL. The PCA is used to compute the weights of each indicator, which eventually constitutes QoL. The PCA is a multivariate statistical technique which analyses a data table presenting observations described by a set of variables, which are assumed to be inter-correlated (Hosseini and Kaneko, 2011). This approach entails a number of chronological steps: construction of a data matrix, creation of standardised variables, computation of a correlation matrix, determination of eigen values (to rank principal components), and eigen vectors, which are a selection of principal components and interpretation of results (Hosseini and Kaneko, 2011). By estimating the weights of individual variables PCA eliminates the bias that could possibly arise from a single indicator-based analysis (Hosseini and Kaneko, 2011). In addition, this process also minimises the subjective bias that may arise from the overweighting or underweighting person-specific indicators (Ali et al., 2020).

The objective of the PCA is to construct new variables (P_i) from a set of variables, X_j ($j = 1, 2, \ldots, n$). These variables are referred to as principal components, which are linear combinations of X's. The following equation is used to construct the composite index, QoL:

$$\text{QoL} = \sum\nolimits_{i=1}^{3} a_{ij} \frac{X_{ij}}{Sd(X)_i}, \tag{1}$$

where QoL is the composite index of the QoL of each individual, Sd is the standard deviation, X_{ij} is the *i*th variable in *j*th year and a_{ij} is the factor loading derived through PCA. Thus, as mentioned earlier, the QoL is composed of four indicators (for details, see Table 1).

3.2. Model specification

To explore the relationship between QoL and Internet access, this study employs a simultaneous equation model. This is a type of statistical model in which the dependent variables are functioned as dependent to other dependent variables, instead of simply explaining the function with independent variables. This implies that some of the independent (explanatory) variables are jointly explained by the dependent variables. The statistical models used in this study are based on a balanced panel data in order to better control unobserved heterogeneity. The first equation specifies the determination of the QoL as follows:

$$QoL_{it} = \alpha_i + \beta_1 hhInt\_accss_{it} + \beta_2 sad\_decile_{it} + \Lambda X_{it} + u_i + \eta_t + \varepsilon_{\ it}, \tag{2}$$

where i stands for an individual and t represents the year. QoL_{it} represents the value of the QoL of person *i* in year *t*. The model also controls for observed time-varying covariates X_{it}. *major_city, regional_city, remote_area, urban_area, age55p, health_con, heavy_drinker and community_part* are the control variables. u_i represents the individual fixed effect, η_t stands for the time effect and ε_{it} is the error term. a_i, β_1, β_2 and the vector Λ are the parameters to be estimated. The estimates β_1 and β_2 represent the average effect of Internet access (*hhInt_accss*) and socio-economic position (*sad_decile*) of an individual on the QoL, respectively.

The estimation specification for Internet access is as follows:

$$hhInt\_accss_{it} = \alpha_i + \beta_1 QoL_{it} + \beta_2 sad\_decile_{it} + \Lambda X_{it} + u_i + \eta_t + \varepsilon_{\ it}, \tag{3}$$

where $hhInt\_accss_{it}$ indicates whether a person has access to the Internet. This model has several control variables denoted by X_{it}. These variables include *hhwtchild, hhICTexp, DII_accss, major_city, regional_city, remote_area urban_area and age55p*. The estimate β_1 and β_2 represent the average effect of the QoL and socio-economic position of an individual on Internet access, respectively.

To detect multicollinearity, the variance inflation factors (VIFs) have been estimated as a part of the diagnostic check. These VIFs are obtained after computing the OLS-based estimations based on Eqs. (2) and (3). The VIFs of the explanatory variables used in the study ranged from 1.01 to 1.40. The decision rule is that multicollinearity among explanatory variable exists if VIF is 5 or higher (Hair et al., 1995). These results show that multicollinearity is not a problem among the regressors.

3.3. Estimation methods

To estimate the simultaneous equations system, two methods are employed: the two-stage instrumental variables (IV-2SLS) method and the full-information maximum likelihood (FIML) method. Both methods provide consistent parameter estimates. However, the FIML method is more efficient (Williams et al., 2016). In addition, the FIML method provides estimates for all parameters in the variance-covariance matrix of disturbance terms, which are necessary to perform the test for homogeneity of the QoL.

3.3.1. Two-stage instrumental variable method

The two-stage least squares (2SLS) method is a widely used approach to estimate instrumental variable regression models. It is an equation-by-equation method, where the (dependent variable on the right-hand side of each equation are being instrumented with the independent variables from all other equations. The method is called two-stage because the estimations involve two steps. In the first stage, the endogenous explanatory (dependent) variables are regressed on the instruments (and exogenous variables), and from these regressions, fitted values are obtained. In the second stage, the regression model is estimated using the fitted values that replace the exogenous regressors (Baum and Christopher, 2006; Schaffer, 2015). For the QoL equation, the panel-data IV-2SLS takes the following form:

$$QoL_{it} = \alpha_i + \gamma Y_{it} + \beta X_{it} + u_i + v_{it} = Z_{it}\delta + u_i + v_{it,} \quad (4)$$

where Y_{it} is an $1 \times g_2$ vector of observations on g_2 endogenous variable (*hhInt_accss*) included as covariates. This variable can be correlated with the v_{it}; X_{it} is an $1 \times K_1$ vector of observations on the exogenous regressors included as covariates; $Z_{it} = [Y_{it}, X_{it}]$; γ is a $g_2 \times 1$ vector of coefficients; β is $k_2 \times 1$ vector of coefficients and δ is $K \times 1$ vector of coefficients, where $K = g_2 + k_1$. In the first stage regressions, *hhwtchild, hhICTexp* and *DII_accss* are used as instrumental variables for the endogenous regressor *hhInt_accss*.

Similarly, for the Internet access equation, the panel data IV-2SLS can be expressed as follows:

$$hhInt\_accss_{it} = \alpha_i + \gamma Y_{it} + \beta X_{it} + u_i + v_{it} = Z_{it}\delta + u_i + v_{it}, \quad (5)$$

where Y_{it} is an $1 \times g_2$ vector of observations on g_2 endogenous variable (QoL) included as covariates, and this variable can be correlated with the v_{it}. In the first stage regressions, *health_con* and *heavy_drinker* are used as instruments for the endogenous regressor QoL.

3.3.2. Full-information maximum likelihood method (FIML)

By optimising a likelihood function, FIML method estimates the parameters of a probability distribution in such a manner so that the observed data become most probable in the assumed statistical model. It simplifies the Structural Equations Modelling (SEM) specification process, making it possible to test and relax a number of constraints that are embodied inherently in the panel data models. It allows for the inclusion of time-variant variables in the model (Williams et al., 2016). The model specifications for the QoL equation using the panel data FIML method can be expressed as follows:

$$QoL_{it} = \alpha_i + \beta X_{it} + w_i\delta + \xi_i + v_{it}, \quad (6)$$

where QoL_{it} is the value of QoL of an individual i at time t; X_{it} is a vector of sequentially exogeneous time-varying variables; w_i is a vector of time-variant exogenous variables; a_i is the unobservable time-invariant fixed-effect; ξ_t captures the unobserved common factors across units in the panel and v_{it} is the time-varying error term.

Similarly, the specification for the Internet access is as follows:

$$hhInt\_accss_{it} = \alpha_i + \beta X_{it} + w_i\delta + \xi_i + v_{it}, \quad (7)$$

4. Empirical results

4.1. Main results

4.1.1. Estimation results of the QoL equation

The estimation results based on the baseline models of the QoL are reported in Table 2. The figures in Panels 1–3 indicate regression coefficient estimates of Eq. (2) using two-stage estimates for regression specification using different degrees of remoteness (i.e. *major_city*, *regional_city* and *remote_area*) without time fixed effects. The results presented in Panels 4–6 report regression outputs of those specifications with time fixed effects. The figures reported in Panels 7–9 represent the regression coefficient estimates of Eq. (2) using the FIML method. Given the heteroscedasticity and autocorrelation issues, conventional OLS or panel data-based regression would not be appropriate in this case because these methods would yield biased coefficients and inconsistent estimates. These problems are fixed with robust and clustered standard errors in two-stage and FIML methods.

As shown in Table 2, the main variable of interest, Internet access, is statistically significant and positive in both specifications for the two-stage method. This finding indicates that the QoL of people living in a household with Internet access is higher than that of the people who do not have Internet access at home. The other variable of interest, the SAD index, is positively associated with the outcome variable (QoL) across all specifications. This result signifies that the QoL of a person from a higher SAD decile is significantly higher than that of a person belonging to a lower SAD decile. As expected, aging and long-term health or physical condition have a significant negative effect on QoL. In addition, the likelihood of living in urban areas and active participation in community activities significantly enhance QoL. Different degrees of remoteness appear to have diverse impacts on QoL. For example, the dummy variable for regional city has a negative impact on QoL while that for remote area has a positive impact. However, the dummy for major city and drinking habits have no significant effect on QoL.

The estimation results of the first-stage regressions for the QoL equation are reported in Appendix Table A1. The Kleibergen-Paap Wald rk F statistics from all the six first-stage regressions are significant, implying that the instruments are relevant, i.e. not weak in both cases. The Hansen J statistics for those regression specifications demonstrate that the instruments used in the first stage regression can be considered as exogenous because the null hypothesis cannot be rejected at the 10 per cent level. Given that the data for *DII_accss* are available for a shorter period (2014–2017), a series of separate regressions are conducted using the *hhwtchild* and *DII_accss* as instrumental variables for the endogenous regression (*hhInt_accss*) in the first-stage regression of Eq. (4). To conserve space, these results are reported in the Appendix section (Table A2). Similar to the previous case, the relevant statistics indicate the instruments are relevant and exogenous.

The results using the FIML method for the QoL equation produce similar estimates as the two-stage method. The results reported in Panels 7–9 of Table 2 show an individual's access to the Internet and position in terms of socio-economic advantage positively influences his/her QoL.

The positive association between QoL and digital inclusion can be explained by the capability approach (Sen, 1985). Access to

Table 2
Estimation results of QoL equation using two-stage and FIML method.

Variables	IV-2SLS						FIML		
	(1) Coef.	(2) Coef.	(3) Coef.	(4) Coef.	(5) Coef.	(6) Coef.	(7) Coef.	(8) Coef.	(9) Coef.
sad_decile	0.0677*	0.0671*	0.0688*	0.0680*	0.0673*	0.0691*	0.0687*	0.0681*	0.0699*
	(0.0033)	(0.0034)	(0.0035)	(0.0034)	(0.0034)	(0.0036)	(0.0016)	(0.0016)	(0.0015)
major_city	0.0161			0.0163			0.0184***		
	(0.0146)			(0.0146)			(0.0107)		
regional_city		−0.0285**			−0.0289**			−0.0306*	
		(0.0140)			(0.0140)			(0.0105)	
remote_area			0.1639**			0.1665**			0.1613*
			(0.0499)			(0.0498)			(0.0373)
urban_area	0.0663*	0.0597*	0.0837*	0.0669*	0.0602*	0.0846*	0.0648*	0.0585*	0.0836*
	(0.0170)	(0.0165)	(0.0148)	(0.0170)	(0.0164)	(0.0148)	(0.0133)	(0.0130)	(0.0115)
age_over55	−0.1683*	−0.1678*	−0.1693*	−0.1781*	−0.1776*	−0.1793*	−0.1752*	−0.1749*	−0.1761*
	(0.0210)	(0.0210)	(0.0211)	(0.0223)	(0.0223)	(0.0224)	(0.0087)	(0.0087)	(0.0087)
health_con	−0.4743*	−0.4741*	−0.4731*	−0.4769*	−0.4767*	−0.4758*	−0.4782*	−0.4781*	−0.4769*
	(0.0152)	(0.0152)	(0.0152)	(0.0155)	(0.0155)	(0.0155)	(0.0097)	(0.0097)	(0.0097)
heavy_drinker	−0.0092	−0.0091	−0.0105	−0.0101	−0.0101	−0.0114	−0.0089	−0.0089	−0.0102*
	(0.0154)	(0.0154)	(0.0153)	(0.0154)	(0.0154)	(0.0153)	(0.0129)	(0.0129)	(0.0129)
community_part	0.1641*	0.1648*	0.1641*	0.1657*	0.1664*	0.1657*	0.1648*	0.1656*	0.1647*
	(0.0104)	(0.0104)	(0.0103)	(0.0104)	(0.0104)	(0.0103)	(0.0084)	(0.0084)	(0.0084)
hhInt_accss	0.3950**	0.3963**	0.3949**	0.3727***	0.3742***	0.3720**	0.3176*	0.3170*	0.3196*
	(0.1966)	(0.1967)	(0.1963)	(0.2008)	(0.2010)	(0.2007)	(0.0151)	(0.0151)	(0.0151)
constant	2.4513*	2.4790*	2.4389*	2.4084*	2.4364*	2.3960*	2.5199*	2.5512*	2.5054*
	(0.1752)	(0.1805)	(0.1745)	(0.1707)	(0.1762)	(0.1701)	(0.0198)	(0.0231)	(0.0198)
Kleibergen-Paap Wald rk F statistic	55.7440*	55.6390*	54.3850*	57.4730*	57.3750*	56.0710*			
Hansen J statistic	0.0010	0.0000	0.0010	0.0240	0.0320	0.0210			
Log-likelihood							−176350.0200	−176787.0700	−143418.4800
Time FE	No	No	No	Yes	Yes	Yes	No	No	No
Number of persons	3281	3281	3281	3281	3281	3281	3281	3281	3281
Number of observations	26,248	26,248	26,248	26,248	26,248	26,248	26,248	26,248	26,248

Note: *, ** and *** denote statistically significant at 1%, 5% and 10%, respectively. Robust standard errors are reported in parentheses.

digital technologies augments the human capabilities through a number of channels including increased efficiency of public health and educational services by improving quality and substantial time saving effects, enlarged access to information that can be used for educational and health purposes, inaugurating new medium of communication using which people can interact with others and thus improve their psychological functioning. To sum up, access to the Internet and other ICTs augments human capabilities by facilitating human being's participation in economic, social and cultural aspects of life (Sen, 1985; Sen, 2010; Wresch, 2009).

4.1.2. *Estimation results for Internet access equation*

The estimation results based on the baseline models of Internet access are reported in Table 3. The figures in Panels 1–6 indicate the regression coefficient estimates of Eq. (3) using two-stage estimates for regression specification without and with time fixed effects, respectively. These results represent regression outputs using different degrees of remoteness. Further, the figure reported in Panel 7–9 represents the regression coefficient estimates of Eq. (3) using the FIML method. Table 3 shows the main variable of interest, QoL, is statistically significant and positive in both specifications of the two-stage method (Panels 1 and 2). The other variable of interest, the SAD index, is positively associated with the outcome variable, Internet access, across all specifications. This result indicates the probability of having Internet access is significantly higher for a person belonging to a higher socio-economic group in contrast to a person from a lower socio-economic tier. As expected, households with children have greater likelihood of having an Internet connection than those without children. In addition, household ICT expenditure and the dummy for urban areas have a positive effect on Internet access. However, the age variable was found to have a negative effect on the QoL. Interestingly, different degrees of remoteness are found to yield heterogeneous impacts on digital inclusion. In other words, locational attributes of a region have different impacts on digital inclusion. To be specific, an individual’s likelihood of residing in a major city increases the probability of having Internet access at home. On the other hand, those who are living in regional and remote areas are found to have less chance of getting Internet access at home because of their isolation.

The estimation results of the first-stage regressions for the Internet access equation are reported in Appendix Table A3. Similar to the previous case, the two Kleibergen-Paap Wald rk F statistics from the six first-stage regressions are significant, implying that instruments are relevant, i.e. not weak in any case. The Hansen J statistics for both regression specifications demonstrate that the instruments used in the first stage regression can be considered as exogenous because the null hypothesis cannot be rejected at the 10 per cent level.

Abiding by the constraints of availability of data of *DII_accss* (for 2014–2017), a series of separate regressions are conducted using

Table 3
Estimation results of Internet access equation using 2SLS and FIML.

Variables	IV-2SLS						FIML		
	(1) Coef.	(2) Coef.	(3) Coef.	(4) Coef.	(5) Coef.	(6) Coef.	(7) Coef.	(8) Coef.	(9) Coef.
QoL	0.0977*	0.0973*	0.0979*	0.0994*	0.0990*	0.0995*	0.0556*	0.0555*	0.0559*
	(0.0105)	(0.0105)	(0.0106)	(0.0105)	(0.0105)	(0.0078)	(0.0023)	(0.0023)	(0.0023)
sad_decile	0.0056*	0.0059*	0.0070*	0.0055*	0.0058*	0.0069*	0.0092*	0.0094*	0.0106*
	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0009)	(0.0007)	(0.0007)	(0.0006)
major_city	0.0280*			0.0277*			0.0284*		
	(0.0059)			(0.0059)			(0.0043)		
regional_city		−0.0233*			−0.0231*			−0.0243*	
		(0.0059)			(0.0059)			(0.0042)	
remote_area			−0.0484**			−0.0469*			−0.0408**
			(0.0228)			(0.0152)			(0.0150)
urban_area	−0.0237*	−0.0196**	−0.0081	−0.0232*	−0.0193**	−0.0078***	−0.0207*	−0.0170**	−0.0045
	(0.0075)	(0.0073)	(0.0064)	(0.0075)	(0.0073)	(0.0047)	(0.0053)	(0.0052)	(0.0047)
hhwtchild	−0.0296*	−0.0295*	−0.0289*	−0.0304*	−0.0303*	−0.0297*	−0.0317*	−0.0316*	−0.0310*
	(0.0037)	(0.0037)	(0.0037)	(0.0037)	(0.0037)	(0.0044)	(0.0044)	(0.0044)	(0.0044)
hhICTexp	< 0.0001*	< 0.0001*	< 0.0001*	< 0.0001*	< 0.0001*	< 0.0000*	< 0.0001*	0.0000*	< 0.0000*
	(< 0.0001)	(< 0.0001)	(< 0.0001)	(< 0.0001)	(< 0.0001)	(< 0.0000)	(< 0.0000)	(0.0000)	(0.0000)
age_over55	−0.0554*	−0.0557*	−0.0566*	−0.0590*	−0.0593*	−0.0602*	−0.0667*	−0.0669*	−0.0679*
	(0.0052)	(0.0052)	(0.0052)	(0.0052)	(0.0052)	(0.0045)	(0.0039)	(0.0039)	(0.0039)
constant	0.6404*	0.6623*	0.6364*	0.6025*	0.6242*	0.5985*	0.7572*	0.7795*	0.7525*
	(0.0305)	(0.0316)	(0.0304)	(0.0299)	(0.0310)	(0.0234)	(0.0110)	(0.0121)	(0.0110)
Kleibergen-Paap Wald rk F statistic	866.3890*	866.1640*	863.9160*	873.0280*	872.8060*	883.0250*			
Hansen J statistic	0.8330	0.7600	0.7330	0.6600	0.6010	0.7170			
Log-likelihood							−390170.8600	−390614.3900	−357303.3300
Time FE	No	No	No	Yes	Yes	Yes	No	No	No
Number of persons	3281	3281	3281	3281	3281	3281	3281	3281	3281
Number of observations	26248	26248	26248	26248	26248	26248	26248	26248	26248

Note: *, ** and *** denote statistically significant at 1%, 5% and 10%, respectively. Robust standard errors are reported in parentheses.

the *DII_accss* as control variable along with other variables as outlined in Eq. (5). For simplicity, these results are reported in Appendix Table A4. As in the previous case, the relevant statistics indicate the instruments are relevant and exogenous. The results using the FIML method for the Internet access equation produce similar estimates following the estimates of the two-stage method (Table 3 and Table A4).

In summary, these results show that digital inclusion is positively associated with QoL and social inclusion. The positive association between Internet access and QoL can be explained in part by the indicators that were used to construct the composite index (QoL). Higher levels of QoL are associated with higher levels of education, health, and economic security which indirectly promote ICT adoption. It is also often argued that existing social exclusion factors widen the digital divide. Those with lower socio–economic status are already facing complex challenges associated with other social exclusion parameters including location, age, income and educational level (Basu and Chakraborty, 2011; Park, 2017). These parameters of social exclusion often intertwine with the issues of digital exclusion. Precisely, a lack of investment in broadband infrastructure in remote areas along with a low level of digital literacy leads to low usage. Ultimately, this impedes to achieve a certain minimum number of users (critical mass) fails to attract adequate investment for telecommunication infrastructure development. The results presented here confirm that the digital divide in Australia is multidimensional in this way.

4.2. Robustness checks

A battery of robustness checks was conducted to cross-examine the results found using baseline models. Due to space constraints, only the regression estimates using Eqs. (2) and (3) with no time effects were reported in the study.

4.2.1. Generalised method of moments (GMM) estimation

GMM estimations for Eqs. (2) and (3) were conducted to examine the robustness of earlier estimates. The GMM, developed by Arellano and Bond (1991) and Arellano and Bover (1995), is used widely to check for potential endogeneity in a dynamic panel model. The GMM has been applied to estimate the effects of Internet access and social exclusion on QoL as outlined in Eq. (2). In this case, one of the regressors, *hhInt_accss*, is assumed to be endogenous. The instruments used in the model are *hhwtchild* and *hhICTexp*. Panels 1–3 of Table 4 report the GMM estimation of the QoL equation using different degrees of remoteness as the explanatory variable. In all cases, the coefficients of the SAD decile and household Internet access are positive and statistically significant, thereby implying that the baseline estimates of the QoL equation are also valid in the dynamic panel models. To check the validity and

Table 4
Robustness checks of QoL equation using GMM and random effect estimations.

Variables	Dependent Variable: QoL											
	GMM						Random effects					
	(1)		(2)		(3)		(4)		(5)		(6)	
	Coef.	Robust SE	Coef.	Robust SE	Coef.	Robust SE	Coef.	Robust SE	Coef.	Robust SE	Coef.	Robust SE
sad_decile	0.0253	0.0375	0.0339	0.0279	0.0654*	0.0265	0.0230*	0.0027	0.0227*	0.0026	0.0248*	0.0026
major_city	0.0753	0.3062					0.0431**	0.0201				
regional_city			0.0063	0.2302					−0.0573*	0.0188		
remote_area					0.9896***	0.6095					0.1433**	0.0455
urban_area	0.6259**	0.2750	0.6354**	0.2881	0.7160*	0.2622	0.0360***	0.0192	0.0328***	0.0185	0.0601**	0.0180
age_over55	−0.0295	0.0939	−0.0328	0.0933	0.0571	0.1045	−0.0336*	0.0113	−0.0334*	0.0113	−0.0338**	0.0113
health_con	−0.0492	0.2141	−0.0402	0.2179	−0.2227	0.2297	−0.1185*	0.0073	−0.1184*	0.0073	−0.1183*	0.0073
heavy_drinker	−0.9628**	0.4067	−0.9918**	0.3904	−0.9250*	0.3730	−0.0104	0.0105	−0.0104	0.0105	−0.0105	0.0105
community_part	−0.3253	0.2206	−0.3230	0.2264	−0.2460	0.2156	0.0328*	0.0067	0.0330*	0.0067	0.0324*	0.0067
hhInt_accss	0.0689**	0.0341	0.0656***	0.0397	0.0679**	0.0309	0.0674*	0.0126	0.0670*	0.0126	0.0684*	0.0126
QoL												
lagged QoL	0.8374*	0.0843	0.8351	0.0907	0.7388*	0.1000						
hhwtchild												
hhICTexp												
constant							2.9107*	0.0278	2.9627*	0.0317	2.9048*	0.0281
R-squared				0.2992	0.2932	0.3082						
AR1 test statistic	−11.2300*	−10.6000	−10.2600*									
AR2 test statistic	5.1700*	4.9700	4.1900*									
Hansen J statistic	19.7700	19.7100										
Time FE	No	No	No	No	No	No						
Number of persons	3281	3281	3281	3281	3281	3281						
Number of observations	26,248	26,248	26,248	26,248	26,248	26,248						

Note: *, ** and *** denote statistically significant at 1%, 5% and 10%, respectively.

Table 5
Robustness checks of Internet access equation using GMM and random effect estimations.

Variables	Dependent Variable: Internet Access											
	GMM						Random effects					
	(1)		(2)		(3)		(4)		(5)		(6)	
	Coef.	Robust SE	Coef.	Robust SE	Coef.	Robust SE	Coef.	Robust SE	Coef.	Robust SE	Coef.	Robust SE
sad_decile	−0.0030	0.0107	−0.0039	0.0103	−0.0073	0.0106	0.0054*	0.0012	0.0056*	0.0012	0.0068*	0.0012
major_city	−0.0556	0.1007					0.0381*	0.0098				
regional_city			0.0521***	0.0823					−0.0334**	0.0097		
remote_area					0.3178	0.3481					−0.0092**	0.0351
urban_area	0.2566***	0.1439	0.2343***	0.1348	0.1776	0.1472	−0.0089	0.0118	−0.0052	0.0116	0.0083	0.0103
age_over55	−0.0438	0.0503	−0.0368	0.0513	−0.0596	0.0537	−0.0187*	0.0051	−0.0187	0.0051		
health_con												
heavy_drinker												
community_part												
hhInt_accss												
QoL	0.0047***	0.0065	0.0047***	0.0064	0.0050***	0.0063	0.0277*	0.0033	0.0276*	0.0033	0.0281*	0.0033
hhwtchild	0.0484	0.0750	0.0299	0.0811	0.0755	0.0808	−0.0231*	0.0040	−0.0232*	0.0040	−0.0230	0.0040
hhICTexp	< 0.0001***	< 0.0001	< 0.0001	< 0.0001	< 0.0001	< 0.0001	< 0.0001**	0.0001	< 0.0001**	0.0001	< 0.0001*	< 0.0001
lagged hhInt_accss	0.7185*	0.0719	0.7154*	0.0698	0.7364*	0.0765						
constant							0.8247*	0.0051	0.8564*	0.0181	0.8252*	0.0152
R-squared					0.1212	0.1219	0.1286					
AR1 test statistic	−13.8700*	−14.2300										
AR2 test statistic	6.4800*	6.5700										
Hansen J statistic	37.1800	37.2500										
Time FE	No	No	No	No	No	No	No					
Number of persons	3281	3281	3281	3281	3281	3281						
Number of observations	26,248	26,248	26,248	26,248	26,248	26,248						

Note: *, ** and *** denote statistically significant at 1%, 5% and 10%, respectively.

reliability of the instruments, the serial correlation test statistics, AR (1), AR (2) and the Hansen J test statistic, are also reported. These tests indicate the absence of a serial correlation and the instruments are endogenous. Combined, these results suggest that the instruments used in the model are valid and reliable.

Internet access as outlined in Eq. (3). In this case, one of the regressors, *QOL*, is assumed to be endogenous. The instruments used in the model are *health_con* and *heavy_drinker*. Panels 1–3 of Table 5 report the system GMM estimation of Internet access equation. In all cases, the coefficients of QoL and SAD decile are evidently positive and statistically significant. In addition, the estimation outputs by plugging in DII_accss as an instrumental variable yielded similar results (Table A5). Altogether, these results imply the baseline estimates of the Internet access equation are also valid in the dynamic panel models. As in the QoL equation, relevant statistics indicate the absence of a serial correlation, and the instruments are endogenous.

4.2.2. Random effects estimation

In a random effects model, the variation across entities is assumed to be random and not correlated with the explanatory variables included in the model (Torres-Reyna, 2007). In this study, the random effects model is used because the differences across entities are believed to have influence over the dependent variable. Random effects estimation also permits the generalisation of the inferences beyond the sample used in the model (Torres-Reyna, 2007). Panels 4–6 of Table 4 report the random effects estimation of the QoL equation, and Table A5 (Panel 4) represents the results of the Internet access equation. Another series of robustness checks were conducted using *DII_accss* as the explanatory variable instead of *hhInt_accss* in the corresponding regression estimation of the Internet access equation (see Tables A4 and A5). The results in all the cases are almost identical to the baseline estimates. Therefore, a simultaneous association exists between digital inclusion and QoL. In addition, like the results of the baseline estimations, different degrees of remoteness are found to yield heterogeneous impacts on digital inclusion across different regression specifications using random effects estimations.

The GMM has also been applied to estimate the effect of QoL and socio-economic position on digital inclusion. Adding different degrees of remoteness into the baseline regression specifications also helps to explain the mechanism through which digital inclusion affects QoL. This has been done in two ways – (i) adding an interaction effect between different level of remoteness and Internet access in the baseline QoL equation, and (ii) running stratified regression based on remoteness, i.e. two separate regressions – one for major city and another for non–major city. Table A6 reports the estimates of interaction effects (Panels 1–3) and stratified regression (Panels 4–5). The result shows that the interaction between remote area and Internet access is positive. It indicates that connectivity reduces the isolation of persons residing in remote areas and thus it improves the QoL. This result is cross–validated by the stratified regression outputs. It is evident from Table A6 that for a resident of non–major city the likelihood of Internet access augments the QoL by 7.31 per cent while for major–city counterparts it increases by a lesser extent (6.22 per cent).

5. Discussion

An extensive body of empirical studies has investigated the association between QoL and digital inclusion (Campisi et al., 2015; Çelik and Odacı, 2013; Chiao and Chiu, 2016; Çikrıkci, 2016; Leung and Lee, 2005; Rosner and Perlman, 2018; Sims et al., 2017). The current study adds to this literature by exploring the association between QoL and digital inclusion within a panel data simultaneous equation approach. Applying the simultaneous equation approach, the endogeneity of QoL originating from unobserved heterogeneity and the reverse causality running from digital inclusion to QoL are estimated. The use of panel data also allows better control for unobserved heterogeneity than what could be realized using cross-sectional data. The study found that the higher the likelihood of digital inclusion, the higher the degree of QoL. This finding is consistent with the findings of a number of studies (Campisi et al., 2015; Çikrıkci, 2016; Gao et al., 2017; Rosner and Perlman, 2018; Siegel and Dorner, 2017). This study also confirmed that in addition to digital inclusion, a number of confounding variables significantly predict QoL. More importantly, the current study found that socio-economic advantages, long-term health conditions, age and community participation significantly explain the variations in QoL. These findings also coincide with the findings reported in previous empirical works (Bartikowski et al., 2018; Castellacci and Tveito, 2018; Chaumon et al., 2014). In contrast, few studies reported that the use of ICT diminishes the subjective well-being in specific contexts (Chaumon et al., 2014; Lachmann et al., 2016; Longstreet and Brooks, 2017; Nimrod, 2017). This decrease may be because of the technostress arising from the excessive use of ICT and problematic Internet use such as Internet addiction or social media addiction. In addition, the evidence on the impact of ICT usage on QoL of elderly people is mixed (Damant et al., 2016; Hirani et al., 2014).

Empirical studies reported that differences in socio-economic and demographic factors affect ICT adoption and usage pattern. In most cases, these factors cause a strong digital divide among users (Cerno and Amaral, 2006; Colombo et al., 2015; Demoussis and Giannakopoulos, 2006; Duplaga, 2017). Specifically, consistent with the literature, this research found that socio-economic advantage is a significant predictor of digital inclusion. In addition, one of the most striking findings from the current study is that life satisfaction is a major determinant of ICT adoption. These results corroborated the findings of a large number of previous works in this field (Çelik and Odacı, 2013; Chiao and Chiu, 2016; Rahman et al., 2018; Tarhini et al., 2013). Moreover, in accordance with previous studies, present results demonstrated that digital inclusion was negatively associated with age (Campos et al., 2017; Lindblom and Räsänen, 2017; Nishijima et al., 2017; Yu et al., 2017). The present research also found that household size, quality of ICT infrastructure, and ICT expenditure were positively related to digital inclusion, which also corresponds with earlier empirical observations (Alam and Imran, 2015; Park, 2017).

Another interesting finding of the study is that remoteness has a significant effect on digital inclusion. However, this effect varies with the extensity of remoteness. In particular, a person's likelihood of residing in a major city positively impacts the digital inclusion while the coefficients of regional and remote area dummy are negative which indicate that persons from those areas have less chance of getting Internet access at home because of their isolation. These findings are corroborated by recent survey conducted by (ABS, 2018). According to the survey, about 87.90 per cent of households in major cities have internet access at home while the corresponding figures for households in regional cities and remote areas are substantially lower – 81.70 and 77.10 per cent, respectively (ABS, 2018). Similarly, different degrees of remoteness are found to have differentiated impact on QoL. For example, the association between QoL and regional city is found to be negative while the association between QoL and remote area is positive. In furtherance, the findings of the study show that the interaction effect of remoteness and Internet access (i.e. multiplication of remoteness and Internet access) on QoL is positive which implies that connectivity lessens the isolation of remote populations and thus it improves QoL. Recent descriptive statistics demonstrate a similar trend. The descriptive data shows that for the period of 2010–2017, the mean QoL score for respondents in a major city is 3.21, while the corresponding figures for inhabitants of regional city and remote areas are 2.94 and 3.19, respectively.

It is evident from previous empirical works that digital inclusion and social inclusion are highly correlated (Alam and Imran, 2015; Ali et al., 2019; Park, 2017). The findings of this current study also revalidate that social inclusion significantly influences digital inclusion. However, to the best of authors' knowledge, no studies have yet investigated at what threshold level the social inclusion becomes significant. To answer this question, the current study estimated the Internet access equation by stratifying the entire sample into ten deciles of index of relative socio–economic advantage (SAD decile). The summed-up results are reported accordingly in Table A7. Interestingly, up to decile 2, the effect of social inclusion on digital inclusion is found insignificant. However, the effects of social inclusion become significant from decile 3. Therefore, SAD decile 2 is the threshold point after which the impact of social inclusion on digital inclusion becomes apparent. However, one may presume that QoL and SAD index are correlated as both composite indices have contents from access to material resources. Given this backdrop, the variance inflation factor (VIF) has been estimated to check the collinearity. For QoL equation, the VIF ranges from 1.09 to 1.56 with a mean VIF of 1.22. Similarly, for the Internet access equation the VIF scores from 1.08 to 1.81 with an average score of 1.37. In both cases, the VIF is well below the threshold value (i.e. VIF < 5) (Hair et al., 1995).

The findings emanating from the current study has a number of policy implications. First, empirical analyses based on the simultaneous equation model aid effective evaluation and prediction of policy actions because they are based on the practical understanding of how key variables of interest evolve and influence each other. Therefore, while devising digital inclusion policies, policymakers should take the simultaneous association between digital inclusion and the QoL into account. Second, increased ICT penetration is a necessary condition for shaping digital inclusion strategies, but not a sufficient one. To address the digital divide, policymakers should emphasise not only supply-side issues but also demand-side aspects. From the supply-side aspects, to promote digital inclusion in socio-economically disadvantaged areas, such as in a regional or remote community, provisions should be arranged to provide more reliable high-speed Internet connections. In this regard, targeted investment should be initiated for the development of telecommunication infrastructure in those areas. The degree of remoteness and accessibility of infrastructure (physical and ICT) together shape the relative adaptive capacity of a region. Particularly, with the end of the mining boom and the need for economic diversification, regional Australia needs investment in both physical and ICT infrastructure to uphold the level of economic development as well as promoting QoL and eradicating social exclusion. In this regard, access to affordable high-speed Internet connections will assist people in remote regional communities to enhance their capability and protect against social exclusion. Third, in reaping digital dividends, specific actions need to be taken to enhance digital skills. These actions require cooperation and collaboration among policymakers, business enterprises, the education sector and community groups in funding, developing and implementing government initiatives. Particular attention should be given to improving the digital skills of the most socio-economically disadvantaged groups and aged population by upskilling community-based services especially for disadvantaged populations residing in remote and regional areas. Service-providing websites should also be designed to be more accommodating and more easily navigable and used by all Australians. Lastly, socio-demographic factors, such as age, level of education and personal income should also be considered to foster digital inclusion.

Finally, a number of important limitations of the study need to be considered. First, the current study defines digital inclusion based on broadband Internet access. However, access is only a part of digital inclusion. Several other dimensions of digital inclusion including digital ability and affordability also influence the adoption of the Internet. However, information on these variables is not readily available in the HILDA survey. Having said that, the current study used digital inclusion index score (a composite index of digital access, ability and affordability reported at a certain geographical level) as a proxy of Internet access and the resultant regression outcomes reconfirmed the simultaneous association between QoL and digital inclusion. In future work, the effects of digital inclusion on the QoL should be examined by considering those aforementioned dimensions along with the quality of ICT infrastructure at the individual level and variables in the empirical models. Second, in future investigations, it would be interesting to see whether digital ability moderates (or mediates) the effect of ICT access on QoL. Thirdly, the finding stating the positive association between QoL and socio-economic should be treated with greater caution as both of the concepts overlap in terms of having contents associated with access to material resources.

6. Conclusion

This paper investigates whether digital inclusion affects QoL and vice versa. The findings from baseline estimations show digital and social-economic inclusion positively affect QoL. Analysing the results conversely, the current work also confirmed that the likelihood of digital inclusion is significantly higher for a person with high QoL and socio-economic profile. Taken these together, these results suggest digital inclusion and QoL predict each other concurrently. In addition, the remoteness and rural–urban divide also significantly influence QoL and digital inclusion.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix

Table A1
Estimation results of QoL equation first-stage regressions.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.
hhwtchild	−0.0310* (0.0036)	−0.0309* (0.0036)	−0.0303* (0.0036)	−0.0319* (0.0036)	−0.0319* (0.0036)	−0.0312* (0.0035)
hhICTexp	< 0.0001* (< 0.0000)	< 0.0001* (< 0.0000)	< 0.0000* (< 0.0000)	< 0.0000* (< 0.0000)	< 0.0000* (< 0.0000)	< 0.0000* (< 0.0000)
sad_decile	0.0129* (0.0008)	0.0131* (0.0008)	0.0144* (0.0008)	0.0129* (0.0008)	0.0131* (0.0008)	0.0144* (0.0008)
major_city	0.0303* (0.0059)			0.0300* (0.0059)		
regional_ctiy		−0.0265* (0.0059)			−0.0264* (0.0058)	
remote_area			−0.0348 (0.0230)			−0.0325 (0.0229)
urban_area	−0.0179** (0.0075)	−0.0144*** (0.0074)	−0.0004 (0.0064)	−0.0172** (0.0075)	−0.0138** (0.0073)	0.0002 (0.0064)
age_over55	−0.0734* (0.0047)	−0.0737* (0.0047)	−0.0747* (0.0047)	−0.0783* (0.0047)	−0.0786* (0.0047)	−0.0796* (0.0047)
health_con	−0.0484* (0.0053)	−0.0482* (0.0053)	−0.0485* (0.0053)	−0.0494* (0.0053)	−0.0492* (0.0053)	−0.0495* (0.0053)
heavy_drinker	0.0047 (0.0058)	0.0045* (0.0058)	0.0043 (0.0058)	0.0040 (0.0058)	0.0038* (0.0058)	0.0036 (0.0058)
community_part	0.0093** (0.0040)	0.0092* (0.0040)	0.0076* (0.0041)	0.0101** (0.0040)	0.0101* (0.0040)	0.0085** (0.0040)
constant	0.9166* (0.0088)	0.9408* (0.0109)	0.9125* (0.0089)	0.8760* (0.0101)	0.9002* (0.0119)	0.8718* (0.0102)

Note: *, ** and *** denote statistically significant at 1%, 5% and 10%, respectively. Robust standard errors are reported in parentheses.

Table A2
Estimation results of QoL equation using two-stage method.

Variables	IV-2SLS					
	(1)		(2)		(3)	
	Coef.	Robust SE	Coef.	Robust SE	Coef.	Robust SE
sad_decile	0.0436*	0.0113	0.0437*	0.0110	0.0422*	0.0105
major_city	−0.0380	0.0338				
regional_city			0.0157	0.0312		
remote_area					0.2630**	0.1100
urban_area	0.1015**	0.0371	0.0866**	0.0349	0.0881*	0.0288
age_over55	0.0146	0.0806	0.0069***	0.0778	0.0122*	0.0693
health_con	−0.3400*	0.0657	−0.3470*	0.0631	−0.3396*	0.0574
heavy_drinker	−0.0266	0.0291	−0.0260	0.0286	−0.0272	0.0288
community_part	0.1492*	0.0222	0.1511*	0.0217	0.1535*	0.0212
hhInt_accss	2.9089**	1.0115	2.7995**	0.9736	2.8872*	0.8614
constant	0.1579	0.9305	0.2467*	0.9123	0.1695*	0.7915
Kleibergen-Paap Wald rk F statistic	13.6010*	13.9350*	15.8320*			
Hansen J statistic	4.6250*	3.1280*	1.9120*			

(*continued on next page*)

Table A2 (*continued*)

Variables	IV-2SLS					
	(1)		(2)		(3)	
	Coef.	Robust SE	Coef.	Robust SE	Coef.	Robust SE
Time FE	Yes	Yes	Yes			
Number of persons	3277	3277	3277			
Number of observations	13,108	13,108	13,108			
		First-stage regression outputs				
	Coef.	Robust SE	Coef.	Robust SE	Coef.	Robust SE
hhwtchild	−0.0203*	0.0041	−0.0203*	0.0041	−0.0200*	0.0041
DII_accss	0.0010***	0.0007	0.0012***	0.0007	0.0017*	0.0006
sad_decile	0.0100*	0.0011	0.0101*	0.0011	0.0104*	0.0011
major_city	0.0155***	0.0083				
regional_city			−0.0119	0.0083		
remote_area					−0.0329	0.0318
urban_area	−0.0160***	0.0094	−0.0139	0.0093	−0.0103	0.0083
age_over55	−0.0677*	0.0055	−0.0678*	0.0055	−0.0677*	0.0055
health_con	−0.0591*	0.0069	−0.0590*	0.0069	−0.0593*	0.0069
heavy_drinker	0.0063	0.0072	0.0063	0.0072	0.0066	0.0072
community_part	0.0103**	0.0052	0.0102**	0.0052	0.0094***	0.0053
constant	0.8906*	0.0392	0.8925*	0.0437	0.8541*	0.0358

Note: *, ** and *** denote statistically significant at 1%, 5% and 10%, respectively.

Table A3
Estimation results of Internet access first-stage regressions.

Variables	(1) Coef.	(2) Coef.	(3) Coef.	(4) Coef.	(5) Coef.	(6) Coef.
health_con	−0.4995*	−0.4994*	−0.4985*	−0.5013*	−0.5013*	−0.5004*
	(0.0120)	(0.0120)	(0.0120)	(0.0120)	(0.0120)	(0.0098)
heavy_drinker	−0.0043	−0.0042	−0.0054	−0.0056	−0.0055	−0.0067
	(0.0157)	(0.0157)	(0.0156)	(0.0157)	(0.0157)	(0.0131)
sad_decile	0.0757*	0.0752*	0.0767*	0.0757*	0.0752*	0.0766*
	(0.0020)	(0.0020)	(0.0019)	(0.0020)	(0.0020)	(0.0015)
major_city	0.0150			0.0143		
	(0.0136)			(0.0136)		
regional_ctiy		−0.0250**			−0.0247***	
		(0.0133)			(0.0133)	
remote_area			0.1339			0.1379*
			(0.0514)			(0.0378)
urban_area	0.0616*	0.0564*	0.0770	0.0629*	0.0574*	0.0781*
	(0.0169)	(0.0165)	(0.0151)	(0.0169)	(0.0165)	(0.0117)
hhwtchild	−0.0144	−0.0147	−0.0142	−0.0160	−0.0163	−0.0159
	(0.0140)	(0.0140)	(0.0140)	(0.0140)	(0.0140)	(0.0111)
hhICTexp	< 0.0001***	< 0.0001***	< 0.0001***	< 0.0001	< 0.0001***	< 0.0001***
	(< 0.0001)	(< 0.0001)	(< 0.0001)	(< 0.0001)	(< 0.0001)	(< 0.0001)
age_over55	−0.1793*	−0.1789*	−0.1803	−0.1880*	−0.187	−0.1890***
	(0.0129)	(0.0129)	(0.0129)	(0.0129)	(0.0129)	(0.0100)
constant	2.8680*	2.8938*	2.8573	2.7970*	2.8226*	2.7859*
	(0.0285)	(0.0321)	(0.0285)	(0.0300)	(0.0334)	(0.0249)

Note: *, ** and *** denote statistically significant at 1%, 5% and 10%, respectively. Robust standard errors are reported in parentheses.

Table A4
Estimation results of Internet access equation using 2SLS and FIML.

Variables	IV-2SLS						FIML	
	(1)		(2)		(3)		(4)	
	Coefficient	Robust SE	Coefficient	Robust SE	Coefficient	Robust SE	Coefficient	Robust SE
QoL	0.1144*	0.0131	0.1141*	0.0131	0.1149*	0.0132	0.0560*	0.0082
sad_decile	0.0016	0.0016	0.0018	0.0016	0.0020	0.0015	0.0094*	0.0022
major_city	0.0183**	0.0083					0.0286**	0.0081
regional_city			−0.0129***	0.0084				
remote_area					−0.0499***	0.0317		
urban_area	−0.0218**	0.0094	−0.0188**	0.0094	−0.0155***	0.0083	−0.0218	0.0092
hhwtchild	−0.0164*	0.0046	−0.0163*	0.0046	−0.0160*	0.0046	−0.0328*	0.0045
DII_accss	0.0002	0.0007	0.0004	0.0007	0.0009	0.0006	0.0004***	0.0003
age_over55	−0.0475*	0.0061	−0.0477*	0.0061	−0.0475*	0.0062	−0.0682**	0.0061
constant	0.6071*	0.0487	0.6064*	0.0529	0.5630*	0.0473	0.7744*	0.0254
Kleibergen-Paap Wald rk F statistic	505.5880*		506.0830*		504.0250*			
Hansen J statistic	0.9130		0.9230		1.0150			
Log-likelihood							−140311.9700	
Time FE	Yes		Yes		Yes		No	
Number of persons	3277		3277		3277		3277	
Number of observations	13,108		13,108		13,108		13,108	
			First-stage regression outputs					
	Coefficient	Robust SE	Coefficient	Robust SE	Coefficient	Robust SE		
health_con	−0.5208*	0.0164	−0.5210*	0.0164	−0.5199*	0.0164		
heavy_drinker	−0.0061	0.0217	−0.0062	0.0217	−0.0068	0.0217		
sad_decile	0.0742*	0.0028	0.0738*	0.0028	0.0736*	0.0028		
major_city	−0.0291	0.0209						
regional_city			0.0155	0.0205				
remote_area					0.1338***	0.0746		
urban_area	0.0523**	0.0229	0.0456*	0.0225	0.0444*	0.0213		
Hhwtchild	−0.0348***	0.0204	−0.0350***	0.0204	−0.0356**	0.0204		
DII_accss	0.0072*	0.0017	0.0066*	0.0017	0.0060*	0.0015		
age_over55	−0.1726*	0.0179	−0.1723*	0.0179	−0.1727*	0.0179		
constant	2.5343*	0.1064	2.5539*	0.1160	2.5993*	0.0952		

Note: *, ** and *** denote statistically significant at 1%, 5% and 10%, respectively.

Table A5
Robustness checks of Internet access equation using GMM and random effect estimations.

Variables	GMM (1)		Random effects (2)	
	Coefficient	Robust SE	Coefficient	Robust SE
QoL	0.0080***	0.0141	0.0051*	0.0015
sad_decile	−0.0053	0.0672	0.0183***	0.0101
major_city	0.4740	0.6792	0.0042	0.0128
urban_area	0.6952	0.5441	0.0336*	0.0039
hhwtchild	−0.0063	0.2711	−0.0196*	0.0048
DII_accss	0.0027***	0.0015	0.0004	0.0004
age_over55	−0.1235	0.1684	−0.0473*	0.0063
lagged hhInt_accss	−0.0770	0.3120		
constant			0.8129*	0.0282
R-squared			0.0947	
AR1 test statistic	−0.4300			
AR2 test statistic	−1.2400			
Hansen J statistic	18.6400			
Time FE	No		No	
Number of persons	3277		3277	
Number of observations	13,108		13,108	

Note: *, ** and *** denote statistically significant at 1%, 5% and 10%, respectively.

Table A6
Interaction effects of remoteness and stratified regression based on remoteness.

Variables	Dependent Variable: QoL									
	Interaction effects of remoteness						Stratified regression			
	(1)		(2)		(3)		(4)		(5)	
	Coef.	Robust SE	Coef.	Robust SE	Coef.	Robust SE	Coef.	Robust SE	Coef.	Robust SE
sad_decile	0.0230*	0.0020	0.0227	0.0019	0.0249*	0.0019	0.0285*	0.0026	0.0201*	0.0035
major_city	0.0440***	0.0265								
regional_city			−0.0551**	0.0257						
remote_area					0.1043	0.0740				
urban_area	0.0360**	0.0152	0.0327**	0.0148	0.0601*	0.0140	−0.0030	0.0486	0.0315	0.0178
age_over55	−0.0336*	0.0092	−0.0334*	0.0092	−0.0338*	0.0092	−0.0383*	0.0112	−0.0336*	0.0161
health_con	−0.1185*	0.0065	−0.1184*	0.0065	−0.1183*	0.0065	−0.1098*	0.0082	−0.1329*	0.0108
heavy_drinker	−0.0104	0.0099	−0.0104*	0.0099	−0.0106	0.0099	−0.0122	0.0124	−0.0091	0.0162
community_part	0.0328*	0.0062	0.0330*	0.0062	0.0324*	0.0062	0.0298*	0.0078	0.0423*	0.0103
hhInt_accss	0.0678*	0.0163	0.0682*	0.0166	0.0673*	0.0119	0.0622*	0.0171	0.0731*	0.0165
major_city*hhInt_accss	−0.0009	0.0235								
regional_city*hhInt_accss			−0.0024	0.0233						
remote_area*hhInt_accss					0.0444*	0.0717				
constant	2.9103*	0.0251	2.9617*	0.0276	2.9058*	0.0229	3.0037*	0.0549	2.8625*	0.0323
R-squared	0.2992						0.2727		0.3181	
Number of persons	3281		3281		3281		2206		1301	
Number of observations	26,248		26,248		26,248		16,776		9472	

Note: *, ** and *** denote statistically significant at 1%, 5% and 10%, respectively.

Table A7
Association between digital and social inclusion.

Variables	SAD decile 1–2 (1)		SAD decile 3–10 (2)	
	Coefficient	Robust SE	Coefficient	Robust SE
sad_decile	0.0167	0.0177	0.0028**	0.0011
major_city	0.0606**	0.0221	0.0285*	0.0073
urban_area	−0.0453	0.0306	−0.0028	0.0078
age_over55	−0.0570*	0.0158	−0.0116**	0.0046
hhwtchild	−0.0593*	0.0167	−0.0163*	0.0045
hhICTexp	< 0.0001***	< 0.0001	< 0.0001*	< 0.0001
QoL	0.0402*	0.0105	0.0246*	0.0030
constant	0.8363*	0.0569	0.8482*	0.0150
R-squared	0.1023		0.0898	
Number of persons	738		2892	
Number of observations	4412		21,836	

Note: *, ** and *** denote statistically significant at 1%, 5% and 10%, respectively.

Table A8
Robustness checks of QoL and Internet access equation using digital inclusion index as proxy variable of Internet access.

Variables	Dependent variable: QoL (1)		Dependent variable: DII (2)	
	Coefficient	Robust SE	Coefficient	Robust SE
sad_decile	0.0422*	0.0034	0.3331*	0.0192
major_city	0.0394***	0.0232	5.3505*	0.1314
urban_area	0.0418***	0.0252	1.0255*	0.1766
age_over55	−0.1159*	0.0158	0.3054**	0.1059
health_con_recoded	−0.1495*	0.0100		
heavy_drinker	0.0119	0.0150		
community_part_recoded	0.0534*	0.0094		
hhwtchild			0.0266	0.1233
hhICTexp			< 0.0001*	< 0.0001
DII	0.0032*	0.0009		

(*continued on next page*)

Table A8 (*continued*)

Variables	Dependent variable: QoL (1)		Dependent variable: DII (2)	
	Coefficient	Robust SE	Coefficient	Robust SE
QoL			0.3235*	0.0613
constant	2.7382*	0.0558	47.6406*	0.3199
R-squared	0.2663		0.5754	
Number of persons	3277		3277	
Number of observations	13,108		13,108	

Note: *, ** and *** denote statistically significant at 1%, 5% and 10%, respectively.

References

ABS, 2011. Australian Statistical Geography Standard, Volume 1 - Main Structure and Greater Capital City Statistical Areas.Catalogue Number 1270.0.55.001. Canberra, Australian Bureau of Statistics.
ABS, 2018. Household Use of Information Technology. Catalogue Number 8146.0. Canberra.
Alam, K., Imran, S., 2015. The digital divide and social inclusion among refugee migrants: a case in regional Australia. Inform. Technol. People 28, 344–365.
Alam, K., Mahumud, R.A., Alam, F., Keramat, S.A., Erdiaw-Kwasie, M.O., Sarker, A.R., 2019. Determinants of access to eHealth services in regional Australia. Int. J. Med. Inf. 131, 103960.
Ali, M.A., Alam, K., Taylor, B., 2019. Do social exclusion and remoteness explain the digital divide in Australia? Evidence from a panel data estimation approach. Econ. Innov. New Technol. 1–17.
Ali, M.A., Alam, K., Taylor, B., 2020. Incorporating affordability, efficiency, and quality in the ICT development index: implications for index building and ICT policymaking. Inform. Soc. 36, 71–96.
Allen, J., Inder, K.J., Harris, M.L., Lewin, T.J., Attia, J.R., Kelly, B.J., 2013. Quality of life impact of cardiovascular and affective conditions among older residents from urban and rural communities. Health Qual. Life Outcomes 11.
Alston, L., Allender, S., Peterson, K., Jacobs, J., Nichols, M., 2017. Rural inequalities in the Australian burden of ischaemic heart disease: a systematic review. Heart Lung Circul. 26, 122–133.
Arbabisarjou, A., Allameh, S.M., Farhang, A., 2012. Relationship between information & communication technology and quality of work-life; A study of faculty members of Zahedan university. Life Sci. J. 9, 3322–3331.
Arellano, M., Bond, S., 1991. Some tests of specification for panel data:monte carlo evidence and an application to employment equations. Rev. Econ. Stud. 58, 277–297.
Arellano, M., Bover, O., 1995. Another look at the instrumental variable estimation of error-components models. J. Econ. 68, 29–51.
Bartikowski, B., Laroche, M., Jamal, A., Yang, Z., 2018. The type-of-internet-access digital divide and the well-being of ethnic minority and majority consumers: a multi-country investigation. J. Business Res. 82, 373–380.
Basu, P., Chakraborty, J., 2011. New technologies, old divides: linking internet access to social and locational characteristics of US farms. Geo J. 76, 469–481.
Baum, C.F., Christopher, F., 2006. An Introduction To Modern Econometrics Using Stata. Stata Press, Texas.
Binder, M., Buenstorf, G., 2018. Smile or die: can subjective well-being increase survival in the face of substantive health impairments? Econ. Human Biol. 31, 209–227.
Böhringer, C., Jochem, P.E.P., 2007. Measuring the immeasurable - A survey of sustainability indices. Ecol. Econ. 63, 1–8.
Cai, L., 2010. The relationship between health and labour force participation: evidence from a panel data simultaneous equation model. Labour Econ. 17, 77–90.
Campisi, J., Folan, D., Diehl, G., Kable, T., Rademeyer, C., 2015. Social media users have different experiences, motivations, and quality of life. Psychiatry Res. 228, 774–780.
Campos, R., Arrazola, M., de Hevia, J., 2017. Economic crisis and benefits of the Internet: differentiated Internet usage by employment status. Econ. Innov. New Technol. 26, 269–294.
Castellacci, F., Tveito, V., 2018. Internet use and well-being: a survey and a theoretical framework. Res. Policy 47, 308–325.
Çelik, Ç.B., Odacı, H., 2013. The relationship between problematic internet use and interpersonal cognitive distortions and life satisfaction in university students. Children Youth Serv. Rev. 35, 505–508.
Cerno, L., Amaral, T.P., 2006. Demand for internet access and use in Spain. Governance of Communication Networks. Heidelberg Physica-Verlag 333–353.
Chaumon, M.-E.B., Michel, C., Tarpin Bernard, F., Croisile, B., 2014. Can ICT improve the quality of life of elderly adults living in residential home care units? From actual impacts to hidden artefacts. Behav. Inform. Technol., Taylor & Francis 574–590.
Chern, K.-C., Huang, J.-H., 2018. Internet addiction: Associated with lower health-related quality of life among college students in Taiwan, and in what aspects? Comput. Hum. Behav. 84, 460–466.
Chiao, C., Chiu, C.H., 2016. The relationships between ICT use and life quality among children with social phobia. In: 2016 IEEE International Conference on Teaching, Assessment, and Learning for Engineering (TALE), pp. 26–31.
Çikrıkci, Ö., 2016. The effect of internet use on well-being: meta-analysis. Comput. Hum. Behav. 65, 560–566.
Colombo, F., Aroldi, P., Carlo, S., 2015. New elders, old divides: ICTs, inequalities and well-being amongst young elderly. Italians Comunicar 23, 47–55.
Curtin J., 2001. A digital divide in rural and regional Australia? : Department of Parliamentary Library.
Damant, J., Knapp, M., Freddolino, P., Lombard, D., 2016. Effects of digital engagement on the quality of life of older people. Health Soc. Care Community 25, 1679–1703.
De Wet, W., Koekemoer, E., Nel, J.A., 2016. Exploring the impact of information and communication technology on employees' work and personal lives A Journal of Industrial. Psychology 42, 1–11.
Dedrick, J., Kraemer, K.L., Shih, E., 2011. IT in Developed and Developing Countries. Personal Computing Industry Center, University of California, Irvine.
Demoussis, M., Giannakopoulos, N., 2006. Facets of the digital divide in Europe: determination and extent of internet use. Economics of Innovation and New Technology 15, 235–246.
Dewan, S., Kraemer, K.L., 2000. Information technology and productivity: evidence from country-level data. Manage. Sci. 46, 548–562.
Ding, N., Berry, H.L., O'Brien, L.V., 2015. One-year reciprocal relationship between community participation and mental wellbeing in Australia: a panel analysis. Soc. Sci. Med. 128, 246–254.
Duplaga, M., 2017;12.. Digital divide among people with disabilities: Analysis of data from a nationwide study for determinants of Internet use and activities performed online. PLoS ONE.
Ganju, K.K., Pavlou, P.A., Banker, R.D., 2016. Does information and communication technology lead to the well-being of nations? A country-level empirical

investigation. MIS Quarterly 40, 417–430.
Gao, T., Xiang, Y.-T., Zhang, H., Zhang, Z., Mei, S., 2017. Neuroticism and quality of life: Multiple mediating effects of smartphone addiction and depression. Psychiatry Res. 258, 457–461.
Gianchandani, E.P., 2011. Toward smarter health and well-being: an implicit role for networking and information technology. J. Inform. Technol. 26, 120–128.
Gopinathan, S., Raman, M., 2016. Information system quality in work-life balance. Knowledge Manage. E-Learn. 8, 216–226.
Habibov, N., Afandi, E., 2016. Does life satisfaction determine subjective health? Appl. Res. Qual. Life 11, 413–428.
Hair, J.F.J., Anderson, R.E., Tatham, R.L., Black, W.C., 1995. Multivariate Data Analysis, 3rd ed. Macmillan, New York.
Hayward, R.D., Taylor, W.D., Smoski, M.J., Steffens, D.C., Payne, M.E., 2013. Association of five-factor model personality domains and facets with presence, onset, and treatment outcomes of major depression in older adults. Am. J. Geriatric Psychiatry 21, 88–96.
Hirani, S.P., Beynon, M., Cartwright, M., Rixon, L., Doll, H., Newman, S.P., 2014. The effect of telecare on the quality of life and psychological well-being of elderly recipients of social care over a 12-month period: the Whole Systems Demonstrator cluster randomised trial. Age Aging 43, 334–341.
Hodge, H., Carson, D., Carson, D., Newman, L., Garrett, J., 2017. Using Internet technologies in rural communities to access services: the views of older people and service providers. J. Rural Stud. 54, 469–478.
Hosseini, M.H., Kaneko, S., 2011. Dynamic sustainability assessment of countries at the macro level: a principal component analysis. Ecol. Ind. 11, 811–823.
Hsiao, C., 2007. Panel data analysis—advantages and challenges. Test 16, 1–22.
Lachmann, B., Sariyska, R., Kannen, C., Cooper, A., Montag, C., 2016. Life satisfaction and problematic Internet use: evidence for gender specific effects. Psychiatry Res. 238, 363–367.
Leung, L., Lee, P.S.N., 2005. Multiple determinants of life quality: the roles of Internet activities, use of new media, social support, and leisure activities. Telemat. Informat. 22, 161–180.
Lindblom, T., Räsänen, P., 2017. Between class and status? Examining the digital divide in Finland, the United Kingdom, and Greece. Inform. Soc 33, 147–158.
Lissitsa, S., Chachashvili-Bolotin, S., 2016. Life satisfaction in the internet age – changes in the past decade. Comput. Hum. Behav. 54, 197–206.
Longstreet, P., Brooks, S., 2017. Life satisfaction: a key to managing internet & social media addiction. Technol. Soc. 50, 73–77.
Mahuteau, S., Zhu, R., 2016. Crime victimisation and subjective well-being: panel evidence from Australia. Health Econ. 25, 1448–1463.
Martin, B.R., 2016. Twenty challenges for innovation studies. Sci. Public Policy 43, 432–540.
Mowery, D.C., Nelson, R.R., Fagerberg, J., 2011. The Oxford Handbook of Innovation. Oxford University Press.
Nimrod, G., 2017. Technostress: measuring a new threat to well-being in later life. Aging Mental Health 1–8.
Nishijima, M., Ivanauskas, T.M., Sarti, F.M., 2017. Evolution and determinants of digital divide in Brazil (2005–2013). Telecommun. Policy 41, 12–24.
Park, S., 2017. Digital inequalities in rural Australia: a double jeopardy of remoteness and social exclusion. J. Rural Stud. 54, 399–407.
Pateman, K.A., Cockburn, N.L., Batstone, M.D., Ford, P.J., 2018. Quality of life of head and neck cancer patients in urban and regional areas: an Australian perspective. Aust. J. Rural Health 26, 157–164.
Rahman, M.S., Mannan, M., Amir, R., 2018. The rise of mobile internet: the adoption process at the bottom of the pyramid Digital Policy. Regul. Govern. 20, 582–599.
Rosner, Y., Perlman, A., 2018. The effect of the usage of computer-based assistive devices on the functioning and quality of life of individuals who are blind or have low vision. J. Visual Impairment Blindness 112, 87–99.
Rotondi, V., Stanca, L., Tomasuolo, M., 2017. Connecting alone: Smartphone use, quality of social interactions and well-being. J. Econ. Psychol. 63, 17–26.
Schaffer M., 2015. XTIVREG2: Stata module to perform extended IV/2SLS, GMM and AC/HAC, LIML and k-class regression for panel data models.
Sen, A., 1985. Commodities and Capabilities. North-Holland, Amsterdam.
Sen, A., 2010. The mobile and the World. Inform. Technol. Int. Develop. 6, 1–3.
Siegel, C., Dorner, T.E., 2017. Information technologies for active and assisted living—Influences to the quality of life of an ageing society. Int. J. Med. Inf. 100, 32–45.
Sims, T., Reed, A.E., Carr, D.C., 2017. Information and communication technology use is related to higher well-being among the oldest-old. J. Gerontol. – Series B Psychol. Sci. Social Sci. 72, 761–770.
Sun, C., Watson, N., Hahn, M., 2016. Program 10 (Stata). Programs Provided By The Hilda Survey Team. Melbourne Melbourne Institute of Applied Economic and Social Research.
Tarhini, A., Hone, K., Liu, X., 2013. Extending the TAM model to empirically investigate the students' behavioural intention to use e-learning in developing countries. In: Proceedings of 2013 Science and Information Conference, SAI 2013. London, United Kingdom, pp. 732–737.
Thomas, J., Barraket, J., Ewing, S., MacDonald, T., Mundell, M., Tucker, J., 2016. Measuring Australia's Digital Divide: The Australian Digital Inclusion Index 2016. RMIT University.
Toda, M., Ezoe, S., Mure, K., Takeshita, T., 2016. Relationship of smartphone dependence to general health status and personality traits among university students. Open J. Prev. Med. 6, 215–221.
Torres-Reyna, O., 2007. Panel data analysis fixed and random effects using Stata (v. 4.2) Data & Statistical Services, Priceton University.
Van den Berg, M., Ranchor, A., Van Sonderen, F., Van Gelder, I., Van Veldhuisen, D., 2005. Paroxysmal atrial fibrillation, quality of life and neuroticism. Netherland J. Med. 63, 170–174.
WHO, 1996. WHOQoL-BREF: Introduction, Administration, Scoring and Generic Version of the Assessment. Geneva.
Williams, R., Allison, P., Benito, E.M., 2016. XTDPDML: Stata module to estimate Dynamic Panel Data Models using Maximum Likelihood, Statistical Software Components S458210, Boston College Department of Economics. Boston, Boston College Department of Economics.
Wooden, M., Freidin, S., Watson, N., 2002. The household, income and labour dynamics in Australia (HILDA) survey: wave 1. Aust. Econ. Rev. 35, 339–348.
Wresch, W., 2009. Progress on the global digital divide: an ethical perspective based on Amartya Sen's capabilities model. Ethics Inf. Technol. 11, 255–263.
Yu, T.K., Lin, M.L., Liao, Y.K., 2017. Understanding factors influencing information communication technology adoption behavior: The moderators of information literacy and digital skills. Comput. Hum. Behav. 71, 196–208.

Cyberpsychology, Behavior, and Social Networking
Volume 23, Number 5, 2020

DOI: 10.1089/cyber.2019.0598

The Mediating Effect of Information and Communication Technology Usages on the Nexus Between Assistive Technology and Quality of Life Among People with Communication Disability

Mohammad Afshar Ali, MSS,[1–3] Khorshed Alam, PhD,[1,2] and Brad Taylor, PhD[4]

Abstract

This study aims to investigate the mediating effect of information and communication technology (ICT) on the nexus between quality of life (QoL) and assistive technology among people with communication disabilities. Using a national-level disability survey data in Australia, this study employs a series of causal mediation models based on counterfactual framework for mediation analysis. The results indicate that about 61% to 73% of the impact of assistive technology on QoL among people with communication disabilities is mediated through ICT use. Furthermore, it is evident that the degree of communication impairment partially moderates the impact of ICT-enabled assistive technology on QoL. The findings of the study have several practical implications. First, this study indicates that better integration of assistive technology with ICT will enhance the quality of people with communication disabilities. The second broad recommendation is that improved accessibility with affordable high-speed broadband Internet can deliver services that people with disabilities need.

Keywords: information and communication technology, assistive technology, quality of life, communication disability, causal mediation analysis

Introduction

Information and communication technologies (ICTs) assist people with disabilities to navigate their day-to-day lives, providing greater access to education, employment, social interaction, culture, and health-related services.[1–6] According to a recent statistics, around 15% of the world's population suffers from some form of disability, and this is projected to increase in many societies with an aging population.[7] Almost one in five Australians reported some form of disability (18.3% of the total population).[8] Although only a small fraction of people with disabilities are people with communication disabilities, deficits in communication and interaction can have a seriously negative impact on quality of life (QoL).[9–11] ICTs are particularly important for people with communication disabilities insofar as they augment communication and interaction.[6,10,12] Although availability of ICT is regarded as one of the basic human rights in the Convention on the Rights of Persons with Disabilities,[13] a number studies have revealed that people with disabilities are less likely than others to have a computer or Internet access at home.[12,14] For example, 84.6% of the Australian population are Internet users,[15] while for people with disabilities cohort, the figure is substantially lower at 64.3%.[8]

Studies have documented that ICTs have significantly enhanced the QoL of people with disabilities by mitigating the disadvantages associated with disability. In particular, for people with communication disabilities, another strand of literature has reported that ICT-based interventions are associated with higher levels of health-related autonomy and reduction of communication impairment. In turn, these outcomes lead to greater social inclusion and improved QoL.[16–20] In this connection, the use of ICT-based assistive technology among people with disabilities has received noticeable research attention.[19,21] By definition, assistive technology is a piece of equipment or a device that helps people with disabilities to maintain their autonomy or improve their QoL.[22] Examples of assistive technology aimed at people with communication disabilities include hearing aids, text-to-speech devices, and screen-reading software. Previous

[1]School of Commerce, Faculty of Business, Education, Law & Arts, University of Southern Queensland, Toowoomba, Australia.
[2]Centre for Health Research, University of Southern Queensland, Toowoomba, Australia.
[3]Department of Economics, Jagannath University, Dhaka, Bangladesh.
[4]School of Commerce, Faculty of Business, Education, Law & Arts, University of Southern Queensland, Springfield, Australia.

studies have shown that ICT-based assistive technology enhances QoL by minimizing communication- and interaction-related deficit faced by people with communication disabilities.[19,23] In analyzing the impact of ICT-based assistive technology on QoL, scholars have controlled for a number of covariates, including sociodemographic factors (age, gender, education, and employment status), economic status (income), social exclusion (degree of discrimination faced and financial support from government), and location-specific factors (remoteness).[1,2,4,19] However, a number of issues in this area remained understudied.

First, several studies in the field underscore the crucial role of ICT-assistive technology integration for independence, social integration, and betterment of overall QoL of people with communication disabilities.[19,24,25] These studies also cautioned that in translating the positive impact of ICT-based assistive technology on QoL, both incompatibly of assistive technology with ICT devices and inaccessibility of compatible ICT devices appeared as major barriers.[26–28] Given this backdrop, technology convergence between ICT and assistive technology helps promote equal opportunities and thus minimizes the digital disability divide.[21,24,26,29] This, in turn, implies that the effectiveness of assistive technology with regard to improving the QoL among people with communication disabilities is subject to accessibility of compatible ICTs. However, to the best of authors' knowledge, existing studies are yet to explore the mediating effect of ICT on the causal association between assistive technology and QoL among people with communication disabilities.

Second, people with communication disabilities are not a homogeneous group, and they face different types of barriers depending upon their type and degree of impairment. Therefore, the way technology is utilized and its subsequent impact on QoL among various groups of people with communication disabilities should be heterogeneous.[12,19] In addition, the impact of ICT-enabled assistive technology on QoL among people with communication disabilities might also differ if a disabled person has multiple impairment.[18,29] Based on this motivation, it is assumed that the effect of ICT-based assistive technology on QoL is heterogeneous, subject to the extensity of communication impairment among people with communication disabilities. This gives a solid motivation to explore the heterogeneity of the impact of ICT-enabled assistive technology on QoL among people with communication disabilities, which has yet to be revealed by empirical study.

Given this backdrop, this study aims to investigate the mediating effect of ICT on explaining the nexus between assistive technology and QoL among people with communication disabilities. To achieve this research objective, two research questions are posed: (1) whether or not ICT mediates the causal association between assistive technology and QoL among people with communication disabilities and (2) whether or not the impact of ICT-based assistive technology on QoL is heterogeneous with respect to the extent of communication impairment among people with communication disabilities. This study makes a number of noteworthy contributions to the literature. First, it constructs a composite index to measure the QoL for people with communication disabilities cohort. In constructing the composite QoL index, this study follows the World Health Organisation Quality of Life (WHOQoL) disabilities module,[30] which constructed the composite QoL for people with disabilities using a number of indicators from five distinctive domains—physical, psychological, social, environment, and disabilities module (see data and variables section for details). Using that composite index, this research investigates the mediating role of ICT in explaining the QoL-assistive technology association among people with communication disabilities, employing advanced causal mediation analysis. Second, this study also explores whether the mediating effect of ICT on QoL-assistive technology nexus varies with the degree of communication impairment. Third, to avoid the potential bias that may arise from the sampling procedure, it uses both perception- and condition-based definition to define communication disability (see data and variables section for more details). Findings from this study are expected to generate better insights from policy perspectives as the study is based on a comprehensive nationwide cross-sectional survey equipped with improved estimation techniques.

Materials and Methods

Data and variables

This study used the Australian Bureau of Statistics (ABS) Microdata—Basic Confidentialized Unit Record Files (CURF)—compiled through the 2015 Survey of Disability, Ageing and Carers (SDAC). The survey methodology is explained in detail in ABS.[8] The survey was conducted across all states and territories, and in all urban, rural, and remote areas of Australia. Data collection consists of two parts: the establishment component and the household component. Accommodation within establishments comprised hospitals, aged care facilities, nursing homes, cared components of retirement villages, and other homes for people with disabilities. The final combined sample consists of 75,211 people, including 23,343 with a disability.

The cohort for this study has been selected on the basis of two criteria: (1) respondent's perception on whether or not they have a communication impairment and (2) whether or not the respondent reports medical conditions that may result in communication impairment. The list of conditions developed for the SDAC is based on the International Classification of Disease (ICD-10) (see Supplementary Table S1 for details). Of the 23,343 respondents with a disability, 10,866 reported having difficulty communicating due to their disability (i.e., satisfied criterion [1]), and 8,515 reported having one of the relevant medical conditions (i.e., satisfied criterion [2]). There were 6,137 respondents meeting both criteria, and it is this group we use as the sample for this study.

The sampling procedure in earlier studies has used either one of the above criteria. For example, some studies defined communication impairment using the respondent's perception,[3,14,29] while others relied on reported or diagnosed medical conditions.[17,19,25,31] However, each definition has its own limitations. Following the first criterion may result in bias since it is a perception-based definition. Self-rated status of outcome is a subjective measure, perception of which can be affected by other factors, including social circumstances.[32,33] Similarly, defining communication impairment on the basis of reported medical conditions may be misleading as many such conditions do not consistently produce communication disabilities. To be specific, in the 2015 SDAC, a total of 2,378 disabled people who reported having a relevant medical condition did not see themselves as suffering from a communication impairment. Considering these facts together, this study defines the sample of people with communication disabilities as those who satisfy both conditions—that is, those suffering from a relevant medical condition and reporting communication difficulties.

Table 1 provides the definitions of the variables included in the models along with their means and standard deviations. The classification of the variables also reflects the model specifications as outlined in Table 1. The variables listed in panel A is the outcome variable, those in panel B is the treatment variable, panel C and D list mediating and moderating variables, respectively, and those in panel E are included as control variables in both output and mediating regression models.

The Principal Component Analysis (PCA) is used to construct the composite index of QoL. Building a composite index considered to be is a better approach than modeling equations with separate indicators as it inherits the aggregate effect of all indicators.[34] The following equation is used to construct the composite index, QoL:

$$\mathrm{QoL} = \sum_{i=1}^{3} a_{ij} \frac{X_i}{SD(X)_i} \tag{1}$$

where QoL is the composite index measuring the quality of life of an individual, SD is the standard deviation, X_i is the ith variable, and a_{ij} is the factor loading derived through the PCA.

Model specification and estimation methods

Causal mediation analysis. Mediation analysis explores the apparatus that cause an observed relationship between an

Table 1. Variable Descriptions and Summary Statistics

Variable name	*Definition of variable*	*Mean*	*SD*
A. Output variable			
QoL	A composite index to measure the QoL for the respondent with a communication impairment. This includes (1) level of mobility limitation, (2) level of negative feelings, (3) level of social or community participation, (4) feelings of safety, and (5) level of self-care limitation. All five indicators are categorical and measured on a 5-point Likert scale. The five indicators used in this study are selected from five respective domains (viz.—physical, psychological, social, environment, and disabilities module) to define the overall QoL of disabled people.[30]	2.034	0.808
B. Treatment or exposure variable			
AT_COM_USE	A dummy variable indicating whether or not the respondent has used assistive technologies for communication purposes (1 = has used assistive technology for communication purposes and 0 = has not used assistive technology)	0.333	0.471
C. Mediating variable			
ICT_USE	A dummy variable indicating whether or not the respondent has used at least one type of ICT tools from the following in the last 3 months to communicate with others. This includes use of mobile phone, telephone, Internet, social networking apps, and disability-specific apps for communication purposes (1 = has used ICT for communication purposes and 0 = otherwise)	0.185	0.389
D. Moderator variable			
LVLCOMMR	A dummy variable indicating the level of communication impairment of the respondent (1 = profound or severe and 0 = mild)	0.819	0.385
E. Control variables			
WHODISC	A categorical variable indicating degree of discrimination that the respondent has experienced due to disability in the last 12 months (1 = very low, 2 = low, 3 = moderate, 4 = high, and 5 = very high)	1.002	0.064
INCDECPN	A categorical variable indicating the quantile of the respondent's personal income (1 = 1st quantile, 2 = 2nd quantile, 3 = 3rd quantile, 4 = 4th quantile, and 5 = 5th quantile)	2.067	0.444
EDU	A categorical variable indicating the respondent's highest level of educational attainment (1 = year 12 or below, 2 = certificate III or IV, 3 = advanced diploma, 4 = bachelor, and 5 = postgraduate)	1.118	0.536
EMPLOY	A dummy variable indicating the labor force status of the respondent (1 = employed and 0 = otherwise)	0.036	0.185
AGE	A categorical variable indicating the age group of the respondent (1 = 0–14 years, 2 = 15–29 years, 3 = 30–44 years, 4 = 45–59 years, and 5 = older than 60 years)	4.591	1.079
GENDER	A dummy variable indicating the gender of the respondent (1 = male and 0 = female)	0.413	0.492
DISAB_SUP	A dummy variable indicating whether or not the respondent received disability support payment from the government	0.025	0.156
REMOTE	A dummy variable indicating whether or not a respondent person lives in a remote area (1 = resident of a remote area and 0 = otherwise)	0.117	0.321
Number of observations		6,137	

ICT, information and communication technology; QoL, quality of life; SD, standard deviation.

exposure variable and outcome variable, and investigates how they relate to a third mediator or intermediate variable. The baseline results of the regression model are estimated using two counterfactual parametric causal mediation regression models—parametric causal mediation regression models and parametric mediation effects. In addition, this study employs another causal mediation regression model based on G-computation procedure to check the robustness of the two baseline counterfactual causal mediation regression models. A detailed description on the rationale of using these three causal mediation regression models is provided in the Supplementary Data. Causal mediation mechanism among the variables investigated is portrayed in Figure 1.

Moderation analysis. A moderation analysis is used to explore when, or under what circumstances, or for which group of subsample the causal effect of mediator and treatment on the outcome exists or does not, and if it exists, what is the magnitude.[35] This study hypothesizes that the causal effect of ICT- enabled assistive technology will vary with the degree of communication impairment. For details on moderation analysis, see the Supplementary Data. Figure 2 illustrates the moderation effect of degree of communication impairment on the nexus between ICT-enabled assistive technology and QoL.

Empirical Results

Causal mediation effect

Main results. The results of causal mediation using parametric causal mediation regression models (*-paramed-*) are presented in Table 2. The results of both the outcome and mediation regression models and the summary estimates of the mediation, direct, and total effects are provided in this study. The regression coefficients of the outcome equation [Eq. (2)] show that both *AT_COM_USE* and *ICT_USE* have

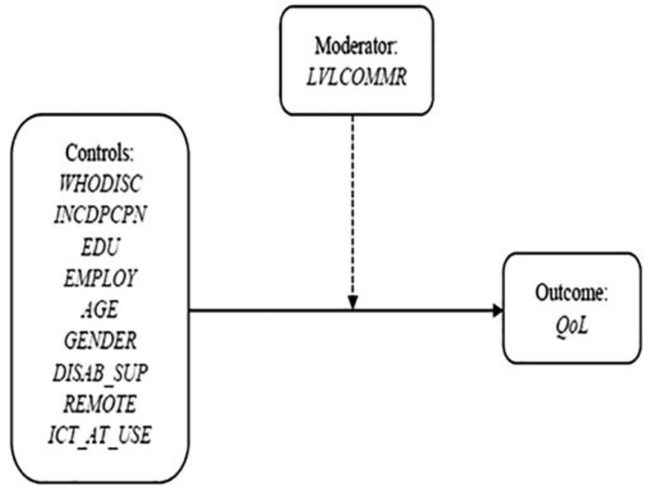

FIG. 2. Moderation effect of degree of communication impairment on the nexus between ICT-enabled assistive technology and QoL. ICT, information and communication technology; QoL, quality of life.

a positive and significant effect on QoL. The coefficient of the interaction effect between assistive technology use and ICT use (*ICT_USE×AT_COM_USE*) is also positively associated with *QoL.* Among sociodemographic variables EDU, EMPOLY, AGE, and GENDER appeared as significant predictors of QoL. However, estimates also come up with an interesting finding that *DISAB_SUP* is found to have a negative impact on the *QoL* among people with communication disabilities. At the same time, the results from mediation equation [Eq. (3)] indicate that ICT_*USE* is dependent upon *AT_COM_USE*. The NIE of the treatment variable on the outcome, which operates through the mediator (ICT_USE), is 0.362, and the estimate of the natural direct effect (NDE) is equal to 0.157. Hence, the indirect or

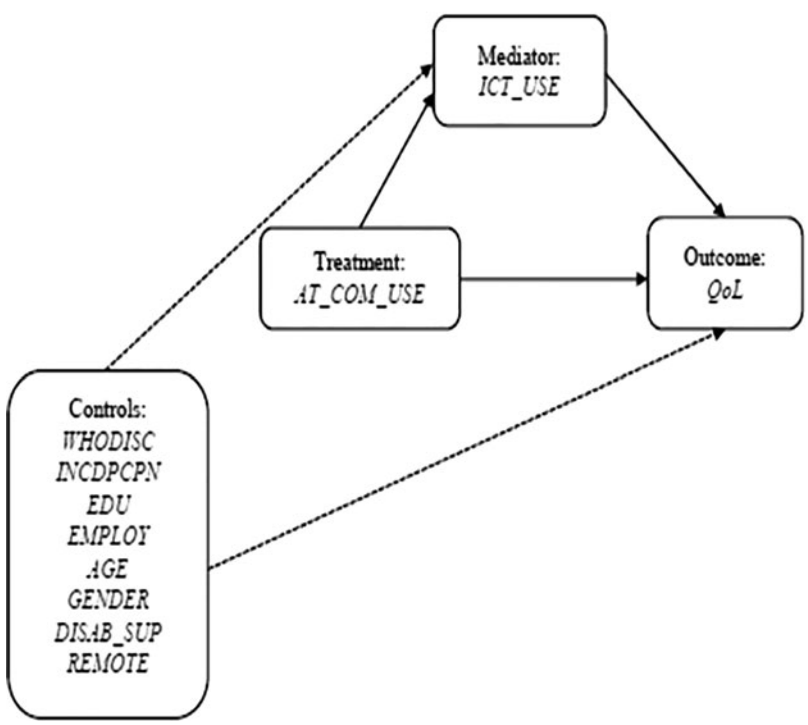

FIG. 1. Causal mediation mechanism among the variables investigated.

TABLE 2. CAUSAL MEDIATION ANALYSIS USING PARAMETRIC CAUSAL MEDIATION REGRESSION MODELS (-*PARAMED*-)

Output equation: dependent variable—QoL			
Variable	*Coefficient*	*SE*	t-*statistics*
AT_COM_USE	0.066*	0.0142	4.670
ICT_USE	0.762*	0.0302	25.260
ICT_USE × AT_COM_USE	0.832*	0.0353	23.560
WHODISC	–0.112	0.0864	–1.300
INCDECPN	0.112*	0.0154	7.250
EDU	0.109*	0.0128	8.560
EMPLOY	0.156*	0.0361	4.310
AGE	–0.143*	0.0061	–23.460
GENDER	0.051*	0.0115	4.410
DISAB_SUP	–0.308*	0.0371	–8.310
REMOTE	0.019	0.0172	1.110
Constant	2.151*	0.0965	22.310
F-statistics		1,411.770*	
R^2	0.717		
Number of observations		6,137	

Mediation equation: dependent variable—ICT_USE			
Variable	*Coefficient*	*SE*	t-*statistics*
AT_COM_USE	0.231*	0.008	28.280
INCDECPN	0.089	0.057	1.550
EDU	0.062*	0.010	6.090
EMPLOY	0.211*	0.008	26.520
AGE	0.248*	0.024	10.450
GENDER	–0.112*	0.004	–31.260
Constant	0.024*	0.008	3.150
F-statistics	581.250*		
R^2	0.460		
Number of observations		6,137	

Effects			
Effect	*Estimate*	*95% CI*	
CDE	0.898*	0.835	0.962
NDE	0.157*	0.130	0.184
NIE	0.368*	0.341	0.396
MTE	0.525*	0.492	0.557

* denotes statistically significant at 1%.
CDE, controlled direct effect; CI, confidence interval; MTE, marginal total effect; NDE, natural direct effect; NIE, natural indirect effect; SE, standard error.

mediation effect represents 70.1% of the total effect, while direct effect accounts 29.9% of the total effect. In other words, more than two-third of the effect of assistive technology on QoL is mediated through ICT.

The Stata outputs from the two regression models [Eq. (2) and (3)] using the parametric mediation effect model (-*medeff*-) along with summary estimates of different effects are reported in Table 3. The results of both outcome and mediation equation are quite similar to the corresponding estimates represented in Table 2. The mediating effect of the treatment variable (i.e., *AT_COM_USE*) on the outcome variable (*QoL*) that mediates through *ICT_USE* is 0.305,

TABLE 3. CAUSAL MEDIATION ANALYSIS USING PARAMETRIC MEDIATION EFFECT MODELS (-*MEDEFF*-)

Output equation: dependent variable—QoL			
Variable	*Coefficient*	*SE*	t-*statistics*
AT_COM_USE	0.198*	0.014	14.530
ICT_USE	1.309*	0.020	65.190
WHODISC	–0.043	0.090	–0.470
INCDECPN	0.150*	0.016	9.310
EDU	0.147*	0.013	11.130
EMPLOY	0.190*	0.038	5.040
AGE	–0.100*	0.006	–16.500
GENDER	0.054*	0.012	4.560
DISAB_SUP	–0.377*	0.039	–9.770
REMOTE	0.025	0.018	1.400
Constant	1.732*	0.099	17.500
F-statistics		1,373.230*	
R^2	0.692		
Number of observations		6,137	

Mediation equation: dependent variable—ICT_USE			
Variable	*Coefficient*	*SE*	t-*statistics*
AT_COM_USE	0.234*	0.008	28.240
INCDECPN	0.057*	0.010	5.500
EDU	0.208*	0.008	25.830
EMPLOY	0.288*	0.024	12.040
AGE_REC	–0.123*	0.004	–34.520
GENDER	0.027*	0.008	3.420
Constant	0.300*	0.025	12.080
F-statistics	813.250*		
R^2	0.443		
Number of observations		6,137	

Effects			
Effect	*Mean*	*95% CI*	
ACME	0.305*	0.284	0.329
DE	0.198*	0.170	0.224
TE	0.504*	0.472	0.535
% of TE mediated	0.608*	0.572	0.648

* denotes statistically significant at 1%.
ACME, average causal mediation effect; DE, direct effect; TE, total effect.

while the direct effect of *AT_COM_USE* on *QoL* is 0.198. These figures imply that 60.8% of the total effect of assistive on QoL is mediated through ICT.

Sensitivity and robustness checks of causal mediation analysis. The results of sensitivity analyses for the estimations conducted in the preceding section are recorded in Supplementary Table S2. To do this, the Stata command (-*medsens*-) is used, which automatically detects which type of sensitivity analysis needs to be conducted.[36] The value of ρ [correlation between the error terms of Eq. (1) and Eq. (2)] where the average causal mediation effect (ACME) is zero along with the sensitivity to both types of R^2 expressions are presented in the table. Here, the rule of thumb is that the larger the value of ρ, the greater will be the chance of having strong confounding between the mediator and the outcome. This, in turn, indicates that there could be a serious violation of

TABLE 4. CAUSAL MEDIATION ANALYSIS USING G-COMPUTATION PROCEDURE (-*GFORMULA*-) (ABRIDGED OUTPUT)

Effect	*G computation estimate*	*Bootstrap SE*	*z-statistics*	p	*Normal based (95% CI)*	
TCE	0.204*	0.015	13.350	0.000	0.174	0.234
NDE	0.055*	0.014	3.920	0.000	0.027	0.082
NIE	0.150*	0.015	10.270	0.000	0.121	0.178

* denotes statistically significant at 1%.
TCE, total controlled effect.

the sequential ignorability assumption.[36] However, the results suggest that the point estimate of the ACME equals to zero when ρ is below 0.514. Alternatively, for the point estimate of the ACME to be zero, the correlation between u_y and u_m must be $\sim$0.264. This indicates a moderate degree of robustness.[37]

To check the robustness of the results of causal mediation analysis reported in main results section, the abridged output of the causal mediation using G-computation formula is recorded in Table 4. The results conclude that *AT_COM_USE* has a causal effect on *QoL*, which is basically mediated through *ICT_USE*. The use of assistive technology for communication purpose improves the QoL by 0.204 U (95% confidence interval [CI] [0.174–0.234]). A majority of this development (73.2%) is mediated through ICT usage. This indicates use of ICT-enabled assistive technology will augment the QoL among people with communication disabilities by 0.150 U (on a 5-point scale) on average (95% CI [0.121–0.178]). This, in turn, indicates that the remaining 26.8% of the total effect of *AT_COM_USE* (0.055 U) on *QoL* is direct (95% CI [0.027–0.082]).

Moderation effect

The results from basic moderating effect estimation are populated in Table 5. The results suggest that the impact of ICT-enabled assistive technology (*ICT_AT_USE*) on QoL is contingent upon the degree of communication impairment (*LVLCOMMR*) of the respondents as the coefficient of *ICT_AT_USE* is statistically significant. In particular, while for disabled persons with mild communication impairment, a one standard deviation increase in *ICT_AT_USE* enhances the outcome (i.e., QoL) by 0.380 standard deviations, for those with severe or profound communication impairment, the resultant change is negligible (0.002 standard deviations) (Supplementary Tables S3 and S4). In turn, the results reported in Table 5 indicate that the impact of the interaction between ICT-enabled assistive technology use and level of communication impairment (*ICT_AT_USE*×*LVLCOMMR*) on QoL among people with communication disabilities is negative. This suggests that those with severe communication impairments lack effective assistive technologies to assist them in using ICTs for communication purposes.

TABLE 5. MODERATING EFFECT OF DEGREE OF COMMUNICATION IMPAIRMENT ON THE RELATIONSHIP BETWEEN INFORMATION AND COMMUNICATION TECHNOLOGY-ENABLED AT AND QUALITY OF LIFE

Variable	*Coefficient*	*SE*	t-*statistics*
AT_COM_USE	0.891*	0.043	20.870
ICT_USE	1.434*	0.046	31.100
WHODISC	–0.250*	0.077	–3.260
INCDECPN	0.061*	0.014	4.460
EDU	0.054*	0.011	4.710
EMPLOY	0.118*	0.032	3.690
AGE	–0.196*	0.006	–35.120
GENDER	0.056*	0.010	5.510
DISAB_SUP	–0.142*	0.033	–4.250
REMOTE	0.005	0.015	0.340
ICT_AT_USE	0.982*	0.034	28.670
ICT_AT_USE× LVLCOMMR	–0.467*	0.020	–23.650
LVLCOMMR	0.453*	0.049	9.170
Constant	3.176*	0.090	35.300
F-statistics		1,644.950*	
R^2	0.777		
Number of observations		6,137	

* denotes statistically significant at 1%.

Discussion and Conclusion

The major finding of the study indicates that the use of assistive technology for communication purposes among people with communication disabilities has a causal effect on their QoL, most of which is mediated through ICT use. To be specific, the results from the three different causal mediation models indicate that about 61% to 73% of the impact of assistive technology on QoL is indirectly mediated through ICT use, while the direct impact of assistive technology on the QoL accounts 27% to 39%. These results suggest that for people with communication disabilities, the compatibility of assistive technology with suitable ICT devices is one of the major prerequisites in yielding the best possible outcome from the perspective of the QoL-assistive technology nexus. In line with this finding, a number of existing empirical works has emphasized the importance of the integration of ICT and assistive technology for the enhancement of QoL among people with communication disabilities.[19,24,25]

The regression-based causal mediation analysis also indicates that apart from ICT and assistive technology use, several economic and sociodemographic factors significantly predict the QoL among people with communication disabilities. As we would expect, higher personal income, education, and employment status are associated with greater QoL. Furthermore, age is negatively associated with QoL of people with communication disabilities. These findings are consistent with the findings of existing empirical research.[2,4,19]

It is also evident that the degree of communication impairment partially moderates the impact of ICT-enabled assistive technology on QoL among people with communication disabilities. For respondents with mild communication impairment, the impact of ICT-enabled assistive technology on QoL is much higher compared with respondents with severe or profound communication impairment. This indicates a lack of availability and appropriateness of assistive technology for those with the most severe communication impairments. These findings accord with the results reported by a number of prior studies.[12,19]

This study makes a number of novel contributions. First of all, instead of investigating only the direct impact of ICT-based assistive technology on QoL, this study explores the mediating impact of ICT in translating the effect of assistive technology on QoL among people with communication disabilities. In addition, in defining the QoL, unlike previous studies,[3,19,25,29] this study builds on a comprehensive composite QoL index following the WHOQoL disability module, which consisted of indicators from five distinctive domains—physical, psychological, social, environment, and disabilities module. Moreover, by combining perception and condition-based definitions of communication disability, this study checks for potential biases that may arise from incorrect sampling procedure. Last but not the least, the study also explores whether or not the mediating effect of ICT on QoL-assistive technology nexus is heterogeneous with respect to the degree of communication impairment.

The findings of the study have several practical implications. First of all, this study indicates that better integration of assistive technology with ICT will enhance the QoL of people with communication disabilities. This suggests a series of possible actions for the government and other actors in the disability sector. First, better integration of assistive technology with ICT requires that carers and disability service providers need to acquire knowledge and skills on assistive technology and ICT use. Targeted training is the most plausible way of pursuing this goal, and here the government could collaborate with private and other nongovernment agencies to deliver effective ICT-assistive technology training. Second, mainstream ICT devices (e.g., mobile and landline phones, television, and Internet) are often incompatible with available assistive technology. To overcome this hurdle, application of principles of universal design in programs run by the government, business, and nongovernment organizations can maximize the usage and accessibility of such programs. Finally, the finding that those with severe or profound communication impairment fail to reap the benefits of ICT suggests that a broader range of assistive technologies catering to these groups is needed.

A second broad recommendation is that improved accessibility with affordable high-speed broadband Internet can deliver services that people with disabilities need. To promote ICT accessibility for people with disabilities, the National Disability Insurance Agency (NDIA) is working on building its long-term ICT infrastructure.[38] In this regard, initiatives such as providing access to high-speed affordable Internet through the National Broadband Network (NBN) can be handy. Improved ICT accessibility for people with communication disabilities can be also attained by integrating market regulation and antidiscrimination approaches in relevant public procurement procedures and consumer protection laws.

However, this study is not free from limitations, and further work is required to build on our understanding of the connections between ICT, assistive technologies, and QoL of people with communication disabilities. First, we couldn't accommodate support received from NDIS as an explanatory variable in the regression models, since the SDAC survey was conducted in 2015, before the NDIS rollout was completed. Therefore, <1% of respondents reported to have access to NDIS. In addition, the relative standard error of the corresponding variable is >50%, which requires further investigation. To be precise, standard error gives a hint of the likely precision of the sample mean compared to the population mean. The larger the standard error, the smaller will be the accuracy of the results. Further studies investing the impact of support received through NDIS on QoL among people with communication disabilities would be worthwhile.

Second, the conclusions drawn are based solely on Australian data, and it is possible that cross-country differences in institutions, economic circumstances, and culture might limit the generalizability of these findings to other countries. Further work using data from other countries would therefore be valuable, and until such work has been done, the findings of this study should be extended to other countries with caution.

Finally, although the survey data used in this study allow for a rigorous test of the hypotheses presented above, more detailed qualitative analysis would no doubt add a great deal of depth to our understanding of the determinants of and barriers to the usage of ICT-enabled health services among people with communication disabilities. In this regard, in-depth focus group discussions with people with communication disabilities, particularly those residing in rural and remote areas, would provide further details on how precisely utilization is constrained by ICT artifacts (e.g., digital skills, affordability, and accessibility) and individual behavioral aspects (e.g., age, level of education, lack of trust, and time and degree of impairment).

Acknowledgments

The article is a part the PhD study of the first author. The PhD program was funded by the University of Southern Queensland, Australia (USQ International Stipend Research Scholarship & USQ International Fees Research Scholarship).

Author Disclosure Statement

No competing financial interests exist.

Funding Information

No funding was received for this article.

Supplementary Material

Supplementary Data
Supplementary Table S1
Supplementary Table S2
Supplementary Table S3
Supplementary Table S4

References

1. Patty NJS, Koopmanschap M, Holtzer-Goor K. A cost-effectiveness study of ICT training among the visually impaired in the Netherlands. BMC Ophthalmology 2018; 18:1–10.
2. Crisp D, Griffiths K, Mackinnon A, et al. An online intervention for reducing depressive symptoms: secondary benefits for self-esteem, empowerment and quality of life. Psychiatry Research 2014; 216:60–66.
3. Kadijevich DM, Odovic G, Maslikovic D. (2016) Using ICT and quality of life: comparing persons with and without disabilities. In *International Conference on Computers Helping People with Special Needs*. Linz, Austria: Springer, pp. 129–133.
4. Keskinen T, Heimonen T, Turunen M, et al. SymbolChat: a flexible picture-based communication platform for users with intellectual disabilities. Interacting with Computers 2012; 24:374–386.
5. Meshur HFA. Opportunities for disabled people through ICTs: a perspective from Turkey. International Journal on Disability and Human Development 2016; 15:311–320.

6. Umeh K, Mackay M, Mulhearn C. Information and communication technology, well-being, and ethnicity. Cyberpsychology, Behavior, and Social Networking 2016; 19: 165–171.
7. Mcclain-Nhlapo CV, Sivonen LHA, Raja DS, et al. (2018) *Disability inclusion and accountability framework*. Washington, DC: World Bank.
8. Australian Bureau of Statistics. (2017) *Survey of Disability, Ageing and Carers, Australia, 2015*. Canberra, Australia: Australian Bureau of Statistics.
9. Alwell M, Cobb B. A map of the intervention literature in secondary special education transition. Career Development for Exceptional Individuals 2006; 29:3–27.
10. Blain-Moraes S, Chau T. Challenges of developing communicative interaction in individuals with congenital profound intellectual and multiple disabilities. Journal of Intellectual and Developmental Disability 2012; 37:348–359.
11. Lancioni GE, O'Reilly MF, Singh NN, et al. Communication opportunities via special messaging technology for two post-coma persons with multiple disabilities. Research in Developmental Disabilities 2011; 32:1703–1708.
12. Sachdeva N, Tuikka A-M, Kimppa KK, et al. Digital disability divide in information society: a framework based on a structured literature review. Journal of Information, Communication and Ethics in Society 2015; 13:283–298.
13. United Nations. (2006) Convention on the rights of persons with disabilities. In United Nations, ed. New York. https://www.un.org/disabilities/documents/convention/convoptprot-e.pdf (accessed September 25, 2019).
14. Dobransky K, Hargittai E. The disability divide in internet access and use. Information, Communication & Society 2006; 9:313–334.
15. ITU. (2016) Yearbook of Statistics. Telecommunication/ICT Indicators 2006–2015. In Union IT, ed. International Telecommunication Union. https://read.itu-ilibrary.org/science-and-technology/yearbook-of-statistics-telecommunication-ict-indicators-2006-2015_pub/80decce2-en#page1 (accessed August 15, 2019).
16. Papanastasiou G, Drigas A, Skianis C, et al. Patient-centric ICTs based healthcare for students with learning, physical and/or sensory disabilities. Telematics and Informatics 2018; 35:654–664.
17. Samuelsson C, Ekström A. Digital communication support in interaction involving people with dementia. Logopedics Phoniatrics Vocology 2019; 44:41–50.
18. Lancioni GE, Singh NN, O'Reilly MF, et al. Further evaluation of a telephone technology for enabling persons with multiple disabilities and lack of speech to make phone contacts with socially relevant partners. Research in Developmental Disabilities 2013; 34:4178–4183.
19. Mavrou K, Meletiou-Mavrotheris M, Kärki A, et al. Opportunities and challenges related to ICT and ICT-AT use by people with disabilities: an explorative study into factors that impact on the digital divide. Technology and Disability 2017; 29:63–75.
20. Siegel C, Dorner TE. Information technologies for active and assisted living—influences to the quality of life of an ageing society. International Journal of Medical Informatics 2017; 100:32–45.
21. Ashraf MM, Hasan N, Lewis L, et al. A systematic literature review of the application of information communication technology for visually impaired people. International Journal of Disability Management 2017; 11:1–18.
22. Steel EJ, Layton NA. Assistive technology in Australia: integrating theory and evidence into action. Australian Occupational Therapy Journal 2016; 63:381–390.
23. Perelmutter B, McGregor KK, Gordon KR. Assistive technology interventions for adolescents and adults with learning disabilities: an evidence-based systematic review and meta-analysis. Computers and Education 2017; 114:139–163.
24. Agree EM. The potential for technology to enhance independence for those aging with a disability. Disability and Health Journal 2014; 7(1, Supplement):S33–S39.
25. O'Neill SJ, Smyth S, Smeaton A, et al. Assistive technology: understanding the needs and experiences of individuals with autism spectrum disorder and/or intellectual disability in Ireland and the UK. Assistive Technology 2019: 1–9. DOI: 10.1080/10400435.2018.1535526.
26. Hakobyan L, Lumsden J, O'Sullivan D, et al. Mobile assistive technologies for the visually impaired. Survey of Ophthalmology 2013; 28:513–528.
27. WHO. (2011) *World report on disability 2011*. Geneva.
28. Archer N, Keshavjee K, Demers C, et al. Online self-management interventions for chronically ill patients: cognitive impairment and technology issues. International Journal of Medical Informatics 2014; 83:264–272.
29. Rosner Y, Perlman A. The effect of the usage of computer-based assistive devices on the functioning and quality of life of individuals who are blind or have low vision. Journal of Visual Impairment & Blindness 2018; 112:87–99.
30. WHO. (2011) The WHOQOL-DISABILITIES module—manual. https://www.who.int/mental_health/evidence/WHOQOL_DIS_Manual.pdf (accessed September 19, 2019).
31. Raghavendra P, Newman L, Grace E, et al. Enhancing social participation in young people with communication disabilities living in rural Australia: outcomes of a home-based intervention for using social media. Disability & Rehabilitation 2015; 37:1576–1590.
32. Bobak M, Pikhart H, Rose R, et al. Socioeconomic factors, material inequalities, and perceived control in self-rated health: cross-sectional data from seven post-communist countries. Social Science & Medicine 2000; 51:1343–1350.
33. Van de Mortel TF. Faking it: social desirability response bias in self-report research. Australian Journal of Advanced Nursing 2008; 25:40–48.
34. Pradhan RP, Arvin MB, Norman NR, et al. Economic growth and the development of telecommunications infrastructure in the G-20 countries: a panel-VAR approach. Telecommunications Policy 2014; 38:634–649.
35. Hayes AF, Rockwood NJ. Regression-based statistical mediation and moderation analysis in clinical research: observations, recommendations, and implementation. Behaviour Research and Therapy 2017; 98:39–57.
36. Hicks R, Tingley D. Causal mediation analysis. The Stata Journal 2012; 11:605–619.
37. Imai K, Keele L, Tingley D. A general approach to causal mediation analysis. Psychological Methods 2010; 15:309–335.
38. NDIS. (2019) National Disability Insurance Agency: 2015–2019 Corporate Plan. https://www.ndis.gov.au/media/410/download (accessed August 20, 2019).

Address correspondence to:
Mohammad Afshar Ali
School of Commerce
Faculty of Business, Education, Law & Arts
Work station No.: 230.18, T Block
University of Southern Queensland
487-535 West Street
Toowoomba, Qld 4350
Australia

E-mail: mohammadafshar.ali@usq.edu.au

Chapter 4: **Introductory note: Relationship between Chapter 4, and Chapters 2 and 3**

The studies included in Chapter 2 examined the nature and factors underlying the digital divide generally in the context of Australia. These findings of those studies suggested that the pursuit of digital inclusion should take the particular needs of disadvantaged communities including PwD into account.

The findings of the empirical studies of Chapter 3 showed that positive impact of ICT on QoL is dependent upon several factors. To this end, Chapter 4 investigates the prerequisites of ICT-enabled health service usage among PwD. Study 6 has been published in the '*Journal of Biomedical Informatics*'. A portion of findings from Study 7 were presented at the *'Digital Health Summit 2020'* in Brisbane, Australia and it is published in the *'International Journal of Medical Informatics'*.

These papers are edited and formatted following the guidelines prescribed by corresponding journals. Hence, for the remainder of Chapter 4, there are two-page numbers for each page. The first relates to the published journal paper while the second one corresponds to this thesis.

Study 6

Journal of Biomedical Informatics 108 (2020) 103480

Contents lists available at ScienceDirect

Journal of Biomedical Informatics

journal homepage: www.elsevier.com/locate/yjbin

Determinants of ICT usage for healthcare among people with disabilities: The moderating role of technological and behavioural constraints

Mohammad Afshar Ali[a,b,c,*], Khorshed Alam[a,b,*], Brad Taylor[d]

[a] School of Commerce, Faculty of Business, Education, Law & Arts, University of Southern Queensland, Toowoomba, Australia
[b] Centre for Health Research, University of Southern Queensland, Toowoomba, Australia
[c] Department of Economics, Jagannath University, Dhaka, Bangladesh
[d] School of Commerce, Faculty of Business, Education, Law & Arts, University of Southern Queensland, Springfield, Australia

ARTICLE INFO

Keywords:
Digital disability divide
Information and communication technology
Health care
Technological constraints
Behavioural aspects

ABSTRACT

Existing studies have demonstrated that people with disabilities (PwD) face a range of technological and behavioural barriers to successful adoption of information and communication technology (ICT)-enabled health services. However, there has been little examination and no scholarly consensus on the relative impact of each factor. This study investigates the determinants of ICT usage for health care among PwD. Using national-level disability survey data in Australia, several multivariate hierarchical regression models are deployed to predict the relationship between ICT-enabled health service adoption and the explanatory variables. In addition, several measures of the overall goodness-of-fit are estimated for each model. The results indicate that age, gender, income, level of education, language proficiency and geographical remoteness are significant predictors of ICT-enabled health care usage among PwD. It is also found that technological constraints have a stronger moderating effect than behavioural factors. This provides valuable insight for policymakers and private organisations on which approaches and interventions are most likely to narrow the digital disability divide.

1. Introduction

A large volume of published studies have concluded that information and communication technologies (ICTs), particularly Internet access, play a major role in increasing the well-being and capabilities of people with disabilities (PwD) [23,39,44]. Approximately 15% of the world's population suffers from some type of disability, and this figure is projected to increase with the aging population of many societies [28]. In Australia, almost one in five people report some form of disability [1]. ICT assists PwD by enabling the creation of new social relations [12], tapping into resources of health information [15,26,32], empowering PwD with a sense of autonomy [14], improving health outcomes and lowering health care costs [22,34].

Disability also presents a number of barriers to the successful adoption of ICT. Research has shown the digital divide in general to be a complex and multidimensional phenomenon [6], and one key result to emerge is that the divide is particularly wide between people with and without disabilities [7,16,17,33,39]. For example, 84.6% of the Australian population are Internet users [20]compared to only 64.3% of Australian PwD [1]. This has been termed as the 'digital disability divide' in several recent studies [16,33]. Empirical work has looked at the factors which have shaped this divide [15,16,17,31,33], but few studies have focused specifically on the determinants of ICT-enabled health service adoption among PwD. For example, studies have examined current practices and future strategies in accessing and using ICT-based health information services, such as telehealth and mobile health care adoption [9,19,25].

Existing studies have revealed several specific economic and technological constraints which impede the capacity of PwD to make use of technology in their everyday lives. Numerous studies have found that the monetary costs of purchasing equipment and subscribing to broadband services present major affordability barriers for PwD [15,23,26,39]. Lack of access, skill and knowledge limitations, and poor service quality have been reported as the most prominent barriers to ICT usage among PwD [8,15,16,38]. Several studies have also identified the incompatibility of electronic devices with assistive technologies as another key barrier [23,27]. In addition to these technological constraints, several behavioural or attitudinal constraints impeding ICT usage among PwD have emerged from research. For example, existing studies have found that lack of interest, resistive attitude, privacy concerns and low motivation are key reasons for the non-usage and non-access of ICT among PwD [10,36,37]. Other behavioural factors

* Corresponding authors.
E-mail addresses: MohammadAfshar.Ali@usq.edu.au (M.A. Ali), Khorshed.Alam@usq.edu.au (K. Alam), Brad.Taylor@usq.edu.au (B. Taylor).

https://doi.org/10.1016/j.jbi.2020.103480
Received 23 March 2020; Received in revised form 3 June 2020; Accepted 7 June 2020
Available online 23 June 2020
1532-0464/

Table 1
Variable descriptions and summary statistics.

Variables	Definition	Mean	SD
A. Output variable			
ICT_USE_HEALTH	A dummy variable indicating whether or not the respondent has used at least one type of ICT tools from the following in the last 3 months for health purposes. This includes use of Internet to access health services, disability specific mobile apps and Internet based health services particularly related with disability (1 = has used ICT enabled health services, 0 = otherwise)	0.07	0.25
B. Explanatory variable			
ICT_ACCESS	A dummy variable indicating whether or not the respondent has access at least one type of ICT devices including use of computer, mobile phone, tablets and Internet (1 = has access to ICT devices, 0 = otherwise)	0.49	0.50
C. Control variables			
HEALTH	A categorical variable indicating level of self-assessed health status (1 = poor, 2 = fair, 3 = good, 4 = very good, and 5 = excellent)	2.96	0.70
HEALTH_CARE_USE	A dummy variable indicating whether or not the respondent has received health care assistance from organised services (1 = has received health care assistance, 0 = otherwise)	0.08	0.27
HH_INCOME	A categorical variable indicating the quintile of the respondent's household income (1 = 1st quintile, 2 = 2nd quintile, 3 = 3rd quintile, 4 = 4th quintile, and 5 = 5th quintile)	2.19	0.85
AGE_REC	A categorical variable indicating the age group of the respondent (1 = 0–14 years, 2 = 15–29 years, 3 = 30–44 years, 4 = 45–59 years, 5 = above 60 years)	4.44	1.07
GENDER_REC	A dummy variable indicating the gender of the respondent (1 = male , 0 = female)	0.41	0.49
EDU_REC	A categorical variable indicating the respondent's highest level of educational attainment (1 = year 12 or below, 2 = certificate III or IV, 3 = advanced diploma, 4 = Bachelor, 5 = postgraduate)	1.41	0.93
EMPLOY_STATUS_REC	A dummy variable indicating the labour force status of the respondent (1 = employed , 0 = otherwise)	0.14	0.35
MARRITAL_STATUS	A dummy variable indicating whether or not the respondent is married or not (1 = married, 0 = otherwise).	0.32	0.47
COB_ENG	A dummy variable indicating whether or not a respondent originated from Australia or any other English speaking country (1 = yes, 0 = no)	0.84	0.37
DISBSTAT_REC	A categorical variable indicating the respondent's level of disability (1 = no limitation, 2 = mild, 3 = moderate, 4 = severe, 5 = profound)	3.69	1.50
REMOTENESS_REC	A dummy variable indicating whether or not a respondent person lives in a remote area (1 = resident of a remote area, 0 = major or inner regional city)	0.14	0.34
DISAB_SUP	A dummy variable indicating whether or not the respondent received disability support payment from the government (1 = yes, 0 = no)	0.07	0.26
D. Moderator variables			
TECH_CONST	Aspects of Information Technology (IT) or Electronic Technology (ET) (viz. no access, lack of digital skill, lack of affordability, poor service quality or lack of Assistive Technology (AT)) which can potentially impede Internet use, and thereby moderate the impact of ICT access on ICT use for health purposes (1 = a respondent reported not being able to use the Internet due to above mentioned IET aspects, 0 = otherwise)	0.07	0.25
BEHAV_CHARAC	Behavioural aspects or characteristics of PwD (viz. lack of trust, lack of time, needs support or lack of interest) which can potentially impede Internet use, and thereby moderate the impact of ICT access on ICT use for health purposes (1 = a respondent reported not being able to use the Internet due to behavioural aspects, 0 = otherwise)	0.16	0.37
Number of observations		23,343	

include a lack of support [2,8,10], and time constraints [37,43] as major barriers to technology adoption by PwD. It is evident from existing empirical research that both technological and behavioural factors impede the ICT usage among PwD.

Although the research cited above provides a number of valuable insights, significant gaps in our knowledge remain. Firstly, studies looking at the connection between disability and telehealth have basically reviewed articles related to consumer health informatics for PwD. The major limitation of these studies is that the conclusions drawn are subjective, thus reflecting the authors' judgment. Secondly, although we know that both technological and behavioural factors matter, there has been no systematic examination, and thus no scholarly consensus, on the relative impact of each factor [8,11]. To address these gaps, the current study poses two research questions: (i) What are the factors that explain ICT-enabled health care usage among PwD? (ii) Do technological or behavioural aspects moderate ICT-enabled health care usage most significantly? This article differs from previous studies in two major ways. First, to the best of the authors' knowledge, the current study is the first of its kind to investigate the determinants of ICT-enabled health care usage among PwD using a quantitative framework based on a comprehensive nationwide survey on disability. Second, this study compares the relative strength of the moderating effects of technological and behavioural aspects on ICT-enabled health care usage among PwD. This study provides a more reliable quantitative answer to the question of which factors matter and enables a broader understanding of the relative importance of each. Thus, it provides insight to policymakers and private actors in responding to the digital disability divide.

The paper proceeds in Section 2 by describing the data and methods, and presents and discusses the empirical results in Sections 3 and 4. Section 5 concludes by pointing to policy implications and discussing the limitations of the current study.

2. Materials and methods

2.1. Data source

The current study is based on the Australian Bureau of Statistics (ABS) Microdata – Basic Confidentialised Unit Record Files compiled through the 2015 Survey of Disability, Ageing and Carers (SDAC). The survey methodology is thoroughly explained in ABS [1]. The survey was conducted across all Australian states and territories and in all urban, rural and remote areas. Respondents are older people, carers, and PwD residing in private homes or establishments such as hospitals and aged care facilities. The final combined sample consisted of 75,211 individuals. The analysis presented in this study was based on the data originating from 23,343 individuals who identified themselves as being disabled.

2.2. Variables

Detailed information about people with disabilities, carers and older people along with a breakdown of key demographic variables and ICT-related information is reported in the 2015 SDAC. The current study uses demographic variables, such as age, gender, educational accomplishment, employment status and personal income. ICT-related information used in this study includes access to ICT tools (e.g. computer, mobile phone, tablets and the Internet) and the use of these tools for health care. To capture the financial situation of an individual beyond income and employment status, variables for disability support payments and other benefits received from the government are also included. For some variables, such as household income and remoteness, data are reported at the household level in the SDAC. Information on these household level variables were then matched with the corresponding individual-level information using household and person identifiers. Following the existing literature [10,36,37], the current study presumes that technological constraints are present if an individual reports any of the following impediments to using Information Technology (IT) or Electronic Technology (ET) – (i) no access to ICT devices, (ii) lack of digital skill, (iii) lack of affordability, (iv) experienced poor quality of service, or (v) lack of Assistive Technology (AT). Guided by previous empirical studies [2,8,10], this study defines a PwD as impeded by behavioural aspects if that person reports being unable to use the internet due to any of the following: (i) lack of trust, (ii) lack of time, (iii) needs support, or (iv) lack of interest. Although other behavioural aspects could no doubt impede ICT usage, we use these characteristics based on definitions used in previous studies and the availability of data in the SDAC.

Table 1 provides the definitions of the variables included in the models along with their means and standard deviations. The classification of the variables also reflects the model specifications, as outlined in Section 2.3.1. The variables listed in Panel A are the outcome variables, those in Panel B are the explanatory variables and those in Panel C and D list control and moderating variables, respectively.

2.3. Model specification and estimation method

2.3.1. Model specification

The multivariate hierarchical regression model is deployed to predict the relationship between the dependent variable and the explanatory variables. This type of modelling is used to show whether the variables of interest can explain a statistically significant portion of variance in the dependent variable after accounting for all other variables. This framework builds several regression models by adding variables to a prior model at each step. The moderating effects of technological and behavioural characteristics and the control for confounding effects are performed following the stepwise procedure advocated by Jaccard et al. [21]. A seven-tier multivariate regression is employed as follows through seven steps: (1) Independent dimensions and potential confounders are introduced into the regression model. (2) The first moderator (i.e. technological characteristics) is introduced. (3) The second moderator (i.e. behavioural characteristics) is introduced. (4) Both moderators are included. (5) The interaction term for the first moderator (i.e. the product of ICT access and technological characteristics) is included. (6) The interaction term is introduced for the second moderator (i.e. the product of ICT access and behavioural characteristics). (7) Finally, interaction terms are introduced along with independent, control and moderator variables.

In accordance with the preceding discussion and existing literature, the following estimation equations are hypothesised:

$$ICT\_USE\_HEALTH = \beta_1 + \beta_2 ICT\_ACCESS + \Lambda X_{it} + \varepsilon_{it} \quad (1)$$

$$ICT\_USE\_HEALTH = \beta_1 + \beta_2 ICT\_ACCESS + \beta_3 IT\_ET\_ARTEFACTS + \Lambda X_{it} + \varepsilon_{it} \quad (2)$$

$$ICT\_USE\_HEALTH = \beta_1 + \beta_2 ICT\_ACCESS + \beta_4 BEHAV\_CHARAC + \Lambda X_{it} + \varepsilon_{it} \quad (3)$$

$$ICT\_USE\_HEALTH = \beta_1 + \beta_2 ICT\_ACCESS + \beta_3 IT\_ET\_ARTEFACTS + \beta_4 BEHAV\_CHARAC + \Lambda X_{it} + \varepsilon_{it} \quad (4)$$

$$ICT\_USE\_HEALTH = \beta_1 + \beta_2 ICT\_ACCESS + IT\_ET\_ARTEFACTS + \beta_4 BEHAV\_CHARAC + \beta_5 ICT\_ACCESS \times IT\_ET\_ARTEFACTS + \Lambda X_{it} + \varepsilon_{it} \quad (5)$$

$$ICT\_USE\_HEALTH = \beta_1 + \beta_2 ICT\_ACCESS + \beta_3 IT\_ET\_ARTEFACTS + \beta_4 BEHAV\_CHARAC + \beta_5 BEHAV\_CHARAC \times IT\_ET\_ARTEFACT S + \Lambda X_{it} + \varepsilon_{it} \quad (6)$$

$$ICT\_USE\_HEALTH = \beta_1 + \beta_2 ICT\_ACCESS + \beta_3 IT\_ET\_ARTEFACTS + \beta_4 BEHAV\_CHARAC + \beta_5 ICT\_ACCESS \times IT\_ET\_ARTEFACTS + \beta_6 BEHAV\_CHARAC \times IT\_ET\_ARTEFACTS + \Lambda X_{it} + \varepsilon_{it} \quad (7)$$

ε_{it} is the error term. $\beta_1, \beta_2, \beta_3, \beta_4, \beta_5, \beta_6$ and the vector Λ are the parameters to be estimated.

2.3.2. Estimation method

Multivariate logistic regression was conducted using Stata 15 package for the baseline (Model 4) and interaction effect (Model 7) estimations. For the independent variables included in the multivariate logistic regression model coefficients, odds ratios (OR) and 95% confidence intervals (95% CI) were calculated. After adjusting for standardised weights from the 23,343 cases, the multivariate logistic regression models of ICT-enabled health service usage were estimated. In addition, the independent variables (ICT access) were centred to obtain a meaningful result from the interaction effects. The addition of an interaction effect to a model may render the main effect of that model uninteresting [41]. To overcome this limitation, the explanatory variable was centred by subtracting the mean from each case, then computing the interaction term and estimating the model [41]. Robustness checks using multivariate probit estimations for baseline and interaction effect estimations were also conducted.

2.3.3. Diagnostic tests and measures of fit

Multivariate logistic regression modelling was followed by multicollinearity diagnostic analysis with estimations of variance inflation factor (VIF) values for independent variables. In addition, to measure the overall goodness-of-fit, a Homer and Lemeshow test and Chi-square test were conducted for each regression model. Moreover, several scalar measures of fit, including such as Nagelkerke R-squared, Bayesian Information Criterion (BIC) and Bayesian Information Criterion prime (BIC′), were also estimated to make a comparative assessment of the appropriateness of several hypothesised models.

3. Results

3.1. Sample characteristics

Exploratory data analysis offers a broad initial view of the sociodemographic characteristics of the respondents. Thus, summary statistics of the variables used in the study and the characteristics of the study group are presented in Tables A2 and A3, respectively. Across the sample, the proportion of women (58.59%) is generally greater than that of men (41.41%), and approximately 72.00% are aged above 60 years. More than three-quarters (79.00%) has an education level equivalent of year 12 or below. A large majority (85.77%) are either unemployed or not in the labour market. Approximately one-third of the respondents (32.38%) are married. More respondents are from English-speaking origins (including Australia) (89.93%) than non-English-speaking counterparts (16.07%). Almost half of the total respondents (48.86%) have profound impairment. As for the place of residence, a significant proportion (28.00%) live in major or inner regional cities.

Around half of the total respondents (51.00%) have no ICT access, whereas the rest (49.00%) has some level of access. Interestingly, 6.69% of respondents have not been able to use Internet due to technological constraints. Meanwhile, 16.39% of respondents cannot use the Internet due to behavioural constraints or characteristics. These numbers are partly corroborated by the high prevalence of PwD with severe and profound impairment. Altogether, these simple cross-tabulations point to a moderate level of adoption of ICT in general among PwD.

3.2. Baseline estimations

At the succeeding step, multivariate logistic regression models were estimated to predict the usage of ICT-enabled health care depending upon several predictors, including ICT access, two different moderating variables and several other socio-demographic and locational variables as control variables. Seven stepwise models were generated from the baseline model (Model 1) to a comprehensive model with interactions of two sets of moderators (Model 7). Given the limitations of space, only the results for Model 4 and Model 7 are discussed here.

As expected, those who report having ICT access are much more likely (12.64 times; 95% CI: 9.24–17.27, p = 0.000) to use ICT-enabled health care than those who report no ICT access (Table 2). Self-assessed health status is also a strong predictor of ICT-enabled health care usage (Table A2). The odds of ICT-enabled health care usage is slightly less pronounced for PwD with very good (OR: 0.57; 95% CI: 0.44–0.73, p = 0.000) and excellent health status (OR: 0.52; 95% CI: 0.37–0.72, p = 0.000) compared with those with poor health status. The likelihood of using health care from organised care increases the odds of using ICT-enabled health care by 33% (95% CI: 1.10–1.60, p = 0.003). Meanwhile, the probability of the ICT-enabled health care usage of the respondents belonging from the highest quintile household income is 1.30 times (95% CI: 1.01–1.67, p = 0.043) compared to those in the lowest household income quintile. The odds of using ICT-enabled health care decreases as the age cohort increases, especially for people aged 60 and older. For people aged 30–44 years, the chance of using ICT-enabled health care is 2.56 times (95% CI: 1.78–3.69), p = 0.000) higher than people aged under 15. For those aged 45–59 years, this chance is 1.51 times (95% CI: 1.05–2.17, p = 0.027) higher. Interestingly, the odds of using ICT-enabled health care is 18% lower among male respondents than their female counterparts (Table A1). Therefore, the well–documented health care utilisation gap in favour of women [5,40] in this case appears to outweigh the ICT utilisation gap in favour of men [24].

The likelihood of using ICT–enabled health care increases with the level of educational attainment (Table 2). People who have Certificate III or IV are 1.24 times (95% CI: 1.05–1.46, p = 0.009) more likely to use ICT–enabled health care than those who have an education level of year 12 or below. For those who have an advanced diploma, bachelor and postgraduate or higher degree, the odds of using ICT-enabled health care are respectively 1.91 (95% CI: 1.57–2.34, p = 0.000), 2.33 (95% CI: 1.93–2.80, p = 0.000) and 2.76 (95% CI: 2.20–3.45, p = 0.000) times higher than the group with lowest level of education (Table 2). The odds of using ICT-enabled health care is 39% higher (95% CI: 1.20–1.62, p = 0.000) among the employed than the odds of those without jobs or unavailable for work (Table 2). The chance of using ICT-enabled health care is 51% higher (95% CI: 1.17–1.94, p = 0.001) for people who have reported profound impairment than for those without any limitation due to disability. However, no statistically significant differences are found between those who reported having mild impairment and no limitation (OR: 1.07; 95% CI: 0.91–1.25, p = 0.417) and between those PwD who reported having severe impairment and no limitation (OR: 1.12; 95% CI: 0.91–1.38, p = 0.283).

The odds of using ICT-enabled health care are 45% higher (95% CI: 1.20–1.75, p = 0.000) among PwD originating from English-speaking origins than PwD from other countries (Table 2). ICT-enabled health service adoption in remote areas among PwD are 17% less (95% CI 0.70–0.99, p = 0.000) than those living in cities (Table 2). No statistically significant differences between recipients of disability support payment (OR: 1.17; 95% CI 0.97–1.42, p = 0.107) and non-recipients in the usage of ICT-enabled health care.

3.2.1. Moderation effect

From the baseline model with direct effects (Model 4), the odds of using ICT-enabled health care among PwD reduce by 27% (95% CI 0.10–0.76, p = 0.013) when the respondent reports access limitations we have included as technological constraints. Meanwhile, the odds of using ICT-enabled health care among PwD reduces by only 2% (95% CI 0.01–0.04, p = 0.000) when respondents report barriers we have listed under behavioural characteristics (Table 2).

The stepwise estimations with moderated effects (Model 7) demonstrate the impact of this moderation effect on the nexus between ICT-enabled health service usage and ICT access. As shown in Table A3 (Model 7), the responsiveness of ICT access on ICT-enabled health service usage is predicted to fall by 1.08 units in the presence of reported technological constraints. In other words, as shown in Table 3, the effect of ICT access on ICT-enabled health care utilisation falls by 34% when the respondent reports some technological constraint (95% CI 0.03–4.42, p = 0.014). Meanwhile, the responsiveness of ICT access on ICT-enabled health service usage is predicted to fall by 5.02 units in the presence of non-accommodative behavioural characteristics (Table A3), a decrease of 1% (95% CI: 0.00–0.04, p = 0.000) (Table 3). The Wald test indicates that the difference between the interaction effects of two moderators (33%) is statistically significant (Chi-squared = 4.91, p = 0.027). Therefore, it can be concluded that the detrimental impact of technological constraints on ICT-enabled health care usage is much greater than that of behavioural constraints when respondents have access to ICT devices. These kinds of interaction effects do not necessarily reflect large differences in practice. However, these two sets of factors moderate the impact of ICT access on ICT-enabled health care use. As a result, the effect of technological constraints on ICT-enabled health care is amplified.

3.2.2. Diagnostics tests and measures of fit

A multicollinearity diagnostics analysis was followed by multivariate logistic regression modelling with a calculation of VIF values for independent variables across all stepwise regression models. No concerns are raised here, since all mean VIF values for Model 4 and Model 7 are below 4.0 (see Table A4). Model 4 and Model 7 reveal adequate overall goodness-of-fit as indicated by the Homer and Lemeshow Chi-square tests (Model 4: Hosmer and Lemeshow test Chi-squared = 14.28, df = 8, p = 0.107; Model 7: Hosmer and Lemeshow test Chi-squared = 6.29, df = 8, p = 0.391).

Pseudo R-squared value for the regression without moderation effects (Model 4) is 0.267, whereas that for the model with both sets of moderation effects (Model 7) is 0.270 (see Tables A2 and A3). The strength of the interaction effect is 0.03. In other words, both interaction effects account for 3% variation in the likelihood of using ICT-enabled health care. This result supports for Model 7 with interaction effects. In addition, scalar measures of fit, namely, Nagelkerke R-squared, BIC and BIC′, also reveal strong support for Model 7 (moderation effects) over other models, namely, Model 4 (direct effects), Model 5 and Model 6 (see Table A5). In particular, the difference of 21.49 in BIC' between Model 4 and Model 7 provides strong support for the current model (Model 7).

3.3. Robustness checks

Robustness checks using multivariate probit regression corroborate the findings of the baseline estimations (Table A6). ICT-enabled health service adoption among PwD is dependent on self-assessed health status, health care use from organised service, personal income, age category, gender, level of education, marital status, employment status,

Table 2
Multivariate hierarchical logistic regression model examining predictors influencing ICT enabled health service use among PwD (direct effects).

Variable	Step 1				Step 2				Step 3				Step 4			
	OR	p	95% CI		OR	p	95% CI		OR	p	95% CI		OR	p	95% CI	
ICT_ACCESS																
- no/yes	5.73*	0.000	4.31	7.63	7.15*	0.000	5.34	9.58	12.29*	0.000	9.00	16.78	12.64*	0.000	9.24	17.27
HEALTH																
- poor																
- fair	0.88	0.266	0.70	1.10	0.83	0.112	0.66	1.04	0.80***	0.067	0.63	1.02	0.80***	0.064	0.63	1.01
- good	0.69*	0.001	0.56	0.86	0.66*	0.000	0.53	0.82	0.62*	0.000	0.49	0.77	0.62*	0.000	0.49	0.77
- very good	0.67*	0.001	0.52	0.85	0.62*	0.000	0.49	0.79	0.57*	0.000	0.44	0.73	0.57*	0.000	0.44	0.73
- excellent	0.59*	0.002	0.43	0.82	0.55*	0.000	0.40	0.77	0.52*	0.000	0.37	0.72	0.52*	0.000	0.37	0.72
HEALTH_CARE_USE																
no/yes	1.17***	0.080	0.98	1.40	1.22**	0.034	1.02	1.46	1.31*	0.004	1.09	1.58	1.33*	0.003	1.10	1.60
HH_INCOME																
- Quintile 1																
- Quintile 2	1.05	0.612	0.87	1.26	0.99	0.928	0.82	1.19	0.91	0.328	0.75	1.10	0.91	0.310	0.75	1.10
- Quintile 3	1.29**	0.021	1.04	1.61	1.20	0.105	0.96	1.49	1.08	0.490	0.87	1.35	1.08	0.517	0.86	1.35
- Quintile 4	1.21	0.121	0.95	1.53	1.13	0.314	0.89	1.44	1.02	0.869	0.80	1.30	1.02	0.903	0.80	1.29
- Quintile 5	1.54*	0.001	1.20	1.97	1.44*	0.004	1.12	1.85	1.30**	0.042	1.01	1.67	1.30**	0.043	1.01	1.67
AGE_REC																
- 0–14 years																
- 15–29 years	1.67*	0.005	1.16	2.40	1.74*	0.003	1.21	2.49	2.02*	0.000	1.41	2.90	2.02*	0.000	1.41	2.91
- 30–44 years	1.88*	0.001	1.31	2.68	2.05*	0.000	1.43	2.94	2.54*	0.000	1.77	3.65	2.56*	0.000	1.78	3.69
- 45–59 years	1.00	0.997	0.70	1.43	1.14	0.489	0.79	1.63	1.49**	0.031	1.04	2.15	1.51**	0.027	1.05	2.17
- 60 years and above	0.54*	0.000	0.38	0.76	0.66**	0.020	0.47	0.94	1.08	0.688	0.76	1.53	1.09	0.616	0.77	1.56
GENDER_REC																
- female/male	0.80*	0.000	0.71	0.90	0.80*	0.000	0.72	0.90	0.82*	0.001	0.73	0.92	0.82*	0.001	0.73	0.92
EDU_REC																
- year 12 or below																
- certificate III or IV	1.46*	0.000	1.24	1.72	1.41*	0.000	1.20	1.65	1.25*	0.008	1.06	1.47	1.24*	0.009	1.05	1.46
- advance diploma	2.53*	0.000	2.07	3.08	2.35*	0.000	1.93	2.87	1.93*	0.000	1.58	2.36	1.91*	0.000	1.57	2.34
- bachelor	3.06*	0.000	2.54	3.68	2.83*	0.000	2.35	3.40	2.35*	0.000	1.95	2.83	2.33*	0.000	1.93	2.80
- postgrad or higher	3.96*	0.000	3.16	4.96	3.55*	0.000	2.84	4.45	2.79*	0.000	2.22	3.49	2.76*	0.000	2.20	3.45
EMPLOY_STATUS_REC																
- otherwise/employed	1.55*	0.000	1.33	1.80	1.51*	0.000	1.29	1.75	1.39*	0.000	1.20	1.61	1.39*	0.000	1.20	1.62
MARRITAL_STATUS																
- otherwise/married	1.25*	0.001	1.09	1.42	1.21*	0.005	1.06	1.38	1.18**	0.016	1.03	1.35	1.18*	0.016	1.03	1.35
COB_ENG																
- no/yes	1.67*	0.000	1.39	2.01	1.60*	0.000	1.33	1.93	1.46*	0.000	1.21	1.76	1.45*	0.000	1.20	1.75
DISBSTAT_REC																
- no limitation																
- mild	1.09	0.314	0.93	1.27	1.06*	0.443	0.91	1.25	1.07	0.398	0.91	1.26	1.07	0.417	0.91	1.25
- moderate	1.22**	0.042	1.01	1.49	1.22**	0.050	1.00	1.48	1.18***	0.099	0.97	1.44	1.18	0.104	0.97	1.43
- severe	1.10	0.365	0.90	1.35	1.08	0.466	0.88	1.33	1.12	0.289	0.91	1.38	1.12	0.283	0.91	1.38
- profound	1.21	0.123	0.95	1.53	1.26***	0.059	0.99	1.61	1.49*	0.002	1.16	1.91	1.51*	0.001	1.17	1.94
REMOTENESS_REC																
- city/remote area	0.79*	0.006	0.67	0.94	0.81**	0.013	0.68	0.96	0.83**	0.036	0.70	0.99	0.83**	0.037	0.70	0.99
DISAB_SUP																
- no/yes	1.15	0.131	0.96	1.39	1.23**	0.033	1.02	1.48	1.17	0.104	0.97	1.42	1.17	0.106	0.97	1.42
TECH_CONST																
- no/yes					0.03*	0.000	0.01	0.07					0.27**	0.013	0.10	0.76
BEHAV_CHARAC																
- no/yes									0.01*	0.000	0.01	0.03	0.02*	0.000	0.01	0.04
Constant	0.01*	0.000	0.01	0.02	0.01*	0.000	0.01	0.02	0.01*	0.000	0.00	0.01	0.01*	0.000	0.00	0.01
Pseudo R-squared	0.221				0.239				0.275				0.276			
N	23,343				23,343				23,343				23,343			

Note: *, ** and *** denotes statistically significant at 1%, 5% and 10%, respectively.

degree of disability and place of residence. Similar to the baseline moderation effects regression (Model 7), multivariate probit regression also indicates that the negative impact of a technological characteristics moderator on the usage of ICT-enabled health care is much greater than that of behavioural constraints.

4. Discussion

This study investigates the determinants of the digital disability divide in the utilisation of health care services. As per the findings of the study, the young, the high-income and the educated are more likely to make use of ICT-enabled health services. This result accords with the findings of previous studies [16,26,35]. However, existing studies have investigated the relationship between the aforementioned

Table 3
Multivariate hierarchical logistic regression model examining predictors influencing ICT enabled health service use among PwD (moderated effects).

Variable	Step 5				Step 6				Step 7			
	OR	p	95% CI		OR	p	95% CI		OR	p	95% CI	
ICT_ACCESS												
- no/yes	7.29*	0.000	5.44	9.78	13.45*	0.000	9.83	18.42	13.86*	0.000	10.12	19.00
HEALTH												
- poor												
- fair	0.83	0.112	0.66	1.04	0.80***	0.068	0.63	1.02	0.80***	0.065	0.63	1.01
- good	0.66*	0.000	0.53	0.82	0.62*	0.000	0.49	0.78	0.62*	0.000	0.49	0.78
- very good	0.62*	0.000	0.49	0.79	0.57*	0.000	0.44	0.73	0.57*	0.000	0.44	0.73
- excellent	0.55*	0.000	0.40	0.77	0.52*	0.000	0.37	0.72	0.52*	0.000	0.37	0.72
HEALTH_CARE_USE												
- no/yes	1.21**	0.037	1.01	1.45	1.30*	0.006	1.08	1.56	1.31*	0.004	1.09	1.58
HH_INCOME												
- Quintile 1												
- Quintile 2	0.99	0.943	0.83	1.20	0.92	0.360	0.76	1.11	0.91	0.339	0.75	1.10
- Quintile 3	1.20	0.104	0.96	1.50	1.08	0.500	0.86	1.35	1.07	0.529	0.86	1.34
- Quintile 4	1.13	0.312	0.89	1.44	1.02	0.864	0.80	1.30	1.02	0.901	0.80	1.29
- Quintile 5	1.44*	0.004	1.12	1.85	1.30**	0.041	1.01	1.67	1.30**	0.043	1.01	1.67
AGE_REC												
- 0–14 years												
- 15–29 years	1.74*	0.003	1.21	2.49	2.03*	0.000	1.41	2.91	2.04*	0.000	1.42	2.92
- 30–44 years	2.05*	0.000	1.43	2.94	2.57*	0.000	1.79	3.70	2.60*	0.000	1.81	3.74
- 45–59 years	1.14	0.480	0.79	1.63	1.52**	0.025	1.06	2.19	1.54**	0.021	1.07	2.21
- 60 years and above	0.67**	0.022	0.47	0.94	1.10	0.582	0.78	1.57	1.13	0.511	0.79	1.60
GENDER_REC												
- female/male	0.80*	0.000	0.71	0.90	0.82*	0.001	0.73	0.92	0.81*	0.001	0.72	0.92
EDU_REC												
- year 12 or below												
- certificate III or IV	1.40*	0.000	1.19	1.65	1.24*	0.010	1.05	1.46	1.24*	0.011	1.05	1.46
- advance diploma	2.35*	0.000	1.93	2.86	1.92*	0.000	1.57	2.34	1.90*	0.000	1.55	2.32
- bachelor	2.82*	0.000	2.35	3.40	2.33*	0.000	1.94	2.81	2.31*	0.000	1.92	2.78
- postgrad or higher	3.55*	0.000	2.83	4.44	2.76*	0.000	2.20	3.46	2.73*	0.000	2.18	3.42
EMPLOY_STATUS_REC												
- otherwise/employed	1.51*	0.000	1.29	1.75	1.39*	0.000	1.20	1.61	1.39*	0.000	1.20	1.62
MARRITAL_STATUS												
- otherwise/married	1.21*	0.005	1.06	1.38	1.17**	0.021	1.02	1.34	1.17**	0.021	1.02	1.34
COB_ENG												
- no/yes	1.60*	0.000	1.33	1.93	1.46*	0.000	1.21	1.76	1.45*	0.000	1.20	1.75
DISBSTAT_REC												
- no limitation												
- mild	1.06	0.448	0.91	1.25	1.07	0.416	0.91	1.25	1.07	0.435	0.91	1.25
- moderate	1.22**	0.050	1.00	1.48	1.18***	0.099	0.97	1.44	1.18	0.105	0.97	1.43
- severe	1.08	0.460	0.88	1.33	1.13	0.260	0.92	1.39	1.13	0.253	0.92	1.39
- profound	1.27***	0.054	1.00	1.62	1.52*	0.001	1.18	1.95	1.55*	0.001	1.20	1.99
REMOTENESS_REC												
- city/remote area	0.81**	0.013	0.68	0.96	0.83**	0.034	0.70	0.99	0.83**	0.036	0.70	0.99
DISAB_SUP												
- no/yes	1.22**	0.036	1.01	1.48	1.15	0.149	0.95	1.40	1.15	0.152	0.95	1.40
TECH_CONST												
- no/yes	0.66**	0.048	0.62	0.75					0.70**	0.047	0.67	0.78
BEHAV_CHARAC												
- no/yes					0.16	0.908	0.38	2.96	0.19**	0.050	0.12	0.22
TECH_CONST × ICT_PENETRATION												
- no/yes	0.03*	0.003	0.00	0.32					0.34**	0.014	0.30	0.40
BEHAV_CHARAC × ICT_PENETRATION												
- no/yes					0.01*	0.000	0.00	0.03	0.01*	0.000	0.00	0.04
Constant	0.01*	0.000	0.01	0.02	0.01*	0.000	0.00	0.01	0.01*	0.000	0.00	0.01
Pseudo R-squared	0.240				0.277				0.278			

sociodemographic factors and ICT adoption in general. The current study provides deep insights into the digital disability divide by focusing particularly on ICT adoption for health care purposes. This study also reports that ICT-enabled health care usage is lower among males than females. This result runs counter to previous findings that women are less likely to use the Internet in general [18,26,39]. However, the result is in line with findings that men are less likely to use health care services in general [30]. These outcomes are presumably driven by cultural factors, such as masculinity conventions and stereotypes of self-reliance among men [42]. These findings can also be partly explained by gender-based differences in health care needs [13,24,30]. In the present context, it appears that traditional male reluctance to make use of health care services dominates traditional female reluctance to make use of ICT tools.

The current study also finds that the higher the level of language proficiency, the higher the odds of using ICT-enabled health care. On this basis, proficiency in a particular language eases the access and use of the content as the contents of ICT-enabled health care are developed in the local language. This finding accords with findings of existing literature in the field of digital disability divide [26]. In addition, the findings of the study also indicate that those in remote areas are less likely to use ICT-enabled health care despite presumably having great need for such care. This result is likely driven partly by the lack of ICT infrastructure and skills in remote areas and partly by broad patterns of disadvantage in regional Australia [3,4].

We find, consistent with previous work, that technological and behavioural constraints both impede the use of ICT-enabled health care usage. However, the current study shows that the relative strength of the two moderators is rather different. This is a novel finding not reported in previous work. The findings indicate that the technological constraints reduce ICT-enabled health care use by 25%. This claim is broadly consistent with previous empirical work focusing on such technological constraints [10,36,37]. On the other hand, attitudinal or behavioural constraints are reported to reduce such utilisation by only a much smaller amount (2%). This finding is congruent with that of similar existing literature which showed that attitudinal factors affect the ICT-enabled health care usage [2,8,10]. These findings are cross-validated by the results generated from the set of regressions used to explore the moderating impact of technological and behavioural characteristics. Here we find a similarly large gap (approximately one third versus 1%). On this basis, it appears that technological constraints are much more significant than behavioural ones.

The current study makes a couple of novel contributions. First, instead of investigating the determinants of ICT adoption among PwD [15,17,33], the current study explores the factors that explain the adoption of ICT-enabled health services. Unlike the previous studies [9,18,19,25], the current study uses a comprehensive nationwide survey on disability following a quantitative framework. Second, this study compares the extent of moderating effect of technological and behavioural aspects on ICT-enabled health service usage.

5. Conclusion

This study investigates the factors explaining ICT-enabled health care usage among PwD. The results show that age, gender, income, level of education, language proficiency and remoteness are significant predictors of ICT-enabled health care usage. The major new finding is that technological constraints have a much larger moderating effect than behavioural constraints on the use of ICT-enabled health care.

The findings of the study have several practical implications. Most obviously, it strengthens the case for tackling the digital disability divide by looking at the underlying technological and economic factors which impede ICT utilisation. Although our results confirm that both technological and behavioural constraints matter (and we further suggest that a comprehensive policy approach must consider both), the stronger effect of technological constraints suggests that policy should be directed to addressing these problems first. ICT can be of great benefit to PwD, but technological and economic constraints are a limiting factor in adoption. Improving access, for example, the expansion of high-speed broadband, would help in this regard. To promote ICT accessibility for PwD in particular, the National Disability Insurance Agency in Australia is developing its long-term ICT infrastructure [29]. In addition, by integrating market regulation and anti-discrimination approaches in relevant public procurement procedures and consumer protection laws, affordable high-speed broadband Internet can be delivered to PwD. Nonetheless, to enhance the digital ability among PwD, the government should initiate targeted training through collaboration with private and other non-government agencies. Furthermore, producers should integrate accessibility features in designing digital products and services to handle the lack of AT.

Another broad implication of the findings of the study is that ICT is complementary to traditional forms of health care. Individuals using ICT for health are those who also use other services. Moreover, those most in need as measured by health status and access to disability support pension are the ones most likely to use ICT for health. Furthermore, a gender divide exists in ICT-enabled health care usage. As men are particularly unlikely to use ICT for health, targeted government programs should be initiated to increase adoption among male users. Finally, ICT-enabled health care usage among PwD in remote areas can be promoted by providing targeted training and facilitating improved access to high-speed affordable Internet through the National Broadband Network (NBN). The NBN can provide access to a wide range of services for disabled Australians.

CRediT authorship contribution statement

Mohammad Afshar Ali: Conceptualisation, Methodology, Data analysis, Formal Analysis, and Writing - Original Draft. **Khorshed Alam:** Conceptualisation, Supervision, Writing- Reviewing & Editing. **Brad Taylor:** Conceptualisation, Supervision, Writing - Reviewing & Editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A

See Tables A1–A6.

Table A1
Characteristics of the study group.

Variable	Freq.	%	Variable	Freq.	%
ICT_USE_HEALTH			EMPLOY_STATUS_REC		
- No	21,822	93.48	- otherwise	20,021	85.77
- Yes	1,521	6.52	- employed	3,322	14.23
ICT_ACCESS			MARRITAL_STATUS		
- No	11,903	51.00	- otherwise	15,784	67.62
- Yes	11,440	49.00	- married	7,559	32.38
HEALTH			COB_ENT		
- poor	1,100	4.71	- other	3,752	16.07
- fair	2,360	10.11	- Australia/ English speaking	19,591	83.93
- good	16,928	72.52	DISBSTAT_REC		
- very good	2,346	10.05	- no limitation	2,627	11.25
- excellent	609	2.61	- mild	4,415	18.91
HEALTH_CARE_USE			- moderate	1,951	8.36
- otherwise	21,471	91.98	- severe	2,944	12.61
received service from organisation	1,872	8.02	- profound	11,406	48.86
HH_INCOME			REMOTENESS_REC		
- Quintile 1	2,550	10.92	- major or inner regional city	20,142	86.29
- Quintile 2	16,904	72.42	- remote area	3,201	13.71
- Quintile 3	1,690	7.24	DISAB_SUP		
- Quintile 4	1,227	5.26	- otherwise	21,597	92.52
- Quintile 5	972	4.16	- received	1,746	7.48
AGE_REC			TECH_CONST		
- 0–14 years	970	4.16	- No	21,782	93.31
- 15–29 years	1,051	4.5	- Yes	1,561	6.69
- 30–44 years	1,570	6.73	BEHAV_CHARAC		
- 45–59 years	2,988	12.8	- No	19,518	83.61
- 60 years and above	16,764	71.82	- Yes	3,825	16.39
GENDER_REC					
- Female	13,676	58.59			
- Male	9,667	41.41			
EDU_REC					
- year 12 and below	18,437	78.98			
- certificate III or IV	2,414	10.34			
- advance diploma	905	3.88			
- bachelor	1,032	4.42			
- postgrad or higher	555	2.38			

Table A2
Multivariate hierarchical logistic regression model examining predictors influencing ICT enabled health service use among PwD (direct effects).

Variable	Step 1		Step 2		Step 3		Step 4	
	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE
ICT_ACCESS	1.84*	0.13	2.04*	0.13	2.50*	0.14	2.51*	0.14
HEALTH	−0.17*	0.03	−0.18*	0.03	−0.19*	0.03	−0.19*	0.03
HEALTH_CARE_USE	0.12	0.09	0.17***	0.09	0.25*	0.09	0.26*	0.09
HH_INCOME	0.09*	0.03	0.08*	0.03	0.06**	0.03	0.06**	0.03
AGE_REC	−0.31*	0.03	−0.26*	0.03	−0.15*	0.03	−0.15*	0.03
GENDER_REC	−0.29*	0.06	−0.29*	0.06	−0.26*	0.06	−0.27*	0.06
EDU_REC	0.39*	0.02	0.37*	0.02	0.30*	0.02	0.30*	0.02
EMPLOY_STATUS_REC	0.69*	0.07	0.65*	0.07	0.52*	0.07	0.52*	0.07
MARRITAL_STATUS	0.27*	0.07	0.23*	0.07	0.19*	0.07	0.19*	0.07
COB_ENG	0.51*	0.09	0.46*	0.09	0.36*	0.10	0.35*	0.10
DISBSTAT_REC	0.02	0.03	0.03	0.03	0.05***	0.03	0.05**	0.03
REMOTENESS_REC	−0.24*	0.08	−0.22*	0.08	−0.19**	0.09	−0.19**	0.09
DISAB_SUP	0.38*	0.09	0.43*	0.09	0.38*	0.09	0.38*	0.09
TECH_CONST			−3.59*	0.50			−1.29**	0.52
BEHAV_CHARAC					−4.28*	0.38	−3.95*	0.39
Constant	−3.92*	0.26	−4.03*	0.26	−4.39*	0.27	−4.41*	0.27
LR Chi-squared	2387.44*		2598.55*		3002.69*		3011.27	
Log-likelihood	−4430.36		−4324.80		−4122.73		−4118.44	
Pseudo R-squared	0.212		0.231		0.267		0.267	
N	23,343		23,343		23,343		23,343	

Note: *, ** and *** denotes statistically significant at 1%, 5% and 10%, respectively.

Table A3
Multivariate hierarchical logistic regression model examining predictors influencing ICT enabled health service use among PwD (moderated effects).

Variable	Step 5		Step 6		Step 7	
	Coef.	SE	Coef.	SE	Coef.	SE
ICT_ACCESS	2.05*	0.13	2.57*	0.14	2.59*	0.14
HEALTH	−0.18*	0.03	−0.19*	0.03	−0.19*	0.03
HEALTH_CARE_USE	0.17***	0.09	0.24**	0.09	0.25*	0.09
HH_INCOME	0.08*	0.03	0.06**	0.03	0.06**	0.03
AGE_REC	−0.26*	0.03	−0.15*	0.03	−0.14*	0.03
GENDER_REC	−0.29*	0.06	−0.27*	0.06	−0.27*	0.06
EDU_REC	0.37*	0.02	0.30*	0.02	0.30*	0.02
EMPLOY_STATUS_REC	0.65*	0.07	0.52*	0.07	0.52*	0.07
MARRITAL_STATUS	0.23*	0.07	0.19*	0.07	0.19*	0.07
COB_ENG	0.46*	0.09	0.35*	0.10	0.35*	0.10
DISBSTAT_REC	0.03	0.03	0.06**	0.03	0.06**	0.03
REMOTENESS_REC	−0.22**	0.08	−0.19**	0.09	−0.19**	0.09
DISAB_SUP	0.43*	0.09	0.36*	0.09	0.36*	0.09
IT_ET_ARTEFACTS	−0.26**	1.02			−0.34**	1.16
BEHAV_CHARAC			−0.34***	0.52	−0.44***	0.59
IT_ET_ARTEFACTS × ICT_PENETRATION	−3.61*	1.17			−1.08**	1.31
BEHAV_CHARAC × ICT_PENETRATION			−5.28*	0.78	−5.02*	0.84
Constant	−4.05*	0.26	−4.48*	0.27	−4.49*	0.27
LR Chi-squared	2603.51*		3032.76*		3041.40*	
Log-likelihood	−4322.32		−4107.70		−4103.38	
Pseudo R-squared	0.232		0.270		0.270	
N	23,343		23,343			

Note: *, ** and *** denotes statistically significant at 1%, 5% and 10%, respectively.

Table A4
VIF and goodness-of-fit test.

Test/statistics		M1	M2	M3	M4	M5	M6	M7
VIF	Min	1.02	1.02	1.02	1.02	1.02	1.02	1.02
	Max	2.99	1.61	1.71	3.45	4.60	3.57	6.53
	Mean	1.45	1.23	1.26	1.53	1.68	1.55	2.50
Hosmer-Lemeshow test	Chi-square	8.08	8.24	19.79**	14.28	7.84	12.23	6.29
	df	8	8	8	8	8	8	8
	p-value	0.232	0.221	0.032	0.107	0.250	0.057	0.391

Note: *, ** and *** denotes statistically significant at 1%, 5% and 10%, respectively.

Table A5
Scalar measures of fit.

Scalar measures	M4	M5	M6	M7	M7-M4	M7-M5	M7-M6
McFadden's R-squared	0.27	0.23	0.27	0.27	0.00	0.04	0.00
McFadden's Adj R-squared	0.27	0.23	0.27	0.27	0.00	0.04	0.00
Cox-Snell R-squared	0.12	0.11	0.12	0.12	0.00	0.02	0.00
Nagelkerke R-squared	0.32	0.28	0.32	0.32	0.00	0.04	0.00
Efron's R-squared	0.16	0.14	0.16	0.16	0.00	0.02	0.00
Count R-squared	0.94	0.94	0.94	0.94	0.00	0.00	0.00
Adj Count R-squared	<0.01	<0.01	<0.00	<0.00	<0.00	−0.01	<0.00
AIC	0.35	0.37	0.35	0.35	0.00	−0.02	0.00
AIC*n	8268.88	8676.65	8247.39	8242.75	−26.13	−433.89	−4.64
BIC	−226387.31	−225979.54	−226397.32	−226408.80	−21.49	−429.26	−11.48
BIC'	−2860.40	−2452.64	−2870.42	−2881.89	−21.49	−429.26	−11.48

Table A6
Multivariate probit regression model examining predictors influencing ICT enabled health service use among PwD (direct and moderated effects).

Variable	Step 4		Step 7	
	Coef.	SE	Coef.	SE
ICT_ACCESS	0.70*	0.07	0.76*	0.07
HEALTH	−0.14*	0.01	−0.14*	0.01
HEALTH_CARE_USE	0.14*	0.05	0.13**	0.05
HH_INCOME	0.04*	0.02	0.04*	0.02
AGE_REC	−0.03*	0.00	−0.03*	0.00
GENDER_REC	−0.11*	0.03	−0.11*	0.03
EDU_REC	0.16*	0.01	0.16*	0.01
EMPLOY_STATUS_REC	0.27*	0.04	0.26*	0.04
MARRITAL_STATUS	0.08**	0.04	0.08**	0.04
COB_ENG	0.16*	0.05	0.15*	0.05
DISBSTAT_REC	0.05*	0.01	0.05**	0.01
REMOTENESS_REC	−0.11**	0.05	−0.11**	0.05
DISAB_SUP	0.15*	0.05	0.13*	0.05
IT_ET_ARTEFACTS	−0.40**	0.19	−0.16	0.45
BEHAV_CHARAC	−1.61*	0.13	−0.22	0.24
IT_ET_ARTEFACTS × ICT_PENETRATION			−0.28**	0.50
BEHAV_CHARAC × ICT_PENETRATION			−1.68*	0.30
Constant	−2.09	0.14	−2.16*	0.14
LR Chi-squared	3102.45*		3134.09*	
Log-likelihood	−4072.85		−4057.034	
Pseudo R-squared	0.276		0.279	
N	23,343		23,343	

Note: *, ** and *** denotes statistically significant at 1%, 5% and 10%, respectively.

Appendix B. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jbi.2020.103480.

References

[1] ABS, Survey of disability, ageing and carers, Australia, 2015, Retrieved from: https://www.abs.gov.au/ausstats/abs@.nsf/Latestproducts/4430.0.30.002Main%20Features12015?opendocument&tabname=Summary&prodno=4430.0.30.002&issue=2015&num=&view=, 2017.
[2] K.A. Ågren, A. Kjellberg, H. Hemmingsson, Access to and use of the Internet among adolescents and young adults with intellectual disabilities in everyday settings, J. Intellectual Dev. Disability (2018) 1–10.
[3] M.A. Ali, K. Alam, B. Taylor, Do social exclusion and remoteness explain the digital divide in Australia? Evidence from a panel data estimation approach, Econ. Innovation New Technol. (2019) 1–17.
[4] M.A. Ali, K. Alam, B. Taylor, Measuring the concentration of information and communication technology infrastructure in Australia: Do affordability and remoteness matter? Socio-Econ. Planning Sci. 70 (2020) 100737.
[5] K.D. Bertakis, R. Azari, L.J. Helms, E.J. Callahan, J.A. Robbins, Gender differences in the utilization of health care services, J. Fam. Pract. 49 (2) (2000) 147–152.
[6] J.C. Bertot, The multiple dimensions of the digital divide: more than the technology'haves' and'have nots', Government Information Quarterly 2 (20) (2003) 185–191.
[7] J.L. Brewer, T. Taber-Doughty, S. Kubik, Safety assessment of a home-based telecare system for adults with developmental disabilities in Indiana: a multi-stakeholder perspective, J. Telemedicine Telecare 16 (5) (2010) 265–269.
[8] A.C. Carey, M.G. Friedman, D.N. Bryen, Use of electronic technologies by people with intellectual disabilities, Ment. Retard. 43 (5) (2005) 322–333.
[9] M.S. Cashen, P. Dykes, B. Gerber, eHealth technology and Internet resources: barriers for vulnerable populations, J. Cardiovasc. Nurs. 19 (3) (2004) 209–214.
[10] S. Caton, M. Chapman, The use of social media and people with intellectual disability: A systematic review and thematic analysis, J. Intellectual Dev. Disability 41 (2) (2016) 125–139.
[11] D. Chadwick, C. Wesson, C. Fullwood, Internet access by people with intellectual disabilities: Inequalities and opportunities, Future Internet 5 (3) (2013) 376–397.
[12] P. Conrad, C. Stults, The internet and the experience of illness, Handbook of Medical Sociology 6 (179–91) (2010).
[13] E.M. Crimmins, J.K. Kim, A. Solé-Auró, Gender differences in health: results from SHARE, ELSA and HRS, Eur. J. Pub. Health 1 (2010) 81–91.
[14] J.N. Cummings, L. Sproull, S.B. Kiesler, Beyond hearing: Where the real-world and online support meet, Group Dynamics: Theory, Res. Practice 6 (1) (2002) 78.
[15] K. Dobransky, E. Hargittai, The disability divide in internet access and use, Information, Commun. Soc. 9 (3) (2006) 313–334.
[16] K. Dobransky, E. Hargittai, Unrealized potential: Exploring the digital disability divide, Poetics 58 (2016) 18–28.
[17] M. Duplaga, Digital divide among people with disabilities: Analysis of data from a nationwide study for determinants of Internet use and activities performed online, PLoS ONE 12 (6) (2017) e0179825.
[18] N.M. Gell, D.E. Rosenberg, G. Demiris, A.Z. LaCroix, K.V. Patel, Patterns of technology use among older adults with and without disabilities, The Gerontologist 55 (3) (2013) 412–421.
[19] B. Hemsley, A. Georgiou, R. Carter, S. Hill, I. Higgins, P. van Vliet, S. Balandin, Use of the my health record by people with communication disability in Australia: A review to inform the design and direction of future research, Health Information Management Journal 45 (3) (2016) 107–115.
[20] ITU, Yearbook of Statistics. Telecommunication/ICT Indicators 2006-2015 (Publication no. http://handle.itu.int/11.1002/pub/810592a6-en). from International Telecommunication Union https://read.itu-ilibrary.org/science-and-technology/yearbook-of-statistics-telecommunication-ict-indicators-2007-2016_pub/810592a6-en#page250, 2016.
[21] J. Jaccard, R. Turrisi, C.K. Wan, Interaction Effects in Multiple Regression, Sage, Newbury Park, CA, 1990.
[22] R.J. Jacobs, J.Q. Lou, R.L. Ownby, J. Caballero, A systematic review of eHealth interventions to improve health literacy, Health Inf. J. 22 (2) (2014) 81–98.
[23] K. Jayakar, C. Liu, G. Madden, E.-A. Park, Promoting broadband and ICT access for disabled persons: Comparative analysis of initiatives in Asia-Pacific region, Inf. Soc. 31 (4) (2015) 299–314.
[24] R. Joiner, C. Stewart, C. Beaney, Gender digital divide, in: L.D. Rosen, N.A. Cheever, L.M. Carrier (Eds.), The Wiley Handbook of Psychology, Technology, and Society, Wiley, 2015, pp. 74–88.
[25] M. Jones, J. Morris, F. Deruyter, Mobile healthcare and people with disabilities: Current state and future needs, Int. J. Environ. Res. Public Health 15 (3) (2018).
[26] S. Lissitsa, G. Madar, Do disabilities impede the use of information and communication technologies? Findings of a repeated cross-sectional study - 2003–2015, Israel J. Health Policy Res. 7 (1) (2018).
[27] K. Mavrou, M. Meletiou-Mavrotheris, A. Kärki, M. Sallinen, E.-J. Hoogerwerf, Opportunities and challenges related to ICT and ICT-AT use by people with disabilities: An explorative study into factors that impact on the digital divide, Technol. Disability 29 (1–2) (2017) 63–75.
[28] C.V. Mcclain-Nhlapo, L.H.A. Sivonen, D.S. Raja, S. Palummo, E. Acul, Disability inclusion and accountability framework. Retrieved from Washington, D.C., 2018, http://documents.worldbank.org/curated/en/437451528442789278/pdf/126977-WP-PUBLIC-DisabilityInclusionAccountabilitydigital.pdf.
[29] NDIS, National Disability Insurance Agency : 2015 – 2019 Corporate Plan. Retrieved from , 2019.
[30] A. Oksuzyan, H. Brønnum-Hansen, B. Jeune, Gender gap in health expectancy, Eur. J. Ageing 7 (4) (2010) 213–218.
[31] P. Raghavendra, L. Newman, E. Grace, D. Wood, Enhancing social participation in young people with communication disabilities living in rural Australia: Outcomes of a home-based intervention for using social media, Disabil. Rehabil. 37 (17) (2015) 1576–1590.
[32] H. Ritchie, P. Blanck, The promise of the Internet for disability: A study of on-line

services and web site accessibility at centers for independent living, Behav. Sci. Law 21 (1) (2003) 5–26.
[33] N. Sachdeva, A.-M. Tuikka, K.K. Kimppa, R. Suomi, Digital disability divide in information society: A framework based on a structured literature review, J. Inf., Commun. Ethics Soc. 13 (3/4) (2015) 283–298.
[34] F. Sadoughi, A. Behmanesh, N. Sayfouri, Internet of things in medicine: A systematic mapping study, J. Biomed. Inform. 103 (2020) 103383.
[35] F. Scholz, B. Yalcin, M. Priestley, Internet access for disabled people: Understanding socio-relational factors in Europe, Cyberpsychology: J. Psychosocial Res. Cyberpspace 11 (1) (2017).
[36] K.A. Segrist, Attitudes of older adults toward a computer training program, Educ. Gerontol. 30 (7) (2004) 563–571.
[37] B. Sharpe, B. Hemsley, Improving nurse-patient communication with patients with communication impairments: Hospital nurses' views on the feasibility of using mobile communication technologies, Appl. Nurs. Res. 30 (2016) 228–236.
[38] B. Šumak, M. Špindler, M. Debeljak, M. Heričko, M. Pušnik, An empirical evaluation of a hands-free computer interaction for users with motor disabilities, J. Biomed. Inform. 96 (2019) 103249.
[39] M.R. Vicente, A.J. Lopez, A multidimensional analysis of the disability digital divide: Some evidence for Internet use, Inf. Soc. 26 (1) (2010) 48–64.
[40] A. White, K. Witty, Men's under use of health services–finding alternative approaches, J. Men's Health 6 (2) (2009) 95–97.
[41] R. Williams, Interpreting Interaction Effects; Interaction Effects and Centering. Retrieved from https://www3.nd.edu/~rwilliam/stats2/l53.pdf, 2015.
[42] World Health Organization, The health and well-being of men in the WHO European region: better health through a gender approach, 2018, Retrieved from www.euro.who.int/en/publications/abstracts/the-health-andwell-being-of-men-in-the-who-european-region-betterhealth-through-a-gender-approach-2018.
[43] T.-F. Wu, M.-C. Chen, Y.-M. Yeh, H.-P. Wang, S.C.-H. Chang, Is digital divide an issue for students with learning disabilities? Comput. Hum. Behav. 39 (2014) 112–117.
[44] Y.J. Wu, W.J. Liu, C.H. Yuan, A mobile-based barrier-free service transportation platform for people with disabilities, Comput. Hum. Behav. 105776 (2018).

Study 7

International Journal of Medical Informatics 149 (2021) 104411

Contents lists available at ScienceDirect

International Journal of Medical Informatics

journal homepage: www.elsevier.com/locate/ijmedinf

Examining the determinants of eHealth usage among elderly people with disability: The moderating role of behavioural aspects

Mohammad Afshar Ali [a,b,c,*], Khorshed Alam [a,b], Brad Taylor [d], Mahfuz Ashraf [e,f]

[a] School of Business, Faculty of Business, Education, Law & Arts, University of Southern Queensland, Toowoomba, Australia
[b] Centre for Health Research, University of Southern Queensland, Toowoomba, Australia
[c] Department of Economics, Jagannath University, Dhaka, Bangladesh
[d] School of Business, Faculty of Business, Education, Law & Arts, University of Southern Queensland, Springfield, Australia
[e] WHO Collaborative Centre on eHealth, UNSW, Australia
[f] Crown Institution of Higher Education, North Sydney, NSW, Australia

A R T I C L E I N F O

Keywords:
Digital disability divide
eHealth
Information and communication technology
Elderly people
Health care
Behavioural aspects

A B S T R A C T

Background: Existing studies have demonstrated that behavioural barriers impede eHealth usage among senior citizens. However, thus far, no analysis of how such barriers affect elderly people with disabilities (PwD) has been conducted. Thus, the study investigates the predictors of eHealth usage among elderly PwD.

Methods: Using data from a 2018 nationwide disability survey comprising 14,798 respondents in Australia, multivariate logistic regression models are used to predict the relationship between eHealth usage and the various characteristics of respondents, including access to information and communication technologies (ICTs), socioeconomic status, and level of education.

Results: Although most participants (approximately 88%) have access to ICTs, few (only around 9%) have used eHealth services. The results show a number of factors are associated with an increased likelihood of using eHealth services, including higher educational attainment (odds ratio [OR] = 3.12, 95% confidence interval [CI]: 2.38, 4.24), employment (OR = 1.43, 95% CI: 1.06, 1.94), higher household income (OR = 1.39, 95% CI: 1.00, 1.96), and ICT access (OR = 15.92, 95% CI: 10.51, 27.01). The probability of eHealth use is lower for the oldest-old (OR = 0.35, 95% CI: 0.22, 0.45). In addition, the estimates from interaction effects suggest the effect of ICT penetration on use of eHealth falls by a negligible amount because of resistive attitudinal barriers (OR = 0.01, 95% CI: 0.01, 0.06).

Conclusion: Given the challenges of ageing populations and pandemics, such as COVID-19, eHealth services are a vital part of an effective, inclusive, and robust health care system. This study demonstrates the presence of a significant digital divide among elderly PwD and suggests that public and private efforts should be made to increase the availability of ICT infrastructure. Training could also increase inclusion in this regard.

1. Introduction

The world is rapidly ageing and has been experiencing increasing rates of disability [1,2]. At present, around 15% of the global population around the world suffers from some sort of impairment [2]. In Australia, the figure is almost 20% [3]. A number of studies have shown that information and communication technology (ICT) can be used to mitigate the disadvantages associated with disability [4,5], particularly among elderly persons with disability (PwD) [6–8].

Electronic health (eHealth) is defined as the delivery of any health services or information that involves the use of the Internet or other forms of ICTs [9], including, for example, the digital storage and transmission of health records and medical consultations conducted via videoconference. Although elderly PwD has much to gain from eHealth, mobility issues and greater vulnerability to infectious diseases such as COVID-19 mean they also face particularly high barriers to eHealth usage. The elderly and PwD are less likely to embrace digital technologies in general [8,10], and this aspect of the digital divide extends to eHealth usage. Although 84.6% of the Australian population are Internet users (ITU, 2016), the proportion is significantly lower for PwD (64.3%),

* Corresponding author at: School of Business, Faculty of Business, Education, Law & Arts, University of Southern Queensland, Toowoomba, Australia.
E-mail addresses: MohammadAfshar.Ali@usq.edu.au (M.A. Ali), Khorshed.Alam@usq.edu.au (K. Alam), Brad.Taylor@usq.edu.au (B. Taylor), mahfuz.ashraf@cihe.edu.au (M. Ashraf).

https://doi.org/10.1016/j.ijmedinf.2021.104411
Received 14 September 2020; Received in revised form 28 December 2020; Accepted 3 February 2021
Available online 6 February 2021

especially the elderly PwD (14.2%) [3].

Previous empirical studies have investigated the predictors of the digital disability divide [11–14], and several studies have considered in general terms the challenges and prospects of eHealth adoption [15,16]. However, to the best of the authors' knowledge, no attempt has been made to empirically examine the determinants of eHealth usage among elderly PwD. A number of studies have focused on older adults and investigated the predictors of ICT adoption in general [6,17,18,54] and eHealth usage in particular [6,8,19]. However, while these studies are informative of the challenges faced by the elderly, it cannot be generalized to the experiences of elderly PwD, who are likely to face additional challenges, which leads us to our first research question:

(i) What factors predict eHealth usage among elderly PwD?

Several studies have suggested that various behavioural or attitudinal factors (including lack of interest, resistive attitudes and low motivation) contribute to the lack of ICT usage among PwD [11,17,20–22]. Among older adults, similar factors appear to limit the use of eHealth services, with findings indicating that negative attitudes towards the value of eHealth services, lack of trust and anxiety about making mistakes as significant concerns [6,8,19]. Other studies suggest the lack of support is one of the major impediments to ICT adoption and usage among PwD [23,24,20] and the elderly [18,19]. For PwD, the lack of time available to learn and use digital technologies also appears to be a significant factor ([22]; Wu et al., 2014). These distinct findings concerning the elderly and PwD prompt our second research question on the elderly PwD:

(ii) Do behavioural and attitudinal factors significantly moderate eHealth usage among elderly PwD?

This study contributes to the existing literature by looking specifically at elderly PwD (whereas previous studies have looked at the elderly or PwD in general) and considers the determinants of eHealth usage and the moderating role of behavioural and attitudinal factors. The study uses a systematic quantitative framework using a nationwide representative survey of elderly and disabled Australians to provide insights into the challenges faced by the doubly disadvantaged group of elderly PwD and assists in the framing of policy priorities in response to digital inequality.

2. Materials and methods

2.1. Study settings, population and sampling

The current research is a population-based, cross-sectional study based on the Australian Bureau of Statistics (ABS) Microdata – Basic Confidentialised Unit Record Files compiled through the 2018 Survey of Disability, Ageing and Carers (SDAC). The survey methodology is detailed in ABS [25]. The survey was conducted across all states and territories including urban and rural areas and includes those living in private homes and institutions, such as hospitals, aged-care facilities and retirement villages. The final sample consisted of 65,487 individuals. This study is based on the data from 14,798 individuals who were both elderly (65 years and above) and who reported having some disability.

2.2. Study variables

The 2018 SDAC provides key demographic variables and responses to survey questions about ICT usage. This study uses demographic variables such as age, gender, educational accomplishment, employment status, household income, and ICT-related information, such as access to ICT tools (e.g. computer, mobile phone, tablets and the Internet) and the use of eHealth services. Information on monetary payments received from the government as disability support is also included to capture the financial situation of an individual beyond income and employment status, which are not reliable indicators of socioeconomic status for the elderly.

The outcome variable is eHealth use, a binary variable indicating whether the respondent has used at least one type of ICT tools, including the Internet and disability-specific mobile applications, to access health services in the last three months. This includes seeking information or services relating to aged care and disability support, making appointment with providers as well as accessing services relating to assistance to carers' support. Explanatory variables include several demographic and socioeconomic indicators (i.e. gender, age, geographic remoteness, educational level, language, employment status and household income) and variables directly related to ICT or health (i.e. self-reported health status, self-reported severity of the disability, health care use, and ICT penetration). The moderating variable of behavioural constraints is defined by the presence of any of the following self-reported attitudinal barriers to ICT usage: lack of trust in the Internet, lack of time, lack of support or lack of interest. These factors might impede Internet use and thereby moderate the effect of ICT access on eHealth usage. This variable is coded as 1 where behavioural barriers are reported and 0 if not. A more detailed description of each variable is provided in Appendix Table A1.

2.3. Theoretical background

The current study is theoretically grounded in the concepts of the digital divide and digital exclusion. Although these are multi-faceted phenomena unlikely to be fully explained by any one theory [26], the concepts are deeply tied to broader theories of social exclusion, social capital and cognitive theories [27–,1–29]. Digital exclusion can be studied independently in economic and social terms without taking the cognitive factors into account [30], but this overlooks the crucial element of 'self-efficacy' which can be realized by accumulation of knowledge and skills required to effectively make use of available technologies [31]. Moreover, inequalities in class, gender, race, and education flow through to inequalities in access to communication technologies [32]. These inequalities are in part mediated by social capital, with the disadvantaged having less access to the social and economic support networks which would help them overcome barriers to technology use [33,34]. Greater access to ICT mediated healthcare contributes positively to the social inclusion of individuals of society, but this access is unevenly shared due to various cognitive, economic, social, and demographic factors mentioned above. A clearer and more nuanced understanding of these factors is crucial to any effort to reduce the digital divide.

Existing empirical research has already provided much in this regard. For example, geographical location and language proficiency are significant predictors of digital technology adoption [8,26,35]. Behavioural or attitudinal factors (viz. lack of trust, lack of time, lack of support or lack of interest) have also been shown limit the use of eHealth services among PwD [11,17,20,22]. This study extends this knowledge by looking specifically at the doubly disadvantaged group of elderly PwD. A set of multivariate logistic regression models is deployed to predict the relationship between the dependent variable and the explanatory variables (see Appendix Table A1).

2.4. Estimation strategy

The characteristics of the respondents were tabulated in terms of frequency (N) and percentages (%) with a 95% confidence interval (CI). Pearson's chi-square test (χ^2) was also applied to examine the relationship between eHealth usage and diverse explanatory variables. The variables found to be statistically significant at 5% level in the unadjusted model were included in the baseline adjusted multiple logistic regression model and in the adjusted model with moderation effects. The group with a lower probability of using eHealth services was used as

Table 1
Distribution of respondents' sociodemographic characteristics (N = 15,223).

Characteristics	Observation (N)	Percentage (%)	95% CI	
			Lower limit	Upper limit
Gender				
- Female	9400	52.05	53.33	54.60
- Male	5479	45.40	46.67	47.95
Age group (years)				
- 65–69	1540	21.09	22.43	23.84
- 70–74	1906	21.05	22.34	23.67
- 75–79	1994	18.42	19.63	20.90
- 80–84	2524	14.80	15.87	17.00
−85 and above	6915	18.58	19.73	20.94
Educational level				
- Year 12 and below	13,095	62.34	63.86	65.35
- Certificate III or IV	821	15.86	17.00	18.20
- Advance diploma	348	6.21	6.98	7.83
- Bachelor	414	7.39	8.21	9.11
- Postgraduate or higher	201	3.38	3.96	4.63
Employment status				
- Otherwise	14,506	90.95	91.93	92.81
- Employed	373	7.19	8.07	9.05
Annual household income				
- Quintile 1	1201	21.82	23.15	24.54
- Quintile 2	12,894	58.20	59.88	61.54
- Quintile 3	460	8.80	9.87	11.06
- Quintile 4	206	3.72	4.41	5.21
- Quintile 5	118	2.16	2.69	3.35
Remoteness				
- Major or inner regional city	13,304	88.68	89.72	90.69
- Remote area	1575	9.31	10.28	11.32
Language				
- Other	3069	18.54	19.87	21.27
- English (Native)	11,810	78.73	80.13	81.46
Heath status				
- Poor	277	4.80	5.49	6.26
- Fair	972	18.01	19.22	20.49
- Good	12,348	47.19	48.72	50.25
- Very good	913	17.73	18.99	20.32
- Excellent	369	6.78	7.58	8.46
Health care use				
- No	13,772	76.00	77.37	78.68
- Yes	1107	21.32	22.63	24.00
Disability status				
- No limitation	494	8.58	9.46	10.42
- Mild	2086	38.59	40.13	41.69
- Moderate	811	13.91	15.03	16.23
- Severe	1447	11.39	12.35	13.38
- Profound	10,041	21.86	23.03	24.23
AT use				
- No	1770	27.82	29.22	30.66
- Yes	13,109	69.34	70.78	72.18
Behavioural constraints				
- No	7427	49.92	52.39	49.44
- Yes	7452	50.08	50.56	47.61
ICT penetration				
- No	10,533	11.62	87.70	88.38
- Yes	4346	86.98	12.30	13.02

Table 1 (*continued*)

Characteristics	Observation (N)	Percentage (%)	95% CI	
			Lower limit	Upper limit
eHealth use				
- No	14,358	89.68	90.61	91.47
- Yes	521	8.53	9.39	10.32

a reference in computing the odds ratios (OR) to independently determine the effects of the different levels of categorical variables. The results of the logistic regression analysis are reported as unadjusted and adjusted OR with a 95% confidence interval. For the baseline model and extended model with moderation effect, the multivariate logistic regression estimates are enumerated after adjusting for standardised weights from the 14,798 cases. Because the introduction of interaction effects causes the results for other variables to be more difficult to interpret, the main independent variable of interest (ICT penetration) was centred to obtain a meaningful result [36].

The goodness-of-fit of the models were estimated using the Hosmer-Lemeshow statistic [37]. In addition, to detect the presence of a multicollinearity problem, the variance inflation factor (VIF) test statistics were reported. The receiver operating characteristic (ROC) curve was deployed to estimate the predictive power of the fitted models and confirm the predictive power of the fitted models (both baseline and extended) [38]. Stata 15 was used for data cleaning, validation and statistical computations.

3. Results

3.1. Background information of respondents

The sociodemographic characteristics of the respondents are presented in Table 1. The study has a total of 14,798 respondents, of which approximately 54% were female. Around 23% were between the ages of 65 and 69 years, while 20% were 85 years or older. Almost half of the respondents stated that their disability posed mild or no limitations, while around 22% reported a profound disability. Around 50% respondents reported attitudinal factors (lack of trust, time, support or interest) potentially impeding eHealth use. Almost 88% have access to ICT services. Alarmingly, only a small portion of respondents (9%) have used eHealth services.

3.2. Relationship between eHealth and participant characteristics

Table 2 presents the relationship between eHealth usage and independent predictors. Factors including respondents' age ($p < 0.001$), level of education ($p < 0.001$), employment status ($p < 0.001$), annual household income ($p < 0.001$), language proficiency ($p < 0.001$), remoteness ($p = 0.03$) disability status ($p < 0.001$), behavioural constraints ($p < 0.001$) and ICT access ($p < 0.001$) were significantly associated with eHealth usage.

3.3. Factors influencing eHealth usage

The results of unadjusted and adjusted OR for regression estimates of eHealth usage with a 95% CI are presented in columns (1) and (2) of Table 3, respectively. The factors found to have a statistically significant effect in the unadjusted model were included in the adjusted model. The odds of eHealth usage decreases with age. Compared to the baseline group of 65–69 year olds, those 80–84 (OR = 0.45, 0.95% CI: 0.29, 0.56; $p < 0.01$) and 85+ (OR = 0.35, 95% CI: 0.22, 0.45; $p < 0.01$) were significantly less likely to use eHealth services. Educational attainment has a positive effect. Respondents with an advanced diploma are 1.75 times (95% CI: 1.40, 2.71; $p < 0.05$) more likely to use eHealth than those in the baseline group of Year 12 or below. Having a bachelor and postgraduate degree increased the odds of using eHealth respectively by 3.12 (95% CI: 2.38, 4.24; $p < 0.01$) and 3.66 (95% CI: 2.47, 5.01; $p < 0.01$) times relative to the baseline group. Respondents who are employed are 43% more inclined to use ICT for health care (95% CI: 1.06, 1.94, $p < 0.01$) compared to those not working. Geographical location is also a strong predictor eHealth usage. The odds of eHealth use is lower among those who live in remote areas (OR: 0.89; 95% CI: 0.62, 1.27; $p < 0.05$) compared with those residing in major or inner regional cities. The severity of disability appears to have no significant effect on the probability of using eHealth services. Finally, as expected, those who reported having ICT access are much more likely (OR = 15.92, 95% CI: 10.51, 27.01; $p < 0.01$) to use eHealth than those reporting no access. The probability of eHealth use of the respondents in the third household income quintile is 1.39 times (95% CI: 1.00, 1.96; $p < 0.01$) compared to those in the lowest household income quintile.

Results of the adjusted model with moderation effects are shown in column (3) of Table 3. The findings are similar to those of the baseline estimation reported in column (2). In addition, the estimates from interaction effect (Behavioural constraints*ICT access) suggest that the effect of ICT access on use of ICT for health care falls marginally by 1% (95% CI: <0.01–0.06; $p < 0.01$) because of the presence of non-accommodative behavioural characteristics. Therefore, it can be concluded that behavioural constraints, at least as measured by the self-reported questions in this survey, have a minimal impact on eHealth usage among elderly PwD at the aggregate level.

A series of diagnostic checks were also conducted to check the validity of the estimations (Table 3). For the baseline model, the VIF statistics scored a mean (max) value of 1.58 (4.68), which indicates that multicollinearity is not a problem in the baseline model. The extended model with moderation effect also appears to be free from significant multicollinearity, with a mean (max) value of 2.23 (4.81). The Hosmer-Lemeshow statistic demonstrates that for the baseline ($p = 0.6110$) and the extended ($p = 0.7091$) models, the difference between the observed data and the full model is statistically insignificant, thereby indicating a good fit between the two [37]. The ROC curve areas for the two models are 0.8839 and 0.8841, respectively (Figs. 1 and 2), thereby confirming the explanatory power of the fitted models [38].

4. Discussion

Although most elderly PwD in the study have access to ICT (87%), only a small proportion (around 9%) had used eHealth services in the previous three months. A significant digital divide that extends to ICT usage for health care purposes exists, and the present study sheds light on the nature of this divide. Older respondents (those aged 80 and above) were less likely than younger elderly PwD to use eHealth services. This finding is in line with prior research showing that the oldest-old are especially digitally disadvantaged [39]. However, it is unclear at this stage whether this finding is driven primarily by life-stage or by cohort effects. On the life stage side, the oldest-old may face greater challenges in adopting new technologies because of disability or age-related personality changes. Cohort effects may result from the fact that many ICT tools were introduced in workplaces after the retirement of the oldest-old [39]. Our finding shows that employment status is strongly related to eHealth usage points towards the workplace cohort effect, although more research is needed to support this view. Our findings regarding age are in line with previous results on the determinants of eHealth usage [11,19,40,41].

Elderly PwD with more education and higher socioeconomic status are more likely to use to eHealth services. This finding is consistent with previous work on how ICT usage is affected by education [11,17,42,43] and socioeconomic status [8,11,42,44]. Past educational attainment may have given elderly PwD general purpose skills or specific ICT knowledge that facilitate eHealth utilization [43], and/or those with lower levels of education may lack knowledge of the value of eHealth tools and thus, are unmotivated to adopt such technologies [42,45].

Table 2
Relationship between eHealth use and participant characteristics (N = 15,223).

Characteristics	eHealth use: No N	No %	Yes N	Yes %	Total N	Total %	p-value[1]
Gender							
- Female	9127	48.56	273	4.77	9400	53.33	0.29
- Male	5231	42.05	248	4.62	5479	46.67	
Age group (years)							
- 65–69	1357	18.74	183	3.70	1540	22.44	<0.001
- 70–74	1771	19.92	135	2.42	1906	22.34	
- 75–79	1897	17.76	97	1.87	1994	19.63	
- 80–84	2470	14.99	54	0.88	2524	15.87	
–85 and above	6863	19.21	52	0.53	6915	19.74	
Educational level							
- Year 12 and below	12,856	60.11	239	3.76	13,095	63.87	<0.001
- Certificate III or IV	748	15.54	73	1.45	821	16.99	
- Advance diploma	290	5.84	58	1.14	348	6.98	
- Bachelor	319	6.33	95	1.89	414	8.22	
- Postgraduate or higher	145	2.80	56	1.16	201	3.96	
Employment status							
- Otherwise	14,062	84.22	444	7.70	14,506	91.92	<0.001
- Employed	296	6.39	77	1.69	373	8.08	
Annual household income							
- Quintile 1	1105	21.24	96	1.92	1201	23.16	<0.001
- Quintile 2	12,587	54.73	307	5.15	12,894	59.88	
- Quintile 3	389	8.57	71	1.30	460	9.87	
- Quintile 4	173	3.73	33	0.67	206	4.40	
- Quintile 5	104	2.34	14	0.35	118	2.69	
Remoteness							
- Major or inner regional city	12,824	80.99	480	8.73	13,304	89.72	0.03
- Remote area	1534	9.62	41	0.66	1575	10.28	
Language							
- Other	3010	18.81	59	1.06	3069	19.87	<0.001
- English (Native)	11,348	71.80	462	8.33	11,810	80.13	
Heath status							
- Poor	244	4.92	33	0.57	277	5.49	0.25
- Fair	844	16.55	128	2.67	972	19.22	
- Good	12,107	44.97	241	3.75	12,348	48.72	
- Very good	821	17.16	92	1.83	913	18.99	
- Excellent	342	7.01	27	0.57	369	7.58	
Health care use							
- No	13,345	69.73	427	7.64	13,772	77.37	0.76
- Yes	1013	20.88	94	1.75	1107	22.63	
Disability status							
- No limitation	422	8.07	72	1.39	494	9.46	<0.001
- Mild	1864	35.68	222	4.45	2086	40.13	
- Moderate	721	13.11	90	1.92	811	15.03	
- Severe	1387	11.30	60	1.06	1447	12.36	
- Profound	9964	22.46	77	0.57	10,041	23.03	
AT use							
- No	1627	26.29	143	2.93	1770	29.22	0.15
- Yes	12,731	64.32	378	6.46	13,109	70.78	

(continued on next page)

Table 2 (*continued*)

Characteristics	eHealth use						p-value[1]
	No		Yes		Total		
	N	%	N	%	N	%	
Behavioural constraints							<0.001
- No	6968	45.65	459	5.26	7427	50.91	
- Yes	7442	49.03	10	0.06	7452	49.09	
ICT penetration							
- No	10,490	12.27	43	0.03	10,533	12.30	<0.001
- Yes	3868	78.34	478	9.36	4346	87.70	

Note: [1]p-values were derived by using chi-square tests.

Such differences in skills and knowledge may also be partly responsible for our finding that those with higher incomes are more likely to use eHealth services. Access to material resources is also likely to play a role [8,46]. Those elderly PwD with high greater income is more able to afford the ICT tools, which make eHealth services more accessible. The importance of education and income reinforces the need to consider the digital disadvantage faced by elderly PwD in an intersectional way. The disadvantages faced by members of this group will be aggravated or mitigated by other dimensions of disadvantage.

Interestingly, self-reported health status is found to have no impact on eHealth use among elderly PwD. Previous studies found that those in good health were less likely to use eHealth services [47–49]. However, this was based on survey data of the general population rather than elderly PwD in particular. We also find that degree of impairment has no significant impact on the use eHealth services. More research in this area is required to look at the specific factors driving this effect.

Table 3
Determinants of eHealth use among aged PwD.

Characteristics	Unadjusted model (1)				Adjusted model (2)				Extended model with moderation effect (3)			
	OR[1]	RSE[2]	95% CI[3]		OR[1]	RSE[2]	95% CI[3]		OR[1]	RSE[2]	95% CI[3]	
			Lower limit	Upper limit			Lower limit	Upper limit			Lower limit	Upper limit
Constant					0.01*	<0.01	<0.01	0.02	0.01*	<0.01		
Gender												
- Female	1.00	–	–	–	1.00	–	–	–	1.00	–	–	–
- Male	0.04*	<0.01	0.04	0.05	0.98	0.10	0.81	1.21	0.97	0.13	0.81	1.30
Age group (years)												
- 65–69	1.00	–	–	–	1.00	–	–	–	1.00	–	–	–
- 70–74	0.07*	0.01	0.06	0.09	0.72**	0.09	0.56	0.94	0.75**	0.11	0.56	0.94
- 75–79	0.05*	0.00	0.04	0.06	0.60*	0.09	0.46	0.81	0.68**	0.12	0.46	0.80
- 80–84	0.02*	0.00	0.02	0.03	0.40*	0.07	0.29	0.57	0.45*	0.09	0.29	0.56
−85 and above	0.01*	0.00	<0.01	0.01	0.31*	0.06	0.22	0.45	0.35*	0.11	0.22	0.45
Educational level												
- Year 12 and below	1.00	–	–	–	1.00	–	–	–	1.00	–	–	–
- Certificate III or IV	0.09*	0.01	0.08	0.12	1.02	0.15	0.76	1.37	1.01	0.15	0.76	1.36
- Advance diploma	0.02*	0.02	0.15	0.27	1.96*	0.33	1.40	2.73	1.75**	0.33	1.40	2.71
- Bachelor	0.29*	0.02	0.24	0.37	3.19*	0.46	2.40	4.24	3.12*	0.46	2.38	4.24
- Postgraduate or higher	0.38*	0.05	0.28	0.53	3.52*	0.64	2.47	5.03	3.66*	0.64	2.47	5.01
Employment status												
- Otherwise	1.00	–	–	–	1.00	–	–	–	1.00	–	–	–
- Employed	0.26	0.03	0.20	0.33	1.43**	0.22	1.06	1.94	1.43*	0.22	1.06	1.94
Annual household income												
- Quintile 1	1.00	–	–	–	1.00	–	–	–	1.00	–	–	–
- Quintile 2	0.02*	<0.01	0.02	0.03	1.20	0.15	0.93	1.54	1.20	0.15	0.93	1.54
- Quintile 3	0.18*	0.01	0.14	0.24	1.38***	0.25	1.00	1.96	1.39***	0.24	1.00	1.96
- Quintile 4	0.19*	0.03	0.13	0.28	1.25	0.30	0.78	1.99	1.25	0.30	0.78	1.99
- Quintile 5	0.13*	0.04	0.08	0.24	0.86	0.29	0.44	1.68	0.87	0.29	0.44	1.68
Remoteness												
- Major or inner regional city	1.00	–	–	–	1.00	–	–	–	1.00	–	–	–
- Remote area	0.02*	<0.01	0.02	0.02	0.60*	0.11	0.43	0.85	0.89*	0.16	0.62	1.27
Language												
- Other	1.00	–	–	–	1.00	–	–	–	1.00	–	–	–
- English (Native)	0.04*	<0.01	0.02	0.03	1.72*	0.26	1.28	2.30	1.73*	0.26	1.28	2.30
Heath status												
- Poor	1.00	–	–	–	1.00	–	–	–	1.00	–	–	–
- Fair	0.15*	0.01	0.13	0.18	1.28	0.23	0.83	1.98	1.28	0.23	0.83	1.98
- Good	0.11*	<0.01	0.10	0.12	1.11	0.21	0.73	1.70	1.11	0.21	0.73	1.70
- Very good	0.07*	0.01	0.09	0.14	1.12	0.15	0.70	1.79	1.12	0.15	0.70	1.79
- Excellent	0.02*	0.02	0.05	0.12	0.87	0.29	0.48	1.58	0.87	0.29	0.48	1.58
Health care use												
- No	1.00	–	–	–	1.00	–	–	–	1.00	–	–	–
- Yes	0.09*	0.01	0.08	0.11	0.93	0.13	0.71	1.21	1.19	0.21	0.85	1.67

(*continued on next page*)

Table 3 (*continued*)

Characteristics	Unadjusted model (1)				Adjusted model (2)				Extended model with moderation effect (3)			
	OR[1]	RSE[2]	95% CI[3]		OR[1]	RSE[2]	95% CI[3]		OR[1]	RSE[2]	95% CI[3]	
			Lower limit	Upper limit			Lower limit	Upper limit			Lower limit	Upper limit
Disability status												
- No limitation	1.00	–	–	–	1.00	–	–	–	1.00	–	–	–
- Mild	0.12*	0.01	0.10	0.16	0.83	0.21	0.59	1.18	0.83	0.21	0.59	1.18
- Moderate	0.11*	0.01	0.10	0.14	0.97	0.26	0.66	1.44	0.97	0.26	0.66	1.44
- Severe	0.04*	0.00	0.03	0.06	0.91	0.33	0.59	1.41	0.90	0.33	0.59	1.41
- Profound	0.01*	0.00	0.01	0.01	0.70	0.37	0.44	1.11	0.69	0.36	0.44	1.10
AT use												
- No	1.00	–	–	–	1.00	–	–	–	1.00	–	–	–
- Yes	0.02*	<0.01	0.02	0.03	1.46*	0.18	1.15	1.87	1.47*	0.18	1.15	1.89
Behavioural constraints												
- No	1.00	–	–	–	1.00	–	–	–	1.00	–	–	–
- Yes	<0.01*	<0.01	<0.01	<0.01	0.01*	0.01	<0.01	0.04	0.05	0.07	0.16	7.72
ICT penetration												
- No	1.00	–	–	–	1.00	–	–	–	1.00	–	–	–
- Yes	0.12*	<0.01	0.11	0.14	13.47*	3.03	8.67	20.92	15.92*	4.06	10.51	27.01
Behavioural constraints*ICT penetration												
- No									1.00	–	–	–
- Yes									0.01*	0.01	0.01	0.06
Observation (N)	14,798				14,798				14,798			
Cox-Snell R-square (%)					27.10%				28.30%			
Likelihood ratio statistic					729.23*				963.71*			
Hosmer-Lemeshow statistic (p-value)					2.69 (0.6110)				2.82 (0.7091)			
Link test (OR for hat of ICT use for health care)					2.73*				2.75*			
Mean VIF[4] (Max)					1.58 (4.68)				2.23 (4.81)			

Note: ***p < 0.10, **p < 0.05, and **p < 0.01. [1]Odds ratio, [2]Robust standard error, [3]Confidence interval, [4]Variance Inflation Factor.

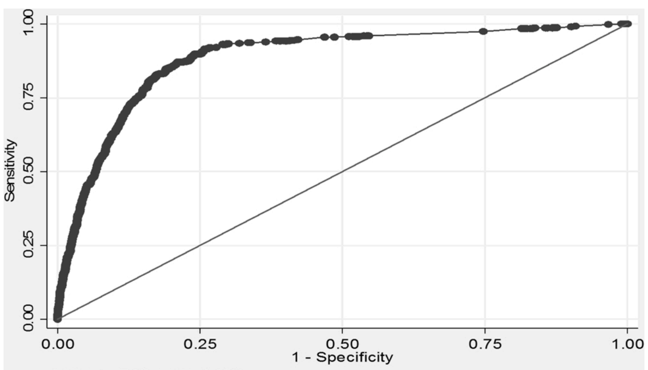

Fig. 1. ROC curve for the baseline model's accuracy text.

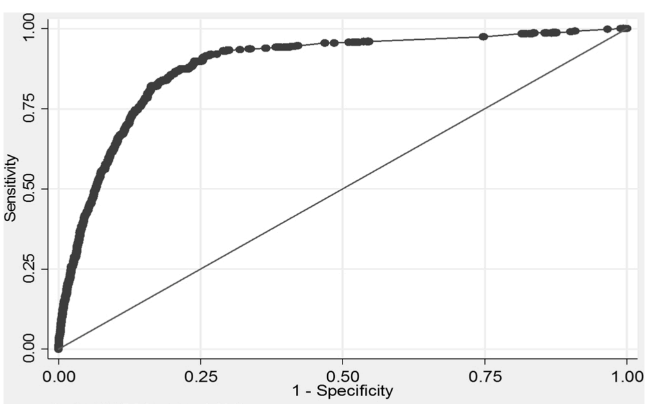

Fig. 2. ROC curve for the extended model's accuracy text.

Study highlights

What was already known on the topic

- Existing empirical works studied the underlying factors that impacts the eHealth adoption among elderly people.
- Prevailing studies have demonstrated that behavioural barriers impede eHealth usage among senior citizens.

What this study added to our knowledge

- A number of studies have focused on older adults and investigated the predictors of ICT adoption in general and eHealth usage in particular. However, while these studies are informative of the challenges faced by the elderly, it cannot be generalized to the experiences of elderly PwD, who are likely to face additional challenges, which leads us to conducting a study with an aim of investigating the determinants of eHealth adoption among elderly PwD.
- Thus far, no analysis of how such barriers affect elderly people with disabilities (PwD) has been conducted. Our model with interaction effects shows that behavioural constraints have a marginal (1%) effect on eHealth use, which suggests that technological and knowledge factors are likely to play a more important role than behavioural or attitudinal issues.

Finally, our model with interaction effects shows that behavioural constraints have a marginal (1%) effect on eHealth use, which suggests that technological and knowledge factors are likely to play a more important role than behavioural or attitudinal issues. Existing work on broader cohorts has found that technological constraints, such as lack of affordability, poor service quality, lack of assistive technology and poor digital literacy impede ICT use [11,50–52]. Although the current study does not include such considerations because of the limitations of data availability, the findings reported above that educational attainment and socioeconomic status are important determinants of eHealth usage suggest that ICT affordability and digital literacy are likely important. Digital literacy is a particularly pressing issue for the elderly, particularly in the oldest-old [51].

5. Conclusion

This study examines the determinants of eHealth use among elderly people with disabilities in Australia. We find that, *inter alia*, age, employment status, income, health status and degree of impairment affect the likelihood that an elderly PwD will use ICT tools for healthcare purposes. This is an important issue because the elderly PwD has the most to gain from eHealth services (given their limited mobility and infection risks associated with in-person medical care during the COVID-19 pandemic) but also face the most serious barriers to eHealth adoption (including digital literacy and need for assistive technologies). The importance of eHealth will increase as populations continue to age and technologies continue to mature.

The current study makes two key contributions to the literature. First, it focuses specifically on elderly PwD rather than on broader age groups [6,12,13,19] or the elderly in general rather than those with disabilities (e.g [6,7,19].). We know that disability and age are important facts and this is the first study to focus on the intersectionally disadvantaged group of elderly PwD in terms of eHealth usage. Second, unlike previous studies [7,8,19], we use nationally representative data and a comprehensive quantitative approach.

In practical terms, the study has implications for ICT and health policy priorities. First, our finding that access to ICT tools is an important prerequisite for eHealth usage suggests that continued programmes aimed at increasing accessibility are important. Of particular importance to Australian PwD are the efforts of the National Disability Insurance Agency in developing its long-term ICT infrastructure [53]. Second, our findings on employment status and education, along with previous findings for different cohorts, suggest that digital literacy is also important. Finally, our finding that the oldest-old (80+) are at a greater disadvantage than younger groups suggests that attention should be given to this group in particular in terms of ensuring ICT access and digital literacy.

This study is not without limitations and represents the first attempt to quantitatively examine the barriers to eHealth usage among elderly PwD rather than the final word. One obvious limitation is the use of cross-sectional data, which makes establishing a causal relationship difficult. Future work based on longitudinal data would be valuable in this respect. Second, due to data limitations, we grouped all elderly PwD into one group rather than disaggregating by specific disability types. Someone with a physical disability faces a very different set of challenges from someone with cognitive impairment, and a more detailed analysis of different subgroups would provide richer insights and more actionable policy advice. Third, we have included in our analysis those who report lacking access to ICT. This is not ideal, since the use of eHealth services is predicated on some sort of ICT access. However, our research design assumes that ICT access is a facilitating factor for eHealth usage and excluding those who report no access would limit generalisability. Moreover, excluding this group would prevent us from running the extended model used to examine the moderating impact of behavioural constraints. A more restricted analysis would be interesting, but is beyond the scope of this paper. Lastly, since it was based on data from 2018, the current research is unable to consider two key developments: support received as part of the NDIS (which was not fully rolled out until 2020), and the effects of the COVID-19 pandemic which has put the elderly and those with co-morbidities at particular risk while forcing the rapid expansion of eHealth services such as telemedicine. Future work is needed to consider the effect of these factors in general and for elderly PwD in particular.

6. Author contribution

1. Conception and design – Mohammad, Khorshed and Mahfuz.
2. Data extraction –Mohammad.
3. Manuscript writing – Mohammad, Khorshed, Brad and Mahfuz.
4. Final approval of manuscript – Mohammad, Khorshed, Brad and Mahfuz.

Author Declaration/Statement

We confirm that the manuscript has been read and approved by all named authors and that there are no other persons who satisfied the criteria for authorship but are not listed. We further confirm that the order of authors listed in the manuscript has been approved by all of us.

Declaration of Competing Interest

We wish to confirm that there are no known conflicts of interest associated with this publication and there has been no significant financial support for this work that could have influenced its outcome.

Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.ijmedinf.2021.104411.

References

[1] H.C. Higgins, J.K. Horton, B.C. Hodgkinson, S.B. Muggleton, Lessons learned: staff perceptions of the Nintendo Wii as a health promotion tool within an aged-care and disability service, Health Promot. J. Aust. 21 (3) (2010) 189–195.
[2] C.V. Mcclain-Nhlapo, L.H.A. Sivonen, D.S. Raja, S. Palummo, E. Acul, Disability Inclusion and Accountability Framework, Retrieved from Washington, D.C., 2018 http://documents.worldbank.org/curated/en/437451528442789278/pdf/126977-WP-PUBLIC-DisabilityInclusionAccountabilitydigital.pdf.
[3] ABS, Survey of Disability, Ageing and Carers, Australia, 2015, Retrieved from Canberra, 2017, https://www.abs.gov.au/ausstats/abs@.nsf/Latestproducts/4430.0.30.002Main%20Features12015?opendocument&tabname=Summary&prodno=4430.0.30.002&issue=2015&num=&view=.
[4] K. Jayakar, C. Liu, G. Madden, E.-A. Park, Promoting broadband and ICT access for disabled persons: comparative analysis of initiatives in Asia-Pacific region, Inf. Soc. 31 (4) (2015) 299–314.
[5] Y.J. Wu, W.J. Liu, C.H. Yuan, A mobile-based barrier-free service transportation platform for people with disabilities, Comput. Human Behav. 105776 (2018).
[6] J.A. Andrews, L.J. Brown, M.S. Hawley, A.J. Astell, Older adults' perspectives on using digital technology to maintain good mental health: interactive group study, J. Med. Internet Res. 21 (2) (2019), e11694.
[7] J. Damant, M. Knapp, S. Watters, P. Freddolino, M. Ellis, D. King, The impact of ICT services on perceptions of the quality of life of older people, J. Assist. Technol. (2013).
[8] A. Poli, S. Kelfve, A. Motel-Klingebiel, A research tool for measuring non-participation of older people in research on digital health, BMC Public Health 19 (1) (2019) 1487.
[9] E.A. Boogerd, T. Arts, L.J. Engelen, T.H. van De Belt, "What is eHealth": time for an update? JMIR Res. Protoc. 4 (1) (2015) e29.
[10] R. König, A. Seifert, M. Doh, Internet use among older Europeans: an analysis based on SHARE data, Univers. Access Inf. Soc. 17 (3) (2018) 621–633.
[11] M.A. Ali, K. Alam, B. Taylor, Determinants of ICT usage for healthcare among people with disabilities: the moderating role of technological and behavioural constraints, J. Biomed. Inform. (2020), 103480. Forthcoming.
[12] K. Dobransky, E. Hargittai, Unrealized potential: exploring the digital disability divide, Poetics 58 (2016) 18–28.
[13] M. Duplaga, Digital divide among people with disabilities: analysis of data from a nationwide study for determinants of Internet use and activities performed online, PLoS One 12 (6) (2017), e0179825.

[14] N. Sachdeva, A.-M. Tuikka, K.K. Kimppa, R. Suomi, Digital disability divide in information society: a framework based on a structured literature review, J. Inf. Commun. Ethics Soc. 13 (3/4) (2015) 283–298.
[15] B. Hemsley, A. Georgiou, R. Carter, S. Hill, I. Higgins, P. van Vliet, S. Balandin, Use of the my health record by people with communication disability in Australia: a review to inform the design and direction of future research, Health Inf. Manag. J. 45 (3) (2016) 107–115.
[16] M. Jones, J. Morris, F. Deruyter, Mobile healthcare and people with disabilities: current state and future needs, Int. J. Environ. Res. Public Health 15 (3) (2018).
[17] S.M. Álvarez-Dardet, B. Lorence Lara, J. Pérez-Padilla, Older adults and ICT adoption: analysis of the use and attitudes toward computers in elderly Spanish people, Comput. Human Behav. 110 (2020), 106377.
[18] M.R. Jokisch, L.I. Schmidt, M. Doh, M. Marquard, H.-W. Wahl, The role of internet self-efficacy, innovativeness and technology avoidance in breadth of internet use: comparing older technology experts and non-experts, Comput. Human Behav. 111 (2020), 106408.
[19] L. Knapova, A. Klocek, S. Elavsky, The role of psychological factors in older adults' readiness to use eHealth technology: cross-sectional questionnaire study, Journal of Medical Internet Reserch 22 (5) (2020), e14670.
[20] S. Caton, M. Chapman, The use of social media and people with intellectual disability: a systematic review and thematic analysis, J. Intellect. Dev. Disabil. 41 (2) (2016) 125–139.
[21] K.A. Segrist, Attitudes of older adults toward a computer training program, Educ. Gerontol. 30 (7) (2004) 563–571.
[22] B. Sharpe, B. Hemsley, Improving nurse-patient communication with patients with communication impairments: hospital nurses' views on the feasibility of using mobile communication technologies, Appl. Nurs. Res. 30 (2016) 228–236.
[23] K.A. Ågren, A. Kjellberg, H. Hemmingsson, Access to and use of the Internet among adolescents and young adults with intellectual disabilities in everyday settings, J. Intellect. Dev. Disabil. (2018) 1–10.
[24] A.C. Carey, M.G. Friedman, D.N. Bryen, Use of electronic technologies by people with intellectual disabilities, Ment. Retard. 43 (5) (2005) 322–333.
[25] ABS, Survey of Disability, Ageing and Carers, Australia, 2018, Retrieved from Canberra, 2019, https://www.abs.gov.au/methodologies/disability-ageing-and-carers-australia-summary-findings/2018.
[26] M.A. Ali, K. Alam, B. Taylor, Do social exclusion and remoteness explain the digital divide in Australia? Evidence from a panel data estimation approach, Econ. Innov. New Technol. (2019) 1–17.
[27] J. Clayton, S.J. Macdonald, The limits of technology: Social class, occupation and digital inclusion in the city of Sunderland, England, Inf. Commun. Soc. 16 (6) (2013) 945–966.
[28] M. Ragnedda, G.W. Muschert, The Digital Divide: the Internet and Social Inequality in International Perspective, Routledge, London, 2013.
[29] J.A.G.M. van Dijk, K. Hacker, The digital divide as a complex and dynamic phenomenon, Inf. Soc. 19 (4) (2003) 315–326.
[30] L. Kvasny, M. Keil, The challenges of redressing the digital divide: a tale of two US cities, Inf. Syst. J. 16 (1) (2006) 23–53.
[31] A. Bandura, Social Foundations of Thought and Action, Vol. 1986, Prentice-Hall, Englewood Cliffs, NJ, 1986.
[32] P. Tsatsou, Digital divides revisited: what is new about divides and their research? Media Cult. Soc. 33 (2) (2011) 317–331.
[33] M. Castells, The Internet Galaxy: Reflections on the Internet, Business, and Society, Oxford University Press, Oxford, 2002.
[34] S. Livingstone, E. Helsper, Gradations in digital inclusion: children, young people and the digital divide, New Media Soc. 9 (4) (2007) 671–696.
[35] M.A. Ali, K. Alam, B. Taylor, Measuring the concentration of information and communication technology infrastructure in Australia: do affordability and remoteness matter? Socioecon. Plann. Sci. 70 (2020), 100737.
[36] R. Williams, Interpreting Interaction Effects; Interaction Effects and Centering, Retrieved from https://www3.nd.edu/~rwilliam/stats2/l53.pdf, 2015.
[37] J.D.W. Hosmer, S. Lemeshow, R.X. Sturdivant, Applied Logistic Regression, Vol. 398, John Wiley & Sons, 2013.
[38] V.E. Seshan, M. Gönen, C.B. Begg, Comparing ROC curves derived from regression models, Stat. Med. 32 (9) (2013) 1483–1493.
[39] M. Zambianchi, M. Rönnlund, M.G. Carelli, Attitudes towards and use of information and communication technologies (ICTs) among older adults in Italy and Sweden: the influence of cultural context, socio-demographic factors, and time perspective, J. Cross. Gerontol. 34 (3) (2019) 291–306.
[40] K. Magsamen-Conrad, S. Upadhyaya, C.Y. Joa, J. Dowd, Bridging the divide: using UTAUT to predict multigenerational tablet adoption practices, Comput. Human Behav. 50 (2015) 186–196.
[41] K.G. Vroman, S. Arthanat, C. Lysack, "Who over 65 is online?" older adults' dispositions toward information communication technology, Comput. Human Behav. 43 (2015) 156–166.
[42] K. Alam, R.A. Mahumud, F. Alam, S.A. Keramat, M.O. Erdiaw-Kwasie, A.R. Sarker, Determinants of access to eHealth services in regional Australia, Int. J. Med. Inform. 131 (2019), 103960.
[43] A.J. Elliot, C.J. Mooney, K.Z. Douthit, M.F. Lynch, Predictors of older adults' technology use and its relationship to depressive symptoms and well-being, J. Gerontol. B Psychol. Sci. Soc. Sci. 69 (5) (2014) 667–677.
[44] B. Kutlu, M. Ozturan, Determinants of E-health readiness of end-users, Int. Med. J. 19 (4) (2012) 287–291.
[45] M. Koo, M.C. Lu, S.C. Lin, Predictors of Internet use for health information among male and female Internet users: findings from the 2009 Taiwan National Health Interview Survey, Int. J. Med. Inform. 94 (2016) (2016) 155–363.
[46] J. Dart, The internet as a source of health information in three disparate communities, Aust. Health Rev. 32 (3) (2008) 559–569.
[47] H.K. Andreassen, M.M. Bujnowska-Fedak, C.E. Chronaki, R.C. Dumitru, I. Pudule, S. Santana, H. Voss, R. Wynn, European citizens' use of E-health services: a study of seven countries, BMC Public Health 7 (1) (2007) 53.
[48] C.L. Huang, S.-C. Yang, C.-H. Chiang, The associations between individual factors, eHealth literacy, and health behaviors among college students, Int. J. Environ. Res. Public Health 17 (6) (2020) 2108.
[49] T.H. Wagner, L.C. Baker, M.K. Bundorf, S. Singer, Use of the Internet for health information by the chronically ill, Prev. Chronic Dis. 1 (4) (2004) A13.
[50] B. Adebayo, A. Durey, L.M. Slack-Smith, Role of information and communication technology in promoting oral health at residential aged care facilities, Aust. J. Prim. Health 23 (3) (2017) 216–222.
[51] W.C. Hsu, The effect of age on electronic health literacy: mixed-Method study, JMIR Hum. Factors 6 (2) (2019), e11480.
[52] M.C. Raven, L.M. Kaplan, M. Rosenberg, L. Tieu, D. Guzman, M. Kushel, Mobile phone, computer, and internet use among older homeless adults: results from the HOPE HOME cohort study, JMIR Mhealth Uhealth 6 (12) (2018), e10049.
[53] NDIS, National Disability Insurance Agency: 2015 – 2019 Corporate Plan, Retrieved from, 2019, https://www.ndis.gov.au/media/410/download.
[54] M.A. Ali, K. Alam, B. Taylor, S. Rafiq, Does digital inclusion affect quality of life? Evidence from Australian household panel data, Telematics and Informatics 51 (2020) 101405.

Chapter 5: Synthesis and conclusion

The central aim of this thesis is to investigate the determinants of digital disparity as well as the effect of digital inclusion on QoL. This chapter summarises the key findings of the thesis, together with recommendations to promote digital inclusion and ensure enhanced access to digital health care services among Australian populations. Further, the limitations of the study along with directions for further research are also discussed. This section, and thereby the thesis, is ended up with the concluding remarks.

5.1 Introduction

Encapsulating a series of quantitative studies – both longitudinal and cross-sectional, this thesis explores the underlying causes of the digital divide and the extent to which digital exclusion can promote QoL among Australian populations with a special focus on PwD. The findings emanating from the study can inform policy aimed at addressing the digital divide, and given the geographic nature of this divide, promoting regional economic and social development in Australia. Consequent recommendations originating from subsequent studies point out several possible courses of action for the government and other actors in the disability sector so that digital inclusion can bring in more effective impacts on the lives of PwD. The following sections provide a synopsis of findings of each study which were detailed out in Chapters 2–4.

5.2 Summary of the key findings

The key findings of the thesis have been outlined in the following three sub-sections which correspond to the three broad themes of the thesis:

5.2.1 Determinants of the digital divide

Panel data models in Study 1 demonstrated that age and educational qualification have statistically significant and positive impacts on household Internet and computer access (i.e. digital inclusion). Meanwhile, digital inclusion was found to be negatively associated with the share of the female population. To put it differently, the extent of the digital divide had been shaped by demographic factors of corresponding states. Further, dependence on the agricultural sector and density of population were found to have a negative effect on access to ICT in most cases. Nevertheless, remoteness and income inequality were reported to have no meaningful impact on digital inclusion following the findings from this analysis of state-wide longitudinal data.

Study 2 of the thesis reported that in terms of access to telephone and mobile phones, urban households of South Australia had the lowest percentage (99.3%) compared to the rest of the states and territories of Australia. Taking all households (both urban and rural) into consideration, South Australia stood last regarding household-level access to telephone and mobile phone (99.4%). In terms of access to the Internet, for urban households, Tasmania (89.6%), and for rural households, the Northern Territory (76.9%) was lagging behind when compared to the households of other states and territories. For all households (urban and rural), South Australia ranked last on Internet access (89.2%). The findings from initial cross-tabulations indicated that the proportion of households with no access to ICT is highest for households in South Australia (0.7%) compared to other parts of Australia. It was also evident from the results of this study that a divide between urban and rural households existed in terms of Internet access. For example, the incidence of Internet access in urban households was at least 5% greater than that of rural counterparts in four states and territories. In terms of ICT infrastructure Concentration Index (CI) score, Rest of Victoria scored the highest (0.3661) for telephone and mobile phone access, and Greater Melbourne had the largest CI scores for Internet access (0.3819). For telephone and mobile phone access, Northern Territory had the lowest CI score (0.2906) while for Internet access, the Rest of South Australia region possessed the minimum concentration (0.2891). Considering the CI score for all households, CI scores for telephone and mobile access were highest for Victoria (0.4117). However, the concentration of Internet access was more prevalent in NSW (0.3603). To recapitulate, regardless of the household location (urban or rural), Victoria and NSW had the largest concentrations for telephone and mobile access, and Internet access, respectively. Apart from these findings, this study demonstrated that the extensity of concentration of ICT infrastructure rose with the levels of socioeconomic status, wealth and education. Nevertheless, for urban households, the incidence of inequality at the greater capital city area level was highest in the Rest of NSW (0.5345) in terms of ICT expenditure. This was much greater than the national average (0.4404).

Study 3 identified the determinants of ICT affordability using a generalised linear mixed model and the random-effects model. The results showed that the key variable of interest, income inequality (Gini coefficient) had a statistically significant positive impact on ICT affordability across all specifications. The other major explanatory variable, the SAD index was found to have a positive impact on ICT affordability which implied that the higher the socioeconomic position of a person, the higher the ICT affordability. ICT affordability of individuals significantly differed with the geo-spatial location of households as results showed that living in major cities and urban areas had enhanced the affordability. Among other factors, demographic factors including age and gender were reported to have no statistically significant impact on ICT affordability. However, a person being employed had a higher chance to afford ICT goods and services. One interesting finding comes up when a series of detailed analysis was conducted using the cohorts from different income brackets (income quintiles). The estimates demonstrated that the impact of income distribution on ICT affordability is non-linear. To be specific, for low-income brackets (households with annual income below AUS$133,070), income inequality enhances affordability, whereas, for the high-income bracket, the effect was quite opposite. However, using subsamples from different income brackets, the estimates indicated that the effect of income distribution was non-linear. For low-income brackets, income inequality seemed to enhance affordability, whereas, for the high-income bracket, this effect completely reversed.

5.2.2 ICT and health outcomes

Study 4 of this thesis applied IV- 2SLS and FIML to examine the nexus between QoL and digital inclusion. These econometric methods were used because conventional OLS- or panel data-based regressions would generate biased coefficients and inconsistent estimates in the presence of heteroscedasticity and autocorrelation. The key variable, i.e. Internet access was found to have a statistically significant and positive impact on QoL across all specifications for both the 2SLS and FIML method. The SAD index, the other variable of interest was found to be positively associated with QoL in all cases. This result implied that the QoL of a person belonging from a higher socio-economic group is significantly higher than that of a person belonging to a lower socio-economic group. As anticipated, QoL was negatively affected by age and long-term health conditions. In addition, the probability of living in urban areas and active participation in community activities significantly improved QoL. The impact of remoteness on QoL was found to be mixed and inconclusive.

Study 5 investigated the mediating impact of ICT use on the nexus between QoL and assistive technology by employing a series of parametric causal mediation regression models. The estimates from the regressions confirmed that both use of assistive technology and the use of ICT has a statistically significant and positive impact on QoL. The study also demonstrated that the interaction between the use of assistive technology use and ICT have a positive impact on QoL. Among other socio-demographic factors, level of education, employment status, age and gender were found to have a statistically significant association with QoL. Interestingly, another variable of interest – monetary support from the government (as disability payments) had a negative impact on QoL among PwCD. Apart from these takeaways, another major finding of the study was that the direct effect of assistive technology on QoL was only 29.9% whereas the indirect effect of assistive technology usage on QoL mediated through ICT was 70.1%. Moreover, the findings also asserted that the effect of ICT-enabled assistive technology on QoL was conditional upon the degree of communication impairment of the respondents. The results from the counterfactual causal mediation analysis also signified that persons with severe communication impairments did not possess effective assistive technology solutions which might have assisted them in using ICTs for communication purposes.

5.2.3 ICT usage for healthcare among people with disabilities

Study 6 employed a set of multivariate hierarchical regression models to predict ICT-enabled health care usage conditional upon several explanatory factors, including ICT access, several socio-demographic factors, locational variables, technological and behavioural constraints. As anticipated, the ICT-enabled health care usage was 12.64 times higher among PwD who reported to have ICT access (95% CI: 9.24–17.27, $p = 0.000$) compared to that of who reported having no access to ICT. The probability of ICT-enabled health care usage was much higher among PwD with very good health status (OR: 0.57; 95% CI: 0.44–0.73, $p = 0.000$) with respect to those with poor health status. The odds of ICT-enabled health care usage were more pronounced (33% higher) among PwD who had used health care from organised care compared to the group which had not (95% CI: 1.10–1.60, $p = 0.003$). At the same time, the likelihood of ICT-enabled health care usage was more prevalent among the respondents coming from the highest quintile households (OR: 1.30; 95% CI: 1.01–1.67, $p = 0.043$).

Surprisingly, the likelihood of using ICT-enabled health care was 18% lower among male respondents with respect to their female counterparts (95% CI: 0.73–0.92, p = 0.001). Therefore, in this case, the existing evidence in health care utilisation divide in favour of women (Bertakis et al. 2000; White & Witty 2009) found to outweigh the ICT utilisation divide in favour of men (Joiner, Stewart & Beaney 2015). The odds of using ICT–enabled health care were much higher for respondents who were more educated and employed. The incidence of ICT-enabled health care usage was 51% higher (95% CI: 1.17–1.94, p=0.001) among respondents who reported to have profound impairment than that of those without any impairment due to disability. The likelihood of ICT-enabled health care usage was 45% higher (95% CI: 1.20–1.75, p = 0.000) among respondents belonging from English-speaking origins compared to PwD from other countries. The odds of ICT-enabled health service adoption was less pronounced (17% less) among PwD residing in remote areas (OR: 0.17; 95% CI 0.70–0.99, p = 0.000) than those living in major cities. With respect to the comparative moderation effect of two constraints on the nexus between ICT-enabled health service usage and ICT access, the findings showed that the likelihood of ICT-enabled health service usage fell by 34% (95% CI 0.03–4.42, p = 0.014) when PwD reported to be confronted by technological constraint. On the other hand, in the presence of behavioural constraints, the odds of ICT-enabled health service usage access fell marginally, only by 1% (95% CI: <0.01–0.04, p = 0.000).

The last study of the thesis investigated the factors that explain the eHealth use among PwD. The findings indicated that the probability of eHealth usage decreases with age. The odds of eHealth usage for age cohort of 85+ year (95% CI: 0.22, 0.45; p < 0.01) were 35% less than of the baseline group of 65–69 years. Likewise, Study 6, the level of education and employment status had a positive impact on the outcome variable. Meanwhile, the probability of using eHealth was 89% lower among respondents living in remote areas (95% CI: 0.62, 1.27; p < 0.05) with respect to that of those residing in major or inner regional cities. The results also indicated that degree of impairment had no significant effect on eHealth usage. Besides, as expected and reported in Study 6, respondents with ICT access had 15.92 times higher chance (OR = 15.92, 95% CI: 10.51, 27.01; p < 0.01) to use eHealth compared to those reporting no access. Nevertheless, the findings of the study confirmed that behavioural restraints have a minimal impact on eHealth usage among elderly PwD at the aggregate level.

5.3 Contribution of the thesis

5.3.1 Contribution to the empirical knowledge

This thesis provided deeper insight into the extent, nature and underlying factors of digital exclusion in Australia. The following paragraphs highlight how each study of the thesis extended the prevailing body of knowledge.

Study 1 of the thesis examined the predictors of digital inequality in Australia and its association with other socio-economic and demographic aspects and remoteness. Unlike prior studies, this study has made a novel attempt in explaining the association among the digital divide, socio-demographic factors and remoteness using a longitudinal framework based on Australian state-wide panel data. This study used a population-based approach to define the remoteness which is time-variant and has the capability of capturing more detailed information on remoteness. Unlike previous work, this study embedded standard panel data estimation techniques which were considered to be more reliable and precise in estimating the nexus between the dependent variable and the predictors. Study 2 captured the impacts of socio-spatial variations and affordability services in gauging the concentration of ICT infrastructure at the least feasible disaggregated spatial unit (i.e. Greater Capital City Area and Rest of the State). From the purview of existing literature, it is clear that the affordability of ICT was sensitive to the level of income distribution and socio-economic inequality. This could be an area of pertinent research interest. To this end, Study 3 enhanced the understanding of digital inequality by examining the extent of responsiveness of ICT affordability with respect to the changes in income distribution using a nationally representative Australian household-level survey dataset (HILDA).

Prior studies investigating the association between the QoL and digital inclusion did not cover the simultaneous association between QoL and digital inclusion, and a major strand of this literature examined the nexus between those two variables using a single indicator based definition of QoL or subjective well-being which may result in biased estimates. Given this backdrop, Study 4 added value to the existing literature by investigating the simultaneous association between QoL and digital inclusion using stronger estimation strategies based on a longitudinal dataset. It is evident that the mediating effect of ICT on the association between assistive technology and QoL had not been unpacked. Since the need for PwCD is diverse, the way technology impacts on QoL among PwCD should differ from the general population. Given these limitations, Study 5 investigated the indirect effect of ICT in studying the effects of assistive technology on QoL among PwCD.

Empirical evidence on the predictors of ICT-enabled health service adoption among PwD is scarce. Besides, though it is evident that both technological and behavioural factors affect ICT adoption among PwD in general, the evidence on the comparative strength of those moderating factors are limited. To address these gaps, Study 6 of the thesis investigated the determinants of ICT-enabled health care usage among PwD with a special focus on the moderating impacts of technological and behavioural aspects. Lastly, Study 7 extended the empirical applicability of Study 6 by examining the precursors of eHealth usage employing advanced statistical modelling on the cohort of elderly PwD.

5.3.2 Contribution to theory and methods

Social capital and cognitive theories, and theories of social exclusion postulate that several economic, social, demographic and cognitive factors explain the extensity of digital inequality (van Dijk & Hacker 2003; Kvasny & Keil 2006; Clayton & Macdonald 2013; Ragnedda & Muschert 2013). This thesis (Studies 1 and 2) contributed to these theories by linking the notion of social exclusion and social capital with the phenomenon of digital exclusion. The thesis also improved the empirical acceptability of those theories by embedding them within a longitudinal study design. Importantly, the existing literature had not incorporated the association of remoteness with socio-economic and demographic dimensions of exclusion and its subsequent impact on digital inclusion. As a result, by integrating remoteness as a main dimension of social exclusion, this study added to the current understanding of theoretical knowledge by studying the nexus between digital and social exclusion.

5.3.2 Contribution to the methods

This thesis has also made several methodological contributions. Firstly, a state-wide panel data estimation confirmed (Study 1) that regions with a high dependency on the agriculture sector, a high proportion of remote populations, high population density and low level of educational attainment were at a digital disadvantage. This study added precision and reliability to those claims by deploying a series of robust and detailed longitudinal statistical methods instead of conventional OLS-based regressions. Secondly, unlike previous research, this thesis used panel data estimation techniques which are regarded to be more rigorous than cross-sectional analysis. This approach has many advantages: it offers more degrees of freedom and sample variability than cross-sectional data, takes individual heterogeneity into account by allowing flexibility to control for variables that are not observed or measured, and has greater potential to generate precise estimations. Thirdly, prevailing empirical studies examining the impact of ICT on QoL had applied the capability approach using a cross-sectional study design. Contrary to those previous works, this thesis (Study 5) applied a wider definition of QoL to study the impact of digital inclusion on human capabilities among PwD. In particular, this broader definition was based on a composite index following the WHOQoL disability module covering three major domains including physical, psychological, social, environmental and disabilities module. Last but not the least, this research incorporated both interpretation and condition-based concepts of communication impairment to minimise possible prejudices that can result from an inaccurate sampling technique.

5.4 Policy implications

A state-wide panel data estimation (Study 1) confirmed that regions with a high dependency on the agriculture sector, a high proportion of remote populations, high population density and low level of educational attainment are at a digital disadvantage. These findings were congruent with those of the previous literature and offer several practical implications. The results of this study suggested that increasing ICT penetration alone would not be sufficient to promote digital inclusion. In addition to the development of telecommunication infrastructure, policymakers should also pay attention on how socio-demographic and economic factors affect the patterns of digital inclusion and exclusion. To do so, digital inclusion policies must be regarded as a key component of Australia's regional economic and social development policy. Policy evidence generated from this study will also be applicable for other advanced ICT user countries with similar geographic and demographic challenges including New Zealand and Canada.

Study 2 of the thesis investigated the spatial concentration of ICT infrastructure using geo-cartographical maps. The results indicated that ICT infrastructure is highly concentrated in the major economic hubs of Australia – the Sydney and Melbourne Central Business Districts (CBDs). On the other hand, the results this study show that ICT infrastructure concentration is less prevalent in remote and very remote areas. The findings of this study emanate several substantial and straightforward practical implications. Most notably, since this study captured the geographic patterns of the digital disadvantage, the findings of this study can be seen as a model for setting goals in terms of narrowing the digital divide in Australia. To put it another way, the information gained from this research will help decision-makers to assess priority areas and establish appropriate spatial and regional digital infrastructure growth strategies. To this end, the NBN Co and major telecommunications providers including Telstra and Optus should assist the local government agencies to provide increased reliable high-speed Internet connections in disadvantaged areas including regional and remote Australia. Besides, alongside efforts to enhanced access, measures must be initiated to upskill the level of digital abilities of the disadvantaged remote communities. In this connection, the Department of Local Government and Communities, and the Department of Training and Workforce Development can assist vulnerable and disadvantaged groups in regional Australia by providing targeted ICT training programmes. Nevertheless, to ease the affordability of telecommunications services, the Australian Competition and Consumer Commission should also revisit the Competition Policy with a special focus on regional community context instead of viewing competition as a whole at the national level. Evidence shows that the regional communities are less capable, and thereof, more vulnerable to costly services prevailing in a monopoly market (Grubesic & Murray 2004).

Results emanating from Study 3 asserted that the effect of income distribution on ICT affordability can be regarded as non-linear. Precisely, in low-income families, ICT affordability is also positively related to income inequality. On the contrary, for high-income households the association between income inequality and ICT affordability is negative. The key practical implication of this study is that low-income households spend close to their affordability limit to avail ICT services. As a consequence, household spending on ICT services rose in real terms but fell as a fraction of total expenditure. Studying these findings in the light of Engel's law (Engel 1857), the consumption, and, therefore, the consequent spending on ICT services can be considered a necessary good. These results will render a great deal of support in easing the affordability of telecommunication services, hence, in articulating digital inclusion policies. Precisely, policy tools designed to enhance affordability for general mass can be effective in the regions with a comparatively lower level of income inequality. In contrast, the provision of universal access can be offered for households with a low-income bracket.

This thesis has contributed to a better understanding of the relationship between digital inclusion and its effect on QoL (Studies 4 and 5). Findings generated from the econometric exercise of Study 4 confirm that digital inclusion and QoL predict each other concurrently. These findings can potentially assist in the true evaluation and prediction of policy actions as they are grounded on the practical understanding of how the major variables of interest evolve and affect each other. Study 5 indicates a major portion of the impact of assistive technology on QoL among PwCD is mediated through ICT use. One of the key practical implications of this study is that better integration of assistive technology will improve the ability of ICT to positively impact the QoL of PwD. To this end, the government and other stakeholders in the disability sector need to (i) initiate targeted training on the use of assistive technology and ICT, (ii) provide a broader range of assistive technologies to meet the special need of PwD, and (iii) execute the principles of universal design while designing programs operated by government, business, and non-government organisations.

The last chapter of the thesis (Studies 6 and 7) had attempted to thoroughly examine the determinants of the digital disability divide with a special focus on ICT-enabled health care utilisation. The results demonstrated that age, gender, income, education level, language proficiency, and geographic location significantly affect ICT-enabled health care use among PwD. Besides, technological constraints were reported to have a much greater moderating impact on the usage of ICT-enabled health care than attitudinal restraints. One of the noteworthy practical implications of these studies is that ICT complements traditional health care service utilisation. Individuals using other ICT-based services are the primary users of eHealth. Nonetheless, by exploring the comparative moderating effect between technological and behavioural factors within a quantitative framework, these studies provide a more robust understanding of the relative importance of each. Thus, it provides deeper insight to policymakers and private actors in devising the digital disability divide mitigation policies. The stronger effect of technological constraints implies that policy should be directed to addressing technological and economic restraints as these factors limits adoption of technology. To overcome these limitations, measures including the provision of reliable and affordable ICT services through NDIA and NBN, and integration of market regulation and anti-discrimination principles in relevant public procurement procedure should be initiated.

5.5 Limitations and future research directions

5.5.1 Limitations

Despite several significant contributions to the existing body of knowledge, the studies included in the thesis are not without limitations. Study 1 used a dichotomous measure to define ICT access which is somewhat partial and unable to capture other important aspects of including quality of services and affordability (Lyons, Morgenroth & Tol 2013; Baller, Dutta & Lanvin 2016). Besides, in this study selection of variables is data-driven. Due to unavailability of data many authors were not being able to include candidate control variables including household size, household income and status of employment. Although state-level data can provide answers to some relevant policy questions, these data cannot be used to infer regional development policies.

In order to generate precise insights for policy design, the construction of a concentration measure and its subsequent reporting should be done at the most disaggregated geographical level. To be specific, the construction of ICT concentration measures in a number of cross-country studies is tabulated up to a considerable level of disaggregated geographical units (Pick, Sarkar & Johnson 2015; De Brito et al. 2016; Lin et al. 2017). Complying with the terms and conditions of using the HILDA Restricted Release database, Study 2 was unable to report the ICT infrastructure concentration scores at the lowest disaggregated spatial unit, i.e. SA4 geographical levels. However, this could have provided deeper insights for policymakers in devising regional infrastructure development policies. Another major shortcoming of this study is that the data points for ICT indicators' data points are sporadic. Therefore, the measurement of ICT concentration in this study is static in nature.

Study 3 used a crude measure to define ICT affordability based on annual household ICT expenditure due to data constraints. This study could have incorporated the ICT price basket data if relevant those data were readily available in the HILDA database. Moreover, this study does not investigate the direction of causality running from ICT concentration to income inequality as the authors' see such considerations beyond the scope of the study. Lastly, this study was not able to indicators on telecommunication market regulations in the regression models as these data are scarce at the disaggregated spatial levels.

The studies exploring the impact of ICT on health-related QoL (Studies 4–5) had a number of pitfalls. The definition of digital inclusion used in these studies is somewhat partial as they are based on single indicator-based measurements (ICT access or use). However, access to and use of ICT represents partial aspects of the digital divide. Having said that due to the scarcity of data, it was not possible to include information on other aspects of ICT artefacts, such as affordability and digital skills. Secondly, the nexus between QoL and socio-economic advantage should be considered with much caution as there is a lot of commonalities between these two phenomena since both of them are linked with material resources. Besides, while investigating the impact of ICT on QoL among PwCD we couldn't incorporate NDIS support as one of the explanatory variables in the regression models as the 2015 SDAC survey was conducted prior to the NDIS rollout period.

The studies predicting the facilitators and barriers to the usage of ICT-enabled health services among people with disabilities (Studies 6–7) also have some shortcomings. The conclusions drawn in these cases are solely based solely on Australian survey data. Hence, these studies may lack generalisability due to cross-country differences in institutions, economic situations, and culture prevailing in other countries. Last but not the least, these studies included both types of respondents who report to have ICT access and have no access to ICT. Since the eHealth usage is conditional upon some sort of ICT access this might not an ideal solution. Having said that, the research paradigm hypothesises that ICT access is a facilitating factor for eHealth usage and dropping respondents those who do not have ICT access would limit generalisability. Besides, one major limitation of Study 6 and 7 is, none of these studies could be considered as causal due to endogeneity issues. While this could have been performed through a filed or quasi-natural experiment, the study has rather taken an observational data-driven method. Future work is needed to establish whether the relationships established here are causal.

5.5.2 Directions for future research

Despite the promising results, there is abundant room for further progress in studying digital inclusion and its subsequent impacts on the QoL. Concentration and competition in the telecommunications market can influence the pace of digital inclusion substantially. Therefore, further work should examine the effects of telecommunication policy and market regulations on the digital divide along with socio-demographic and other control variables included in the respective research models (Studies 1–4). Nonetheless, to develop a comprehensive picture of digital concentration, empirical investigations should incorporate various service quality dimensions (e.g. Broadband Internet speed, network coverage and frequency of call drops) in measuring the concentration of ICT services along with access and affordability of ICT services.

Future research investigating the effect of ICT access on QoL should explore whether digital skills moderates (or mediates) the effect of the former on the later. Though investigations in this thesis (Study 5) examined the impact of ICT and assistive technology on QoL among PwD on the basis of a nationally representative and widely acknowledged disability survey data, more profound insights can be drawn if qualitative analysis can be done by conducting several in-depth focus group discussions with PwD living in disadvantaged areas including rural and remote Australia. The studies on digital disability divide (Studies 5–7) are solely based on the evidence drawn from cross-sectional data which makes it difficult to draw any causal relationship among ICT-enabled health service usage and its predictors. Future investigations based on longitudinal data would help in gaining a better understanding of this prospect. Particularly, we could apply experiments to identify causations among the outcome and dependent variables in future studies. Last but not least, further research is needed to conduct a more detailed analysis using different subgroups of PwD to capture the different set of challenges those cohorts.

Lastly, the COVID-19 pandemic fostered the expansion of eHealth services such as telemedicine as it put the elderly and persons with co-morbidities at particular risk. Future studies can consider the effects of the COVID-19 pandemic on the adoption and usage of eHealth. Precisely, more detailed work needs to be done to explore which factors can facilitate the uptake of usage of eHealth in general as well as for elderly PwD during and beyond the COVID-19 pandemic.

References

ABS 2010, Australian Statistical Geography Standard, Volume 1 - Main Structure and Greater Capital City Statistical Areas.Catalogue Number 1270.0.55.001, Australian Bureau of Statistics, Canberra.

ABS 2011, Census of Population and Housing: Socio-Economic Indexes for Areas (SEIFA), ABS Catalogue no. 2033.0.55.001, Australian Bureau of Statistics, Canberra, http://www.abs.gov.au/AUSSTATS/abs@.nsf/DetailsPage/2033.0.55.0012016?OpenDocument>.

ABS 2012, Household Use of Information Technology. Catalogue Number 8146.0, Canberra.

ABS 2016a, Education and Work. Catalogue Number 6227.0, Canberra.

ABS 2016b, 'Household Use of Information Technology. Catalogue Number 8146.0', Canberra.

ABS 2016c, Australian Demographic Statistics. Catalogue Number 3101.0, Canberra.

ABS 2017a, Regional Population Growth. Catalogue Number 3218.0, Canberra.

ABS 2017b, Labour Force, Australia, Detailed, Quarterly. Catalogue Number 6291.0.55.003, Canberra.

ABS 2017c, Survey of Disability, Ageing and Carers, Australia, 2015, Canberra, <https://www.abs.gov.au/ausstats/abs@.nsf/Latestproducts/4430.0.30.002Main%20Features12015?opendocument&tabname=Summary&prodno=4430.0.30.002&issue=2015&num=&view=>.

ABS 2018, Household Use of Information Technology 2016-17, ABS, Canberra, <https://www.abs.gov.au/statistics/industry/technology-and-innovation/household-use-information-technology/latest-release#data-download>.

ABS 2019, Survey of Disability, Ageing and Carers, Australia, 2018, Canberra, https://www.abs.gov.au/methodologies/disability-ageing-and-carers-australia-summary-findings/2018>.

Agree, EM 2014, 'The potential for technology to enhance independence for those aging with a disability', Disability and Health Journal, vol. 7, no. 1, Supplement, pp. S33-S9.

Ågren, KA, Kjellberg, A & Hemmingsson, H 2018, 'Access to and use of the Internet among adolescents and young adults with intellectual disabilities in everyday settings', Journal of Intellectual & Developmental Disability, pp. 1-10.

Alam, K & Imran, S 2015, 'The digital divide and social inclusion among refugee migrants: A case in regional Australia', Information Technology and People, vol. 28, no. 2, pp. 344-65.

Albuja, J, Navas, A, Paguay, D, Moreno, A & Nájera, P 2015, 'Technological GINI: A study of the inequality in Ecuador', 2015 2nd International Conference on eDemocracy and eGovernment, Quito, Ecuador, April 2015., pp. 133-7, <https://www.scopus.com/inward/record.uri?eid=2-s2.0-84936791807&doi=10.1109%2fICEDEG.2015.7114480&partnerID=40&md5=93fa0be7868a5470788ceb0738e668eb>.

Ali, MA, Alam, K & Taylor, B 2020, 'Incorporating affordability, efficiency, and quality in the ICT development index: Implications for index building and ICT policymaking', The Information Society, vol. 36, no. 2, pp. 71-96.

Alozie, NO & Akpan-Obong, P 2017, 'The Digital Gender Divide: Confronting Obstacles to Women's Development in Africa', Development Policy Review, vol. 35, no. 2, pp. 137-60.

Arbabisarjou, A, Allameh, SM & Farhang, A 2012, 'Relationship between information & communication technology and quality of work-life; A study of faculty members of Zahedan university', Life Science Journal, vol. 9, no. 4, pp. 3322-31.

Ashraf, MM, Hasan, N, Lewis, L, Hasan, MR & Ray, P 2017, 'A systematic literature review of the application of information communication technology for visually impaired people', International Journal of Disability Management, vol. 11, pp. 1-18.

Baller, S, Dutta, S & Lanvin, B 2016, 'The global information technology report 2016', World Economic Forum, Geneva, pp. 1-307.

Bandura, A 1986, Social foundations of thought and action, vol. 1986, Prentice-Hall, Englewood Cliffs, New Jersey.

Banks, G 2001, The Role of ICT in Australia’s Economic Performance, https://www.pc.gov.au/news-media/speeches/cs20010926/cs20010926.pdf>.

Barnes, C & Mercer, G 2005, The social model of disability: Europe and the majority world, Disability Press Leeds.

Bertakis, KD, Azari, R, Helms, LJ, Callahan, EJ & Robbins, JA 2000, 'Gender differences in the utilization of health care services', *Journal of Family Practice*, vol. 49, no. 2, pp. 147-52.

Billon, M, Marco, R & Lera-Lopez, F 2009, 'Disparities in ICT adoption: A multidimensional approach to study the cross-country digital divide', Telecommunications Policy, vol. 33, no. 10-11, pp. 596-610.

Bohman, H 2008, 'Income distribution and the diffusion of networks: An empirical study of Brazilian telecommunications', Telecommunications Policy, vol. 32, no. 9, pp. 600-14.

Brewer, JL, Taber-Doughty, T & Kubik, S 2010, 'Safety assessment of a home-based telecare system for adults with developmental disabilities in Indiana: a multi-stakeholder perspective', Journal of Telemedicine and Telecare, vol. 16, no. 5, pp. 265-9.

Campisi, J, Folan, D, Diehl, G, Kable, T & Rademeyer, C 2015, 'Social media users have different experiences, motivations, and quality of life', Psychiatry Research, vol. 228, no. 3, pp. 774-80.

Campos, R, Arrazola, M & de Hevia, J 2017, 'Economic crisis and benefits of the Internet: differentiated Internet usage by employment status', Economics of Innovation and New Technology, vol. 26, no. 3, pp. 269-94.

Carey, AC, Friedman, M. G., & Bryen, D. N. 2005, 'Use of electronic technologies by people with intellectual disabilities', Mental Retardation, vol. 43, no. 5, pp. 322-33.

Cashen, MS, Dykes, P & Gerber, B 2004, 'eHealth technology and Internet resources: barriers for vulnerable populations', Journal of Cardiovascular Nursing, vol. 19, no. 3, pp. 209-14.

Castellacci, F & Tveito, V 2018, 'Internet use and well-being: A survey and a theoretical framework', Research Policy, vol. 47, no. 1, pp. 308-25.

Castells, M 2002, The Internet galaxy: Reflections on the Internet, business, and society, Oxford University Press, Oxford.

Caton, S & Chapman, M 2016, 'The use of social media and people with intellectual disability: A systematic review and thematic analysis', Journal of Intellectual and Developmental Disability, vol. 41, no. 2, pp. 125-39.

Çelik, ÇB & Odacı, H 2013, 'The relationship between problematic internet use and interpersonal cognitive distortions and life satisfaction in university students', Children and Youth Services Review, vol. 35, no. 3, pp. 505-8.

Chaumon, M-EB, Michel, C, Tarpin Bernard, F & Croisile, B 2014, 'Can ICT improve the quality of life of elderly adults living in residential home care units? From actual impacts to hidden artefacts', in Behaviour & Information Technology, Taylor & Francis, vol. 33, pp. 574-90.

Chiao, C & Chiu, CH 2016, 'The relationships between ICT use and life quality among children with social phobia', 2016 IEEE International Conference on Teaching, Assessment, and Learning for Engineering (TALE), pp. 26-31.

Çikrıkci, Ö 2016, 'The effect of internet use on well-being: Meta-analysis', Computers in Human Behavior, vol. 65, pp. 560-6.

Clayton, J & Macdonald, SJ 2013, 'The limits of technology: Social class, occupation and digital inclusion in the city of Sunderland, England', Information, Communication & Society, vol. 16, no. 6, pp. 945-66.

Curtin, J 2001, 'A digital divide in rural and regional Australia. ', Information and Research Services, Department of the Parliament Library., no. Current issues brief 1.

Damant, J, Knapp, M, Freddolino, P & Lombard, D 2016, 'Effects of digital engagement on the quality of life of older people', Health & Social Care in the Community, vol. 25, no. 6, pp. 1679-703.

De Brito, SR, Silva, ADSD, Cruz, AG, De Monteiro, MA, Vijaykumar, NL, Silva, MSD, Costa, JCWA & Francês, CRL 2016, 'Concentration of access to information and communication technologies in the municipalities of the brazilian legal amazon', PloS one, vol. 11, no. 4.

De Queiroz Ribeiro, LC, Salata, A, Costa, L & Gomes Ribeiro, M 2013, 'Digital inequalities: Internet access and use, social-economic position, and spatial segmentation in the Brazilian metropolitan areas', Analise Social, vol. 48, no. 207, pp. 288-320.

Dedrick, J, Kraemer, KL & Shih, E 2011, IT in Developed and Developing Countries, Personal Computing Industry Center, University of California, Irvine, http://pcic.merage.uci.edu/papers/2011/ITandProductivity.pdf>.

Dewan, S & Kraemer, KL 2000, 'Information technology and productivity: evidence from country-level data', Management Science, vol. 46, no. 4, pp. 548-62.

Dobransky, K & Hargittai, E 2006, 'The disability divide in internet access and use', Information, Communication & Society, vol. 9, no. 3, pp. 313-34.

Dobransky, K & Hargittai, E 2016, 'Unrealized potential: Exploring the digital disability divide', Poetics, vol. 58, pp. 18-28.

DSS & Melbourne Institute of Applied Economic and Social Research 2017, The Household, Income and Labour Dynamics in Australia (HILDA) Survey, RESTRICTED RELEASE 16 (Waves 1-16), ADA Dataverse, <http://dx.doi.org/10.4225/87/QFUIBM>.

DSS & Melbourne Institute of Applied Economic and Social Research 2018, The Household, Income and Labour Dynamics in Australia (HILDA) Survey, RESTRICTED RELEASE 167 (Waves 1-17), ADA Dataverse, <http://dx.doi.org/10.4225/87/QFUIBM>.

Duplaga, M 2017, 'Digital divide among people with disabilities: Analysis of data from a nationwide study for determinants of Internet use and activities performed online', PloS one, vol. 12, no. 6, p. e0179825.

Engel, E 1857, 'The productions and consumptions of the kingdom of saxony.', Journal of the Statistical Bureau of the Royal Saxon, Ministry of the Interior, vol. 8, pp. 1-54.

Fisk, M, Livingstone, A & Pit, SW 2020, 'Telehealth in the Context of COVID-19: Changing Perspectives in Australia, the United Kingdom, and the United States', Journal of Medical Internet Research, vol. 22, no. 6, p. e19264.

Forestier, E, Grace, J & Kenny, C 2002, 'Can information and communication technologies be pro-poor?', Telecommunications Policy, vol. 26, no. 11, pp. 623-46.

Gao, T, Xiang, Y-T, Zhang, H, Zhang, Z & Mei, S 2017, 'Neuroticism and quality of life: Multiple mediating effects of smartphone addiction and depression', Psychiatry Research, vol. 258, pp. 457-61.

Gibson, C 2003, 'Digital Divides in New South Wales: A research note on socio-spatial inequality using 2001 Census data on computer and Internet technology', Australian Geographer, vol. 34, no. 2, pp. 239-57.

Goggin, G 2017, 'Disability and digital inequalities: Rethinking digital divides with disability theory', in Theorizing digital divides, Routledge, pp. 69-80.

Grubesic, TH & Murray, AT 2004, 'Waiting for broadband: Local competition and the spatial distribution of advanced telecommunication services in the United States', *Growth and Change*, vol. 35, no. 2, pp. 139-65.

Guo, B, Bricout, JC & Huang, J 2005, 'A common open space or a digital divide? A social model perspective on the online disability community in China', Disability & Society, vol. 20, no. 1, pp. 49-66.

Hakobyan, L, Lumsden, J, O'Sullivan, D & Bartlett, H 2013, 'Mobile assistive technologies for the visually impaired', Survey of Ophthalmology, vol. 28, no. 6, pp. 513-28.

Hayward, RD, Taylor, WD, Smoski, MJ, Steffens, DC & Payne, ME 2013, 'Association of five-factor model personality domains and facets with presence, onset, and treatment outcomes of major depression in older adults', The American Journal of Geriatric Psychiatry, vol. 21, no. 1, pp. 88-96.

Hemsley, B, Georgiou, A, Carter, R, Hill, S, Higgins, I, van Vliet, P & Balandin, S 2016, 'Use of the my health record by people with communication disability in Australia: A review to inform the design and direction of future research', Health Information Management Journal, vol. 45, no. 3, pp. 107-15.

Hirani, SP, Beynon, M, Cartwright, M, Rixon, L, Doll, H & Newman, SP 2014, 'The effect of telecare on the quality of life and psychological well-being of elderly recipients of social care over a 12-month period: the Whole Systems Demonstrator cluster randomised trial. ', Age and Aging, vol. 43, no. 3, pp. 334-41.

Hodge, H, Carson, D, Carson, D, Newman, L & Garrett, J 2017, 'Using Internet technologies in rural communities to access services: The views of older people and service providers', Journal of Rural Studies, vol. 54, pp. 469-78.

Hong, Z, Li, N, Li, D, Li, J, Li, B, Xiong, W, Lu, L, Li, W & Zhou, D 2020, 'Telemedicine During the COVID-19 Pandemic: Experiences From Western China', Journal of Medical Internet Research, vol. 22, no. 5, p. e19577.

Hüsing, T & Selhofer, H 2002, 'The Digital Divide Index-A Measure of Social Inequalities in the Adoption of ICT', European Conference on Information Systems 2002, pp. 1273-68.

ITU 2014, Measuring the Information Society Report 2014, International Telecommunication Union, https://www.itu.int/en/ITU-D/Statistics/Documents/publications/mis2014/MIS2014_without_Annex_4.pdf>.

ITU 2016a, Measuring the Information Society Report 2016, Geneva, Switzerland, https://www.itu.int/en/ITU-D/Statistics/Documents/publications/misr2016/MISR2016-w4.pdf>.

ITU 2016b, Yearbook of Statistics. Telecommunication/ICT Indicators 2006-2015, International Telecommunication Union, <https://read.itu-ilibrary.org/science-and-technology/yearbook-of-statistics-telecommunication-ict-indicators-2007-2016_pub/810592a6-en#page250>.

Jayakar, K, Liu, C, Madden, G & Park, E-A 2015, 'Promoting broadband and ICT access for disabled persons: Comparative analysis of initiatives in Asia-Pacific region', The Information Society, vol. 31, no. 4, pp. 299-314.

Joiner, R, Stewart, C & Beaney, C 2015, 'Gender Digital Divide', in LD Rosen;, et al. (eds), *The Wiley Handbook of Psychology, Technology, and Society* Wiley, pp. 74-88.

Jones, M, Morris, J & Deruyter, F 2018, 'Mobile healthcare and people with disabilities: Current state and future needs', International Journal of Environmental Research and Public Health, vol. 15, no. 3.

Katz, JE & Rice, RE 2002, Social consequences of Internet use: Access, involvement, and interaction, MIT press, Cambridge.

Kivunike, FN, Ekenberg, L, Danielson, M & Tusubira, FF 2011, 'Perceptions of the role of ICT on quality of life in rural communities in Uganda', Information Technology for Development, vol. 17, no. 1, pp. 61-80.

Kvasny, L & Keil, M 2006, 'The challenges of redressing the digital divide: A tale of two US cities', Infomration Systems Journal, vol. 16, no. 1, pp. 23-53.

Lancioni, GE, Singh, NN, O'Reilly, MF, Sigafoos, J, Oliva, D & Campodonico, F 2013, 'Further evaluation of a telephone technology for enabling persons with multiple disabilities and lack of speech to make phone contacts with socially relevant partners', Research in Developmental Disabilities, vol. 34, no. 11, pp. 4178-83.

Lindblom, T & Räsänen, P 2017, 'Between class and status? Examining the digital divide in Finland, the United Kingdom, and Greece', The Information Society, vol. 33, no. 3, pp. 147-58.

Lin, J, Yu, Z, Wei, YD & Wang, M 2017, 'Internet Access, Spillover and Regional Development in China', *Sustainability*, vol. 9, no. 6, p. 946.

Lissitsa, S & Chachashvili-Bolotin, S 2016, 'Life satisfaction in the internet age – Changes in the past decade', Computers in Human Behavior, vol. 54, pp. 197-206.

Lissitsa, S & Madar, G 2018, 'Do disabilities impede the use of information and communication technologies? Findings of a repeated cross-sectional study - 2003-2015', Israel Journal of Health Policy Research, vol. 7, no. 1.

Livingstone, S & Helsper, E 2007, 'Gradations in digital inclusion: Children, young people and the digital divide', New Media and Society, vol. 9, no. 4, pp. 671-96.

Longstreet, P & Brooks, S 2017, 'Life satisfaction: A key to managing internet & social media addiction', Technology in Society, vol. 50, pp. 73-7.

Lyons, S, Morgenroth, E & Tol, RSJ 2013, 'Estimating the value of lost telecoms connectivity', *Electronic Commerce Research and Applications*, vol. 12, no. 1, pp. 40-51.

Mann, WC, Belchior, P, Tomita, MR & Kemp, BJ 2005, 'Computer use by middle-aged and older adults with disabilities', Technology and Disability, vol. 17, no. 1, pp. 1-9.

Martin, BR 2016, 'Twenty challenges for innovation studies', Science and Public Policy, vol. 43, no. 3, pp. 432-540.

Mavrou, K, Meletiou-Mavrotheris, M, Kärki, A, Sallinen, M & Hoogerwerf, E-J 2017, 'Opportunities and challenges related to ICT and ICT-AT use by people with disabilities: An explorative study into factors that impact on the digital divide', Technology and Disability, vol. 29, no. 1-2, pp. 63-75.

Mcclain-Nhlapo, CV, Sivonen, LHA, Raja, DS, Palummo, S & Acul, E 2018, Disability inclusion and accountability framework, Washington, D.C., http://documents.worldbank.org/curated/en/437451528442789278/pdf/126977-WP-PUBLIC-DisabilityInclusionAccountabilitydigital.pdf>.

Milne, C 2000, 'Affordability of basic telephone service: an income distribution approach', Telecommunications Policy, vol. 24, no. 10, pp. 907-27.

Milne, C 2006, Telecoms demand: measures for improving affordability in developing countries, A toolkit for action. Main report, January. Department of Media and Communications, mimeo, http://www.ruralict.ftml.net/publications/TD_main_report.pdf>.

Mumporeze, N & Prieler, M 2017, 'Gender digital divide in Rwanda: A qualitative analysis of socioeconomic factors', Telematics and Informatics, vol. 34, no. 7, pp. 1285-93.

Nimrod, G 2017, 'Technostress: measuring a new threat to well-being in later life', Aging & Mental Health, pp. 1-8.

Norris, P 2001, Digital Divide: Civic Engagement, Information Poverty, and the Internet Worldwide, Cambridge University Press.

O’Neill, SJ, Smyth, S, Smeaton, A & O’Connor, NE 2019, 'Assistive technology: Understanding the needs and experiences of individuals with autism spectrum disorder and/or intellectual disability in Ireland and the UK', Assistive Technology, pp. 1-9.

Oliver, M & Barnes, C 2012, The new politics of disablement, Palgrave Macmillan, Houndsmills, UK.

Papanastasiou, G, Drigas, A, Skianis, C, Lytras, M & Papanastasiou, E 2018, 'Patient-centric ICTs based healthcare for students with learning, physical and/or sensory disabilities', Telematics and Informatics, vol. 35, no. 4, pp. 654-64.

Park, S 2017, 'Digital inequalities in rural Australia: A double jeopardy of remoteness and social exclusion', Journal of Rural Studies, vol. 54, pp. 399-407.

Park, S, Freeman, J, Middleton, C, Allen, M, Eckermann, R & Everson, R 2015, 'The multi-layers of digital exclusion in rural Australia', Proceedings of the Annual Hawaii International Conference on System Sciences, pp. 3631-40, <https://www.scopus.com/inward/record.uri?eid=2-s2.0-84944216496&doi=10.1109%2fHICSS.2015.436&partnerID=40&md5=0d61e6cc9ebe19c252a46c96a15261b0>.

Pearce, KE & Rice, RE 2013, 'Digital Divides From Access to Activities: Comparing Mobile and Personal Computer Internet Users', Journal of Communication, vol. 63, no. 4, pp. 721-44.

Perelmutter, B, McGregor, KK & Gordon, KR 2017, 'Assistive technology interventions for adolescents and adults with learning disabilities: An evidence-based systematic review and meta-analysis', Computers and Education, vol. 114, pp. 139-63.

Pick, JB, Sarkar, A & Johnson, J 2015, 'United States digital divide: State level analysis of spatial clustering and multivariate determinants of ICT utilization', *Socio-Economic Planning Sciences*, vol. 49, pp. 16-32.

Prakash, A 2007, 'Importance of development context in ICT4D projects', Information Technology & People, vol. 20, no. 3, pp. 262-81.

Pratama, AR 2017, 'Cross-country analysis of ICT and education indicators: an exploratory study', The International Conference on Information Technology and Digital Applications IOP Publishing, p. 012006.

Raghavendra, P, Newman, L, Grace, E & Wood, D 2015, 'Enhancing social participation in young people with communication disabilities living in rural Australia: Outcomes of a home-based intervention for using social media', Disability & Rehabilitation, vol. 37, no. 17, pp. 1576-90.

Ragnedda, M & Muschert, GW 2013, The digital divide: The Internet and social inequality in international perspective, Routledge, London.

Ratan, AL & Bailur, S 2007, 'Welfare, agency and “ICT for Development”', 2007 International Conference on Information and Communication Technologies and Development, IEEE, pp. 1-12.

Rice, RE & Pearce, KE 2015, 'Divide and diffuse: Comparing digital divide and diffusion of innovations perspectives on mobile phone adoption', Mobile Media & Communication, vol. 3, no. 3, pp. 401-24.

Roulstone, A 1998, Enabling Technology, Disabled People, Work and New Technology, Open University Press, Buckingham.

Roulstone, A 2016, Disability and technology: An interdisciplinary and international approach, Palgrave Macmillan, Basingstoke, UK.

Sachdeva, N, Tuikka, A-M, Kimppa, KK & Suomi, R 2015, 'Digital disability divide in information society: A framework based on a structured literature review', Journal of Information, Communication and Ethics in Society, vol. 13, no. 3/4, pp. 283-98.

Samuelsson, C & Ekström, A 2019, 'Digital communication support in interaction involving people with dementia', Logopedics Phoniatrics Vocology, vol. 44, no. 1, pp. 41-50.

Segrist, KA 2004, 'Attitudes of older adults toward a computer training program', Educational Gerontology, vol. 30, no. 7, pp. 563-71.

Sen, A 1985, Commodities and Capabilities, North-Holland, Amsterdam.

Sen, A 2010, 'The Mobile and the World', Information Technologies and International Development, vol. 6, no. special issue, pp. 1-3.

Sharpe, B & Hemsley, B 2016, 'Improving nurse-patient communication with patients with communication impairments: Hospital nurses' views on the feasibility of using mobile communication technologies', Applied Nursing Research, vol. 30, pp. 228-36.

Siegel, C & Dorner, TE 2017, 'Information technologies for active and assisted living—Influences to the quality of life of an ageing society', International Journal of Medical Informatics, vol. 100, pp. 32-45.

Sims, T, Reed, AE & Carr, DC 2017, 'Information and communication technology use is related to higher well-being among the oldest-old', Journals of Gerontology - Series B Psychological Sciences and Social Sciences, vol. 72, no. 5, pp. 761-70.

Smith, AC, Thomas, E, Snoswell, CL, Haydon, H, Mehrotra, A, Clemensen, J & Caffery, LJ 2020, 'Telehealth for global emergencies: Implications for coronavirus disease 2019 (COVID-19)', Journal of Telemedicine and Telecare, vol. 26, no. 5, pp. 309-13.

Sujarwoto, S & Tampubolon, G 2016, 'Spatial inequality and the Internet divide in Indonesia 2010–2012', Telecommunications Policy, vol. 40, no. 7, pp. 602-16.

Šumak, B, Špindler, M, Debeljak, M, Heričko, M & Pušnik, M 2019, 'An empirical evaluation of a hands-free computer interaction for users with motor disabilities', Journal of Biomedical Informatics, vol. 96, p. 103249.

Thomas, J, Barraket, J, Wilson, C, Holcombe-James, I, Kennedy, J, Rennie, E, Ewing, S & MacDonald, T 2020, Measuring Australia’s Digital Divide: The Australian Digital Inclusion Index 2020, RMIT and Swinburne University of Technology, and Telestra Melbourne.

Toda, M, Ezoe, S, Mure, K & Takeshita, T 2016, 'Relationship of smartphone dependence to general health status and personality traits among university students', Open Journal of Preventive Medicine, vol. 6, no. 10, pp. 215-21.

Tsatsou, P 2011, 'Digital divides revisited: what is new about divides and their research?', Media, Culture & Society, vol. 33, no. 2, pp. 317-31.

United Nations 2006, Convention on the rights of persons with disabilities, United Nations, New York, https://www.un.org/development/desa/disabilities/convention-on-the-rights-of-persons-with-disabilities.html>.

Ünver, H 2017, 'Measuring the global information society - Explaining digital inequality by economic level and education standard', IOP Conference Series: Materials Science and Engineering, <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85016197074&doi=10.1088%2f1757-899X%2f173%2f1%2f012021&partnerID=40&md5=4b367dd57e839924e94b8989428690a0>.

Van den Berg, M, Ranchor, A, Van Sonderen, F, Van Gelder, I & Van Veldhuisen, D 2005, 'Paroxysmal atrial fibrillation, quality of life and neuroticism', Netherland Jouranl of Medicine, vol. 63, no. 5, pp. 170-4.

van Dijk, JAGM 2005, The deepening divide: Inequality in the information society, Sage Publications, London.

van Dijk, JAGM 2006, 'Digital divide research, achievements and shortcomings', Poetics, vol. 34, no. 4-5, pp. 221-35.

van Dijk, JAGM & Hacker, K 2003, 'The Digital Divide as a Complex and Dynamic Phenomenon', Information Society, vol. 19, no. 4, pp. 315-26.

Vehovar, V, Sicherl, P, Hüsing, T & Dolnicar, V 2006, 'Methodological challenges of digital divide measurements', Information Society, vol. 22, no. 5, pp. 279-90.

Vicente, MR & Lopez, AJ 2010, 'A multidimensional analysis of the disability digital divide: Some evidence for Internet use', The Information Society, vol. 26, no. 1, pp. 48-64.

Weiss, JW, Gulati, GJ, Yates, DJ & Yates, LE 2015, 'Mobile Broadband Affordability and the Global Digital Divide - An Information Ethics Perspective', 2015 48th Hawaii International Conference on System Sciences, Kauai, HI, USA, pp. 2177-86.

White, A & Witty, K 2009, 'Men's under use of health services–finding alternative approaches', *Journal of Men's Health*, vol. 6, no. 2, pp. 95-7.

Wu, T-F, Chen, M-C, Yeh, Y-M, Wang, H-P & Chang, SC-H 2014, 'Is digital divide an issue for students with learning disabilities?', Computers in Human Behavior, vol. 39, pp. 112-7.

Wu , YJ, Liu, WJ & Yuan, CH 2018, 'A mobile-based barrier-free service transportation platform for people with disabilities', Computers in Human Behavior, vol. 105776.

Yu, TK, Lin, ML & Liao, YK 2017, 'Understanding factors influencing information communication technology adoption behavior: The moderators of information literacy and digital skills', Computers in Human Behavior, vol. 71, pp. 196-208.

Appendix A

Supplementary Materials of Study 5

I. Model specification and estimation methods

Causal mediation analysis

Mediation analysis explores the apparatus that cause an observed relationship between an exposure variable and outcome variable, and investigates how they relate to a third mediator or intermediate variable. This study uses the counterfactual framework for mediation analysis [1-5] which allows for decomposition of total effects into direct and indirect effects in settings where non-linearities and interactions are present. This is a methodological improvement over the classical mediation analysis of Baron and Kenny [6]. Among a number of counterfactual causal mediation regression models, the current study uses the following three models to carry out the empirical analysis due to their suitability over others in this particular context.

Parametric causal mediation regression models (-paramed-)

To extend the classical regression–based mediation analysis, VanderWeele and Vansteelandt [5] used the counterfactual framework by deriving results for direct and indirect effects for linear and logistic regressions in the presence of exposure–mediator interaction. Valeri and VanderWeele [4] extend this work by allowing dichotomous mediators in the mediation analysis for parametric models.

Within the framework of current study, there is a continuous outcome and a binary mediator, the outcome regression model and mediation regression model can be formulated, respectively, as follows:

$$E[y|a,m,c] = \theta_0 + \theta_1 a + \theta_2 m + \theta_3 am + \theta'_4 c + u_y \tag{2}$$

$$logit\ [p(m=1|a,c)] = \beta_0 + \beta_1 a + \beta'_2 c + u_m \tag{3}$$

where, a = exposure, m = mediator, y = outcome, c = covariates. In this study, the exposure is AT_COM_USE, the mediator and outcome variable are ICT_USE and QoL, respectively (see Table 1 for details).

If the covariates c satisfy the no-unmeasured confounding assumptions [4] , then controlled direct effect (CDE), average natural direct effect (NDE) and average natural indirect effect (NIE) would be given by:

$$CDE = (\theta_0 + \theta_1 m)\,(a - a^*) \tag{4}$$

$$NDE = \theta_1(a - a^*) \; + \{\theta_3(a - a^*)\}\frac{\exp(\beta_0 + \beta_1 a^* + \beta'_2 c\,)}{1 + \exp(\beta_0 + \beta_1 a^* + \beta'_2 c\,)} \tag{5}$$

$$NIE = (\theta_2 + \theta_3 a) + \frac{\exp(\beta_0 + \beta_1 a + \beta'_2 c)}{1 + \exp(\beta_0 + \beta_1 a + \beta'_2 c)} - \frac{\exp(\beta_0 + \beta_1 a^* + \beta'_2 c)}{1 + \exp(\beta_0 + \beta_1 a^* + \beta'_2 c)} \quad (6)$$

Parametric mediation effects (-medeff-)

Another counterfactual causal mediation analysis was developed by Imai, Keele and Tingley [3] which can integrate parametric and non-parametric models, linear and non-linear relationships, continuous and discrete mediators and different types of outcome variables. Considering the outcome regression model and mediation regression model, outlined respectively in Eq. (2) and (3), the average causal mediation effect (ACME), the direct effect (DE) and average total effect (TE) can be expressed as follows:

$$ACME = E\left[y_i\left(a, m_i(1)\right) - y_i\left(a, m_i(0)\right)\right] \quad (7)$$

$$DE = E\left[y_i\left(1, m_i(a)\right) - y_i\left(0, m_i(a)\right)\right] \quad (8)$$

$$TE = E[y_i\left(1, m_i(1)\right) - y_i\left(0, m_i(0)\right)] = \frac{1}{2}\ [ACME + DE] \quad (9)$$

Imai, Keele and Tingley [3] advocated running a sensitivity analysis once the causal mediation has been conducted. This analysis examines the degree of the sensitivity of the results to the violation of the SI assumption.

G-computation procedure (-gformula-)

In estimating causal mediation, a methodological problem arises if there exist other confounders which might influence the mediator-outcome (*m*–*y*) relationship. If such confounders exist, the causal mediation regression models may yield inconsistent estimates of the direct effect of the treatment (*a*) on the outcome (*y*). To overcome this complexity, Daniel, De Stavola[1] developed the G-computation procedure. The current study employs this procedure in order to check the robustness of the two-baseline counterfactual causal mediation regression models.

Taking the outcome regression model and mediation regression model outlined respectively in Eq. (2) and (3), the total controlled effect (TCE), the natural direct effect (NDE) and natural indirect effect (NIE) can be written as follows:

$$TCE = [y(a, m(a))] - E[y(0,m(0))] \quad (10)$$

$$NDE = E[y(a, m(0))] - E[y(0, m(0)] \quad (11)$$

$$NIE = E[y(a, m(x))] - E[y(x, m(0))] \quad (12)$$

Moderation analysis

A moderation analysis is used to explore when, or under what circumstances, or for which group of sub-sample the causal effect of mediator and treatment on the outcome exists or does not, and if exists what is the magnitude [7]. The term 'interaction' is also interchangeably used with 'moderation'. If *x*'s effect on *y* is moderated by *w*, then *x* and *w* are interacting each other. The current study hypothesises that the causal effect of ICT enabled assistive technology will vary with the degree of communication impairment. For the current analysis, the simple linear regression without the interaction effect can be expressed as follows:

$$\hat{y} = \beta_0 + \beta_1 ICT\_AT\_USE + \beta_2 LVLCOMMR + \wedge Z + u \quad (13)$$

where, y = QoL, *ICT_AT_USE*= the interaction between the ICT and assistive technology use, *LVLCOMMR*= level of communication impairment, Z = covariates, and u = error term.

But, as specified in Eq. (13), the effect on *ICT_AT_USE* on *QoL* is fixed to be the same– β_1 – regardless of the value of moderating variable *LVLCOMMR*. By testing the moderation hypothesis, this constraint on *ICT_AT_USE* can be eradicated. This can be done by specifying the effect of *ICT_AT_USE* as a function of *LVLCOMMR*. Substituting (β_1+β_3 *LVLCOMMR) for* b_1 in Eq. (13), the following expression will be obtained

$$\hat{y} = \beta_0 + (\beta_1 + \beta_3\, LVLCOMMR)\, ICT\_AT\_USE + \beta_2 LVLCOMMR + \wedge Z + u \quad (14)$$

Mathematically, this is equivalent to

$$\hat{y} = \beta_0 + \beta_1 ICT\_AT\_USE + \beta_2 LVLCOMMR + \beta_3\,(LVLCOMMR \times ICT\_AT\_USE) + \wedge Z + u \quad (15)$$

If the effect of interaction *(LVLCOMMR× ICT_AT_USE)* measured by β_3 does not equal zero, then it can be claimed that the effect of *ICT_AT_USE* on *QoL* varies with the *LVLCOMMR*, i.e. *LVLCOMMR* moderates the impact of *ICT_AT_USE* on *QoL*.

II. Supplementary Tables

Table S1: List of conditions that may affect communication ability.

SN	Condition	ABS Code	ICD-10 Code
1	Mental and behavioural disorders	500	F00–F99
2	Dementia	511	F00–03
3	Schizophrenia	512	F20
4	Intellectual and developmental disorders	530	F80–89
5	Mental retardation/intellectual disability	531	F70–F79
6	Autism and related disorders (including Rett's syndrome and Asperger's syndrome)	532	F84
7	Other developmental/learning disorders	539	F80.1–F80.9, F83, F88–89
8	Attention deficit disorder/hyperactivity	595	F90
9	Speech impediment	596	F98.5
10	Other mental and behavioural disorders	599	F04–09, F51.1–52, F54–55, F59, F99
11	Parkinson's disease	604	G20–21
12	Alzheimer's disease	605	G30
13	Brain disease/disorders—acquired	606	G45–G46, G90–93.2, G93.4–G94.8
14	Multiple sclerosis	607	G35
15	Cerebral palsy	611	G80
16	Diseases of the middle ear and mastoid	802	H65–75
17	Diseases of the inner ear	803	H80–83.2, H83.8–83.9
18	Deafness/hearing loss	810	H83.3, H90–H91
19	Deafness/hearing loss—noise induced	811	H83.3
20	Deafness/hearing loss—congenital	812	H90
21	Deafness/hearing loss—due to accident	813	No ICD–10 equivalent
22	Other deafness/hearing loss	819	H91.0–91.3, H91.9
23	Other diseases of the ear and mastoid process	899	H92–95
24	Stroke	923	I64
25	Congenital brain damage/malformation	1605	Q00–04
26	Unspecified speech difficulties	1705	R47.0, R47.8–48
27	Memory loss	1709	R41.1–41.3
28	Dysphagia (difficulty in swallowing)	1713	R13
29	Head injury/acquired brain damage	1801	S00–09
30	Memory problems or periods of confusion	1908	N/A

Table S2: Sensitivity analysis using *medsens.*

Rho (ρ) at which ACME = 0	0.514
R^2_M*R^^{2}_Y* at which ACME = 0	0.264
R^^{2}_M~R^^{2}_Y~ at which ACME = 0	0.068

Table S3: Standardized estimates of QoL for cluster with profound communication impairment.

Variable	**Standardized Coefficient**	**t-statistics**	**bStdX**	**bStdY**	**BStdXY**	**SDofX**
AT_COM_USE	-0.019	-0.230	-0.006	-0.020	-0.006	0.312
ICT_USE	0.883	8.776	0.405	0.925	0.424	0.459
WHODISC	-0.154	-1.431	-0.023	-0.161	-0.024	0.150
INCDECPN	0.029	1.379	0.027	0.031	0.028	0.918
EDU_REC	0.023	1.349	0.025	0.024	0.026	1.092
EMPLOY_REC	0.171*	3.288	0.063	0.180	0.066	0.366
AGE_REC	-0.064	-3.694	-0.066	-0.067	-0.069	1.027
GENDER_REC	0.132*	4.066	0.066	0.139	0.069	0.500
DISAB_SUP	-0.294*	-3.438	-0.059	-0.308	-0.062	0.200
REMOTE_REC	-0.011	-0.244	-0.004	-0.011	-0.004	0.365
ICT_USE*AT_COM_USE	0.755*	7.078	0.363	0.791	0.380	0.481
F-statistics			226.110*			
R-squared			0.694			
Number of observations			1109			

Note: *, ** and *** denote statistically significant at 1%, 5% and 10%, respectively.

Table S4: Standardized estimates of QoL for cluster with profound communication impairment.

Variable	**Standardized Coefficient**	**t-statistics**	**bStdX**	**bStdY**	**BStdXY**	**SDofX**
AT_COM_USE	-0.013	-1.055	-0.005	-0.027	-0.011	0.4071
ICT_USE	0.372*	13.464	0.096	0.799	0.207	0.2585
WHODISC	-0.145	-1.431	-0.021	-0.151	-0.023	0.151
INCDECPN	0.031	1.425	0.031	0.035	0.026	0.929
EDU_REC	0.161*	5.394	0.026	0.344	0.055	0.1597
EMPLOY_REC	0.239*	7.690	0.022	0.512	0.046	0.0899
AGE_REC	0.118**	2.029	0.128	0.252	0.275	1.0899
GENDER_REC	-0.238*	-43.537	-0.116	-0.510	-0.249	0.4877
DISAB_SUP	0.027	2.791	0.004	0.059	0.009	0.1443
REMOTE_REC	-0.062***	-1.736	-0.019	-0.133	-0.041	0.3102
ICT_USE*AT_COM_USE	0.007	0.464	0.001	0.015	0.002	0.1563
F-statistics			508.450*			
R-squared			0.503			
Number of observations			5028			

Note: *, ** and *** denote statistically significant at 1%, 5% and 10%, respectively.

References

1. Daniel RM, De Stavola BL, Cousens SN. gformula: Estimating causal effects in the presence of time-varying confounding or mediation using the g-computation formula. The Stata Journal. 2011;11(4):479-517.
2. Emsley R, Liu H. PARAMED: Stata module to perform causal mediation analysis using parametric regression models. 2013.
3. Imai K, Keele L, Tingley D. A general approach to causal mediation analysis. Psychological Methods. 2010;15(4):309-35.
4. Valeri L, VanderWeele TJ. Mediation analysis allowing for exposure–mediator interactions and causal interpretation: theoretical assumptions and implementation with SAS and SPSS macros. Psychological Methods. 2013;18(2):137-50.
5. VanderWeele TJ, Vansteelandt S. Conceptual issues concerning mediation, interventions and composition. Statistics and Its Interface. 2009;2(4):457-68.
6. Baron RM, Kenny DA. The moderator-mediator variable distinction in social psychological research. Conceptual, strategic, and statistical considerations. Journal of Personality and Social Psychology. 1986;51(6):1173-82.
7. Hayes AF, Rockwood NJ. Regression-based statistical mediation and moderation analysis in clinical research: Observations, recommendations, and implementation. Behaviour Research and Therapy. 2017;98:39-57.

Appendix B

Paper 1

An empirical investigation of the relationship between e-government development and the digital economy: the case of Asian countries

Mohammad Afshar Ali, Md. Rakibul Hoque and Khorshed Alam

Mohammad Afshar Ali is based at the Faculty of Business, Education, Law and Arts, University of Southern Queensland, Toowoomba, Australia. Md. Rakibul Hoque is based at the Department of Management Information Systems, University of Dhaka, Dhaka, Bangladesh. Khorshed Alam is based at the Faculty of Business, Education, Law and Arts, University of Southern Queensland, Toowoomba, Australia.

Abstract

Purpose – *This paper aims to investigate and comprehend the nature of the relationship between e-government development and the digital economy.*

Design/methodology/approach – *A multidimensional research paradigm is developed on the basis of the technology adoption model and Fountain's technology enactment theory. The model is empirically examined using a regional study of 20 Asian countries.*

Findings – *A positive two-way relationship between e-government development and the digital economy has been indicated by the findings. Moreover, along with social, economic, political, technological and demographic factors, certain national cultural characteristics have significant effects on the digital economy and e-government development.*

Research limitations/implications – *One of the key limitations of the study is that it is based on publicly available secondary data. Therefore, some degree of caution should be kept in mind when making generalisations about the findings of this study.*

Originality/value – *The contribution of this study is that it provides a more accurate and comprehensive understanding of the dynamic association between e-government development and the digital economy by providing aid to policymakers in understanding the nature of dynamic relationships between the digital economy, government organisations and citizens' adoption of technologies.*

Keywords *Asian countries, Digital economy, E-government development, Multidimensional approach, Technology adoption model*

Paper type *Research paper*

1. Introduction

In present times, digital economy pervades insurmountable prospects for world economy, influencing different sectors such as energy, banking, retail, publishing, transportation, education, health and media (OECD, 2015; World Bank, 2016). Social interactions and personal relationships are now going through a dynamic transformation by means of information and communications technologies (ICTs). In short, the term "digital economy" indicates an economy empowered by digital technologies (Alam *et al.*, 2018; Tapscott, 1997), and it is now regarded as one of the most important catalysts of economic growth (Brynjolfsson and McAfee, 2011; Mohamed *et al.*, 2010). According to a recent study, it is estimated that 22.5 per cent of the global gross domestic product (GDP) can be attributed to the digital economy, that is, some form of digital skills, capital, goods or services (Knickrehm *et al.*, 2015).

Received 18 October 2017
Revised 11 December 2017
8 January 2018
Accepted 9 January 2018

Paper 2

Economic Analysis and Policy 68 (2020) 163–174

Contents lists available at ScienceDirect

Economic Analysis and Policy

journal homepage: www.elsevier.com/locate/eap

Recent trends in economic research

Does ICT maturity catalyse economic development? Evidence from a panel data estimation approach in OECD countries

Mohammad Afshar Ali [a,b,c,*], Khorshed Alam [a,b], Brad Taylor [d], Shuddhasattwa Rafiq [e]

[a] School of Commerce, Faculty of Business, Education, Law & Arts, University of Southern Queensland, Toowoomba, Australia
[b] Centre for Health Research, University of Southern Queensland, Toowoomba, Australia
[c] Department of Economics, Jagannath University, Dhaka, Bangladesh
[d] School of Commerce, Faculty of Business, Education, Law & Arts, University of Southern Queensland, Springfield, Australia
[e] Faculty of Business and Law, BL Deakin Business School, Deakin University, Melbourne, Australia

ARTICLE INFO

Article history:
Received 10 February 2020
Received in revised form 6 September 2020
Accepted 7 September 2020
Available online 11 September 2020

Keywords:
Economic development
Panel data
ICT maturity
Information and communication technology
OECD

ABSTRACT

To date, definitions of information and communication technology (ICT) development used in quantitative studies on the relationship between economic development and ICT are incomplete and often based on single indicators. Thus, this study investigates the link between ICT maturity and economic development in the Organisation of Economic Cooperation and Development (OECD) countries. A novel composite index of ICT maturity that includes previously neglected dimensions of ICT maturity, such as affordability and quality of internet connectivity, is utilised. The baseline estimations using the feasible generalised least squares indicate that ICT maturity is associated with an increase in economic development by 1%–3.8% in OECD countries. These findings have been cross-validated by applying the generalised method of moments estimation. Results imply that the holistic development of ICT, including infrastructure, skills, and affordability, can augment economic development.

1. Introduction

Many empirical studies have confirmed that information and communication technology (ICT) can play a significant role in the socio-economic development of a nation (Asongu and Le Roux, 2017; Ferrigno-Stack et al., 2003; Obijiofor, 2009). Consequently, the governments of developed and developing countries have greatly invested in the development and diffusion of ICTs (Ali et al., 2020a). Undoubtedly, ICT is a major catalyst for economic development. However, the nexus between ICT and economic development has been the subject of much debate. Some researchers are optimistic about the role of ICT in development (Palvia et al., 2018), whereas others suggest that ICT alone will not lead to economic development unless accompanied by social changes and other complementary factors (Morales–Gómez and Melesse, 1998). Thus, the literature is inconclusive on whether ICT is a significant driver of economic development. Importantly, some scholars have argued that the definitions used to measure ICT maturity in the literature are not comprehensive (Baller et al., 2016; Sridhar and Sridhar, 2008). Therefore, the assessment of ICT's contribution to economic development might be flawed.

* Corresponding author at: School of Commerce, Faculty of Business, Education, Law & Arts, University of Southern Queensland, Toowoomba, Australia.
E-mail addresses: MohammadAfshar.Ali@usq.edu.au (M.A. Ali), Khorshed.Alam@usq.edu.au (K. Alam), Brad.Taylor@usq.edu.au (B. Taylor), srafiq@deakin.edu.au (S. Rafiq).

https://doi.org/10.1016/j.eap.2020.09.003

Paper 3

THE INFORMATION SOCIETY
https://doi.org/10.1080/01972243.2019.1702601

Routledge
Taylor & Francis Group

Check for updates

Incorporating affordability, efficiency, and quality in the ICT development index: Implications for index building and ICT policymaking

Mohammad Afshar Ali[a,b], Khorshed Alam[a], and Brad Taylor[c]

[a]School of Commerce, University of Queensland, Toowoomba, Australia; [b]Department of Economics, Jagannath University, Dhaka, Bangladesh; [c]School of Commerce, University of Southern Queensland, Springfield, Australia

ABSTRACT

International Telecommunication Union's ICT Development Index and related measures of a country's ICT development maturity suffer from several limitations, including subjective estimation of the weights of individual indicators and sub-indices, use of inappropriate quantitative models, specification bias arising from the exclusion of potential predictors from the estimation models, and a failure to capture the disparities among different groups of countries. To overcome these problems and provide a more reliable measure of ICT development, this study develops the Modified ICT Maturity Level Index using the 2015 data of 166 countries. This index adds affordability, efficiency, and quality to the existing sub-indices of access, use, and skills. Sub-index and indicator weights are determined in an outcome-orientated way using Partial Least Squares Structural Equation Modeling. We find that affordability, quality, and efficiency significantly explain the variation in the level of maturity of ICT development in addition to the previously used dimensions of International Telecommunication Union's ICT Development Index and modified ICT Development Index (mIDI) developed by Gerpott and Ahmadi, and that their explanatory power differ by a country's level of economic development. The new index produces significantly different country rankings. This has important implications for ICT policy priorities and provides a measure of ICT development maturity less prone to the innocent or intentional distortion of such policy priorities.

ARTICLE HISTORY
Received 9 October 2018
Accepted 24 November 2019

KEYWORDS
Economic development; ICT Development Index; information and communication technology; quantitative model

Introduction

Information and communication technology (ICT) plays a significant role in economic growth and socio-economic development (Dimelis and Papaioannou 2011, Ihm and Hsieh 2015, Polikanov and Abramova 2003, Shahiduzzaman and Alam 2014), which has prompted the development of a number of indices for a country's ICT development maturity (Billon, Lera-Lopez, and Marco 2010, Bruno et al. 2011, ITU 2009, Barzilai-Nahon 2006, Waverman, Dasgupta, and Rajala 2011). The most notable of these is International Telecommunication Union's (ITU) ICT Development Index (IDI), which was first published in 2009. This annually updated index comprises of 11 indicators grouped in three sub-indices, namely ICT access (5 indicators), ICT use (3 indicators), and ICT skills (3 indicators) (ITU 2013).

The IDI and other existing ICT indices have a number of pitfalls. Firstly, subjective estimation of the weights of individual indicators and sub-indices can yield flawed results as they depend on the judgment of the index builder. Secondly, the existing computational technique behind the index fails to determine the explanatory power of the index, since it is not tied to any socioeconomic outcome variable such as national income or growth. As a result, in the case of IDI, we cannot be sure that IDI scores reflect socioeconomically meaningful differences in ICT maturity at the country level. Thirdly, the process of selecting an indicator may lead to specification bias since issues such as affordability, quality of ICT services, and efficiency of telecommunication sector are not considered.

These pitfalls ill-inform the formulation of policies. When we correct for them, we find that the weighting of the dimensions and indicators of ICT maturity change significantly. Correspondingly, many countries move up or down the rankings significantly, and

CONTACT Mohammad Afshar Ali MohammadAfshar.Ali@usq.edu.au School of Commerce, Faculty of Business, Education, Law & Arts, University of Southern Queensland, T Block, Room No. T230, 487-535 West Street, Toowoomba, Queensland 4350, Australia.

Supplemental data for this article is available online at https://doi.org/10.1080/01972243.2019.1702601