Received: 6 May 2024 | Accepted: 22 July 2024

DOI: 10.1111/aphw.12584

ORIGINAL ARTICLE

APPLIED PSYCHOLOGY: Health and Well-Being IAAP

Socio-demographic factors and mental health trajectories in Australian children and primary carers: Implications for policy and intervention using latent class analysis

Nahida Afroz[1,2] | Enamul Kabir[2] | Khorshed Alam[3]

[1]Department of Statistics, Faculty of Science, Comilla University, Cumilla, Bangladesh

[2]School of Mathematics, Physics, and Computing, Faculty of Health, Engineering and Sciences, University of Southern Queensland, Toowoomba, Queensland, Australia

[3]School of Business, Faculty of Business, Education, Law & Arts, University of Southern Queensland, Toowoomba, Queensland, Australia

Correspondence
Nahida Afroz, Department of Statistics, Faculty of Science, Comilla University, Cumilla-3506, Bangladesh.
Email: n.afroz@cou.ac.bd

Funding information
This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Abstract

Children's mental health status (MHS) is frequently influenced by their primary carers (PCs), underscoring the significance of monitoring disparities longitudinally. This research investigated the association between socio-demographic clusters and mental health trajectories among children and their PCs over time. Data from waves 6-9c2 of the Longitudinal Study of Australian Children (LSAC) were analyzed using Latent Class Analysis (LCA) to identify four socio-demographic classes among children aged 10–11 years at wave 6. Multinomial logistic regression and predictive marginal analysis explored associations between classes and mental health outcomes. PCs in Class 4 (disadvantaged and separated families with indigenous children) exhibited higher odds of borderline and abnormal MHS compared to Class 1 (prosperous and stable working families) across all waves. However, while MHS of PCs' impacted children consistently, the association with socio-demographic classes was significant only in wave 6. Class 4 children had elevated risks of mental illness compared to Class 1, while Class 3, characterized by educated working mothers, had lower risks. Reducing mental health risks entails addressing socio-economic disparities, supporting stable family structures, and offering tailored interventions like counseling and co-parenting support. Longitudinal monitoring and culturally sensitive approaches are crucial for promoting mental well-being across diverse groups.

KEYWORDS

Children and primary carer, Kessler depression scale summed score, latent class analysis, longitudinal Study of Australian Children, socio-demographic factors, strengths and difficulties questionnaire score

INTRODUCTION

Mental illness disrupts behavior, emotion regulation, and thought processes, impacting individuals, families, and society with detrimental effects (Davies, 2013; World Health Organization 2022). Young people's mental health strongly influences their overall sense of well-being, life satisfaction, education, employment, and future prospects (Christensen et al., 2017). Around 22% of Australians aged 16–85 reported mental illness in 2020–2022 (Australian Institute of Health and Welfare (AIHW), 2024a), while 10–20% of children and adolescents in developed countries experience internalizing and externalizing issues (A. J. K. Bayer & Obioha, 2011; J. K. Bayer et al., 2012; Lawrence & Johnson, 2015). Australia, along with other prosperous nations, confronts a substantial mental health burden (Rehm & Shield, 2019; Whiteford et al., 2013), urging targeted interventions to identify high-risk groups. Categorizing based on socio-demographic factors is vital for targeted health policies, aiding effective implementation. Factors such as age, location, gender, parental education, income, and indigenous background predict mental health status (MHS) and psychological distress in youth (Australian Institute of Health and Welfare (AIHW), 2024b; Magklara et al., 2015; Robert et al., 1997). Children and adolescents in low-income households face heightened mental health risks (Reiss, 2013), with family structure significantly influencing their well-being (Park & Lee, 2020). Parental separation, indicative of non-intact families, is associated with increased mental health challenges (Brown, 2004; Karhina et al., 2023; Lenciauskiene & Zaborskis, 2008). Previous studies often analyzed socioeconomic and demographic factors individually. Bronfenbrenner's ecological systems theory emphasizes the influence of various environmental levels, from immediate family to broader societal contexts, on child development (Paquette & Ryan, 2001). Instead of analyzing individual socio-demographic factors separately, a recent study used Latent Class Analysis (LCA) to identify socio-demographic clusters and their association with mental disorders in children and adolescents (Afroz et al., 2023). However, limited to one-time cross-sectional data, it hampers understanding of mental health and socio-demographic dynamics over time, potentially overlooking crucial developmental trajectories.

The short and long-term consequences of mental disorders can affect the mental well-being of the next generations (Patel et al., 2007). Longitudinal analyses offer a deeper understanding of mental health patterns in children transitioning into adolescence. This study utilizes

Longitudinal Study of Australian Children (LSAC) data to provide a comprehensive view of MHS using updated socio-economic, demographic, and family structure information. Previous research, such as Motoc's work in the Longitudinal Ageing Study Amsterdam (LASA), has explored long-term associations between socioeconomic factors and mental health difficulties across multiple time points (Motoc et al., 2019). However, to the researcher's knowledge, no study has demonstrated a cluster-based relationship between socio-demographic characteristics and mental health problems using repeated measures from a nationally representative sample. Additionally, children with poor mental health are more likely to have parents experiencing mental health issues (Leone Huntsman, 2008; Slomian et al., 2019; Wickersham et al., 2024; Wolicki et al., 2022), highlighting the importance of tracking mental health disparities between children and primary carers (PC) over time.

According to the World Health Organization (WHO), globally one in seven individuals aged 10–19 years suffer from mental health issues (World Health Organization, 2022). A study by Telethon Kids Institute revealed that children aged 12–17 are nearly three times more likely than children aged 4–11 to experience severe mental disorders (TELETHON KIDS INSTITUTE, n.d.). Additionally, other studies have shown that mental health issues are typically less prevalent among children under the age of ten (Centers for Disease Control and Prevention, 2020; Lawrence et al., 2015). Consequently, several key research questions arise: What are the clusters of socio-demographic characteristics most accurately represent Australian children aged 10–11 years at wave 6? How do these socio-demographic clusters relate to the mental health status (MHS) and psychological distress of children in wave 6? How do the socio-demographic clusters identified at wave 6 relate to the mental health status and psychological distress of children across waves 7 (aged 12–13 years), 8 (aged 14–15 years), 9c1 (aged 16–17 years), and 9c2 (aged 17–18 years)? Do the socio-demographic clusters identified at wave 6 directly impact changes in children's mental health outcomes over time? How do these clusters affect the mental health outcomes of primary caregivers (PCs) across the different waves?

Based on these research questions, the objectives of this study are: to identify the clusters of items that most accurately depict the socio-demographic characteristics of Australian children (aged 10–11 years) at wave 6; to explore their relationship with the MHS and psychological distress of each group of children, and their PCs across various waves, including wave 6 (aged 10–11 years), 7 (aged 12–13 years), 8 (aged 14–15 years), 9c1 (aged 16–17 years), and 9c2 (aged 17–18 years to ascertain whether these clusters directly impact changes in children's and PCs mental health outcomes over time. The study also aims to highlight the policy implications of the findings by offering recommendations for targeted interventions, policy development, and resource allocation to address socio-economic disparities and enhance mental well-being among children and primary carers in Australia.

MATERIAL AND METHODS

Study sample and design

This study analyzed five waves of LSAC birth cohort data, spanning ages 10–18 years. LSAC, initiated in 2004, is a biennial survey capturing various aspects of Australian children's development and welfare (Edwards, 2014). The study utilizes multi-stage, stratified, and clustered

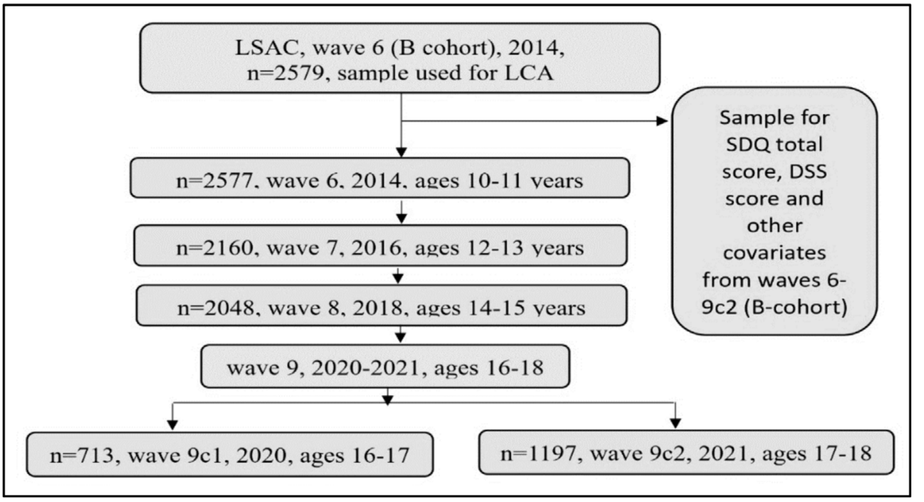

FIGURE 1 Data framework.

techniques to select participants, with households as primary units for selection. For further details on LSAC survey design and methodology, see Soloff et al. (2005).

This study used LCA on 2,579 children aged 10–11 years at wave 6 to identify socio-demographic clusters and then examined their relationship with MHS over time using the Strengths and Difficulties Questionnaire (SDQ) and Depression Scale Summed (DSS) scores for both children and their PCs. In the LSAC dataset, the PC of the children, referred to as Parent 1, is typically the biological mother, who is considered to know the child best (Australia et al., 2011). To measure the SDQ score for children and PC, and the DSS score for PC, samples were selected from waves 6 to 8, with sample sizes of 2,577, 2,160, and 2048, respectively. SDQ total scores were unavailable for children and PCs in waves 9c1 and 9c2, while DSS scores for children were unavailable prior to wave 9. The sample size for measuring the DSS score of the children in waves 9c1 and 9c2 was 713 and 1,197, respectively. Samples were selected, excluding missing values for the respective measures. The attrition of the sample, particularly evident in Wave 9, notably in Wave 9c1, which was collected in 2020 amid the COVID-19 pandemic, posed a significant challenge. During this period, responses to related questions experienced a substantial decline, possibly due to the disruptive effects of the pandemic on data collection efforts. Unfortunately, we did not estimate missing values, a limitation explicitly addressed in our study's limitations section. The entire data framework is shown in Figure 1.

Latent class analysis variables and measurements

The LCA utilized socio-demographic variables obtained from the 6th wave of the LSAC survey to delineate socio-demographic categories. These variables were selected from three distinct tiers: personal, household/family, and socio-economic/community levels. Additionally, this study employed the Strength and Difficulties Questionnaire (SDQ) total score and the Kessler Depression Scale summed (DSS) score to assess the MHS and psychological distress of children and their PCs across different waves. The mental health status of children in the LSAC data is assessed from Wave 6 (age 10–11 years) in the Birth cohort, recognizing this as a critical period for mental health development. Consequently, to measure mental health outcomes of children, the SDQ score was employed in waves 6–8, while the K10 DSS score was utilized in waves 9c1 and 9c2. For primary carers, mental health outcomes were determined using the SDQ score across all waves except waves 9c1 and 9c2, where the DSS score was employed throughout. Specifically, the K6 DSS score was applied in waves 6–8, while the K10 DSS score was utilized in waves 9c1 and 9c2. The K6 DSS score aggregates scores from six items, covering feelings of nervousness, hopelessness, restlessness, worthlessness, and others. In contrast, the K10 DSS score encompasses the same six items plus an additional four, providing a broader assessment of emotional states and behaviors. LSAC data used questions related to these 10 items to assess psychological distress in waves 9c1 and 9c2 for both children and primary carers. As only six items were available for calculating the DSS total score before wave 9 for primary caregivers, the K6 DSS score was employed during those waves. From wave 9c1 onwards, the expanded K10 DSS score was introduced to offer a more comprehensive evaluation of psychological distress.

According to the SDQ scoring guide (SDQinfo, 2016; Woerner et al., 2004), SDQ scores range from 0 to 40, while the Australian Bureau of Statistics (ABS) (Australian Bureau of Statistics, 2012) specifies that K6 and K10 DSS scores range from 6 to 30 and 10 to 50, respectively. The details of the latent class variables and the measurements used are summarized in Table 1.

The parental separation status in this study denotes the family structure of the respective household. When parents are separated, it signifies a non-intact family structure (Weston et al., 2013), which is associated with perceptions of relatively poorer family functioning (Shek et al., 2015).

Statistical analysis

Latent class analysis (LCA)

Our research intends to identify sociodemographic classes at a single time point (wave 6) and investigate their relationship with mental health outcomes over subsequent waves. LCA is specifically designed for cross-sectional analysis and is particularly useful for identifying latent subgroups based on observed characteristics at a single time point. Unlike other models (Nguena Nguefack et al., 2020) that concentrate on modeling developmental paths throughout time, LCA captures socio-demographic profiles at a particular time point, offering a consistent and transparent foundation for investigating longitudinal connections. This method provides insightful information without making strict assumptions and is crucial for identifying distinct profiles within our dataset.

The LCA, performed with the poLCA package in R version 4.2.2, identified socio-demographic clusters for 2,579 children. LCA, an advanced clustering method increasingly used in social, psychological, and educational research, unveils underlying subgroups within diverse populations, illuminating heterogeneity in observed data (Collins & Lanza, 2010; Depaire et al., 2008; Laska et al., 2009; Vermunt & Magidson, 2002a). It maximizes similarity within clusters while minimizing similarity across cluster members to identify homogeneous groups based on a variety of characteristics. LCA assumes that data originate from a mixed model with various probability distributions (Mohamed et al., 2013), segmented into exclusive subgroups by a latent variable. It's considered advantageous over traditional cluster analysis (Hair et al., 1998;

TABLE 1 Summary of latent class analysis variables and measurements.

Latent class variables		Categories/descriptions
Variables level	Variables	Categories/descriptions
Personal	Gender	Male, female
	Indigenous status	No, yes
	Main language spoken at home	English, non-English
Household/family	Number of individuals in the household	≤3, 4–6, ≥7
	Parental separation status	No, yes, never lived together
Socio-economic/ community	Remoteness	Highly accessible, accessible, moderately accessible, remote/very remote
	Mother's highest educational qualifications	University qualification, diploma/certificate, trade/ apprenticeship, year 12 or less
	Father's highest educational qualifications	University qualification, diploma/certificate, trade/ apprenticeship, year 12 or less
	Household income quantile	1st, 2nd, 3rd, 4th, 5th
	Socio-economic position (SEP)	Below average, average, above average
	Father's employment status	Employed, unemployed, not in the labor force
	Mother's employment status	Employed, unemployed, not in the labor force
Measurements		
SDQ score (ranges from 0 to 40) were used in waves 6–8 for both children and PCs		0–15: Normal, 16–19: Borderline, 20–40: Abnormal
K6 DSS score (ranges from 6 to 30) were used in waves 6–8 for PCs only		6–13: Normal, 14–19: Borderline, 20–30: Abnormal
K10 DSS score (ranges from 10 to 50) were used in waves 9c1-9c2 for both children and PCs		10–15: Normal, 16–29: Borderline, 30–50: Abnormal

Vermunt & Magidson, 2002b). Membership in subgroups was determined based on individual responses to behavioral questions, with all socio-demographic variables treated as categorical. An exploratory approach was used due to uncertainty in the number of latent classes, starting with a 1-class model and gradually adding more classes. This method closely examined item loadings and model fit indices for estimated latent classes (Vermunt, 2010). The final number of classes was determined based on the conceptual meaning, smallest estimated class proportions (Nylund et al., 2007), entropy, statistical model fit indices (Nylund et al., 2007), such as the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), G^2 (LR/deviance statistic) and log-likelihood. Latent classes with less than 5% of the total sample were not considered to avoid over-extraction (Bauer & Curran, 2003) and poor generalizability (William Holmes Finch et al., 2015). Clusters were named to reflect key findings in the data, aiding communication with audiences (Reedy et al., 2010). However, it's argued that labels may not fully convey differences across clusters. Each cluster's identifying traits were carefully considered for their naming, without intending to present them linearly.

Bivariate, multinomial logistic regression, and predictive marginal analysis

Following the identification of the required number of latent classes, several cross-tabulations and bivariate analyses were conducted to examine the distribution and associations of MHS and psychological distress among children and PCs with the identified classes. Multinomial logistic regressions were utilized to predict MHS and psychological distress, adjusting for housing tenure and general/global health of PC/study children. Significance was set at $p < 0.05$. Predictive marginal analysis was used to assess the influence of latent class variations on MHS probabilities comparing the estimated impacts on mental health outcomes for each class.

Ethical approval and consent

The Australian Institute of Family Studies Ethics Committee granted ethical approval for the LSAC study. The database was accessed by contacting the Longitudinal Study of Australian Children Dataverse of the National Centre for Longitudinal Data. Researchers are permitted to use this dataset in accordance with national regulations, provided that identifiable individual information is not present. Given that the secondary data used in this study did not contain identifiable information, consent for publication is not applicable.

RESULTS

Findings of the latent-class analysis

Clusters of socio-demographic variables from three distinct levels were identified for 2,579 children by using LCA and are displayed in Table 2.

The lower BIC and highest entropy values suggested a four-class model. The entropy of the 4-class model (0.653) exceeded the criteria for good class separation (i.e., entropy = 0.60 (Asparouhov & Muthén, 2014)) and was the highest among all estimated models. Thus, the four-class model was selected as the best-fitting model based on the entire dataset, even though the other indices decreased as the number of classes increased. The estimated item probabilities for the four latent classes are presented in Table 3, and the characteristics of these classes are summarized in Table 4.

Class-1 (prosperous and stable working families in affluent residential environments; 21.1%) comprises children with high maternal employment and the lowest parental separation. The majority of households exhibit above-average SEP, with income primarily falling within the top 4th and 5th quantiles, and a high proportion of residents live in highly accessible areas. Class-2 (employed but separated families in average socioeconomic environments; 50.9%) has the highest rate of parental separation. The majority of parents are employed but have lower education levels, with most households having an average SEP (92.3%) and 46% falling within the second quantile of household income. Compared to other classes, fewer residents live in highly accessible areas. Class 3 (highly educated workforce with family transitions) comprises 12.7% of the sample.

Most parents in this class have a high level of education, and the majority of fathers are employed. The second-highest percentage of households in this class have above-average

TABLE 2 Summary of latent class model identification and fit statistics.

No. of classes	AIC	BIC	G^2 (LR/deviance statistic)	Log-likelihood	Smallest class	Entropy
1	42606.2	42758.5	7669.9	−21277.1	-	-
2	41622.9	41933.2	6632.5	−20758.4	42.7%	0.593
3	41213.3	41681.7	6169.0	−20526.6	17.8%	0.594
4	40978.3	41604.8	5879.9	−20382.1	12.7%	0.653
5	40875.7	41660.3	5723.4	−20303.8	7.8%	0.641
6	40807.5	41650.2	5601.1	−20242.7	8.1%	0.642
7	40790.7	41491.5	5530.4	−20207.4	5.4%	0.632

socioeconomic positions and live in highly accessible areas. Children from underprivileged backgrounds were classified as Class-4 (disadvantaged and separated families with indigenous children; 15.2%), where most parents have the lowest level of education, and both parents have a low employment rate, with approximately 25% of parents being separated. The majority of households are in below-average socioeconomic positions, with none in the higher 4th or 5th quantiles. This class exhibits the lowest percentage of residents living in highly accessible areas, with around 4% of the children identified as Aboriginal/Torres Strait Islander, and over 20% speaking a non-English language at home.

Association of latent class membership with MHS and psychological distress of children and PC in various waves

A greater proportion of children and PC with mental health issues falling into borderline and abnormal categories were from Class 4 in waves 6–8, as depicted in Figures 2 and 3. This association is notably significant for PC across all waves (Figure 2 [a]) but for children in waves 6 and 8 only (Figure 3 [a]). Figures 2(b) and 3(b) show the relationship between latent class membership and the psychological distress of children and the PC as indicated by the DSS score. Class 4 PCs comprised a larger proportion of the sample, with their psychological distress falling into the borderline and abnormal categories across waves 6–9c2. This association remained significant for all waves except wave 7. Although there was a higher proportion of children in borderline and abnormal psychological distress categories across all classes in waves 9c1 and 9c2, no significant association was found between adolescents' psychological distress and their latent class membership.

Regression results

Table 5 depicts the results of multinomial logistic regressions exploring the associations between the predictors socio-demographic classes and the response variables MHS (measured by SDQ score) and psychological distress (measured by DSS score) while adjusting for covariates.

Compared to Class 1 (Prosperous and stable working families in affluent residential environments), children from disadvantaged and separated families with indigenous status (class 4)

TABLE 3 Probabilities of latent class membership in the four-class model.

Socio-demographic characteristics (wave 6)		Population proportion (weighted)	Class- 1 21.1% (n = 544)	Class-2 50.9% (n = 1,314)	Class-3 12.7% (n = 327)	Class-4 15.2% (n = 394)
Sex	Male	0.506	0.516	0.480	0.527	0.553
	Female	0.494	0.484	0.520	0.473	0.447
Indigenous status	No	0.977	0.993	0.980	0.995	0.959
	Yes (aboriginal/ Torres Strait islander)	0.023	0.008	0.020	0.005	0.041
Main language	English	0.895	0.926	0.980	0.926	0.795
	Not English	0.105	0.074	0.020	0.074	0.205
Remoteness	Highly accessible	0.543	0.773	0.363	0.669	0.492
	Accessible	0.264	0.171	0.364	0.215	0.242
	Moderate accessible	0.161	0.053	0.226	0.082	0.233
	Remote/very remote	0.032	0.003	0.047	0.033	0.033
Mothers' education	University qualification	0.098	0.037	0.045	0.579	0.040
	Diploma/ certificate	0.152	0.175	0.158	0.373	0.057
	Trade/ apprenticeship	0.049	0.025	0.068	0.048	0.026
	Year 12 or less	0.701	0.763	0.728	0.000	0.876
Fathers' education	University qualification	0.169	0.211	0.061	0.799	0.088
	Diploma/ certificate	0.078	0.106	0.076	0.124	0.041
	Trade/ apprenticeship	0.222	0.177	0.306	0.060	0.165
	Year 12 or less	0.532	0.506	0.558	0.018	0.705
Household income quantile	1st quantile	0.181	0.000	0.084	0.128	0.587
	2nd quantile	0.284	0.062	0.460	0.163	0.171
	3rd quantile	0.236	0.247	0.232	0.216	0.242
	4th quantile	0.298	0.686	0.224	0.494	0.000
	5th quantile	0.001	0.005	0.000	0.000	0.000
Socio-economic position	Below average SEP	0.122	0.000	0.036	0.000	0.409
	Average SEP	0.682	0.327	0.923	0.566	0.583
	Above average SEP	0.196	0.673	0.041	0.435	0.008

(Continues)

TABLE 3 (Continued)

Socio-demographic characteristics (wave 6)		Population proportion (weighted)	Class- 1 21.1% (n = 544)	Class-2 50.9% (n = 1,314)	Class-3 12.7% (n = 327)	Class-4 15.2% (n = 394)
Parents separation	No	0.756	0.819	0.735	0.760	0.744
	Yes	0.242	0.182	0.263	0.236	0.251
	Never lived together	0.002	0.000	0.002	0.004	0.004
Fathers' employment status	Employed	0.928	0.974	0.985	0.973	0.762
	Unemployed	0.019	0.007	0.006	0.000	0.061
	Not in labor force	0.052	0.019	0.009	0.027	0.178
Mothers' employment status	Employed	0.782	0.886	0.880	0.754	0.538
	Unemployed	0.022	0.014	0.015	0.030	0.040
	Not in labor force	0.196	0.100	0.106	0.216	0.422
No. people in household	Less than or equal 3	0.059	0.049	0.051	0.075	0.053
	4 to 6	0.884	0.925	0.904	0.878	0.839
	Greater or equal 7	0.058	0.026	0.046	0.047	0.108

Class-1: Prosperous and stable working families in affluent residential environments; **Class-2:** Working Families with varied SES and living environments; **Class-3:** Educated working moms in diverse socio-environments; **Class-4:** Disadvantaged and separated families with indigenous children.

TABLE 4 Identified latent classes and their characteristics.

Classes	Descriptions	Key characteristics
Class 1 (21.1%)	Prosperous and stable working families in affluent residential environments	High maternal employment, lowest parental separation, above-average SEP, affluent areas
Class 2 (50.9%)	Employed but separated families in average socioeconomic environments	High parental separation, employed parents, average SEP, fewer residents in highly accessible areas
Class 3 (12.7%)	Highly educated workforce with family transitions	High parental education, employed fathers, second-highest percentage of households with above-average SEP, and live in highly accessible areas
Class 4 (15.2%)	Disadvantaged and separated families with indigenous children	Lowest parental education and employment, high parental separation, below-average SEP, remote areas, higher indigenous status

were 1.75 and 1.99 times more likely to fall into the borderline (95% CI = 1.12–2.73) and abnormal (95% CI = 1.17–3.40) levels of MHS (measured by SDQ score), respectively, in Wave 6. In contrast, children in Class 3, characterized by a highly educated workforce with family transitions, showed lower odds (OR: 0.44, 95% CI: 0.19–1.02 in wave 6 (for SDQ score); OR: 0.59, 95%

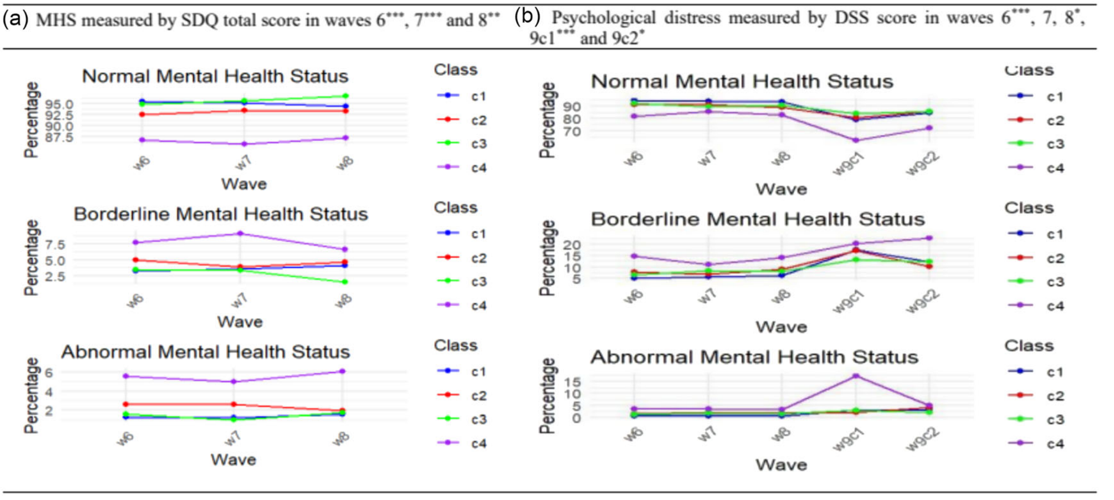

FIGURE 2 Association of primary carer MHS/psychological distress and latent class membership. *Note*: MHS-Mental Health Status; DSS-Depression Scaled Summed Score; w6-wave 6; w7-wave 7; w8-wave 8; w9c1-wave 9c1; w9c2-wave 9c2; c1-class 1; c2-class 2; c3-class 3; c4-class 4. Significant association are shown by superscript with *, where * for p<0.05; ** for p<0.01; *** for p<0.001.

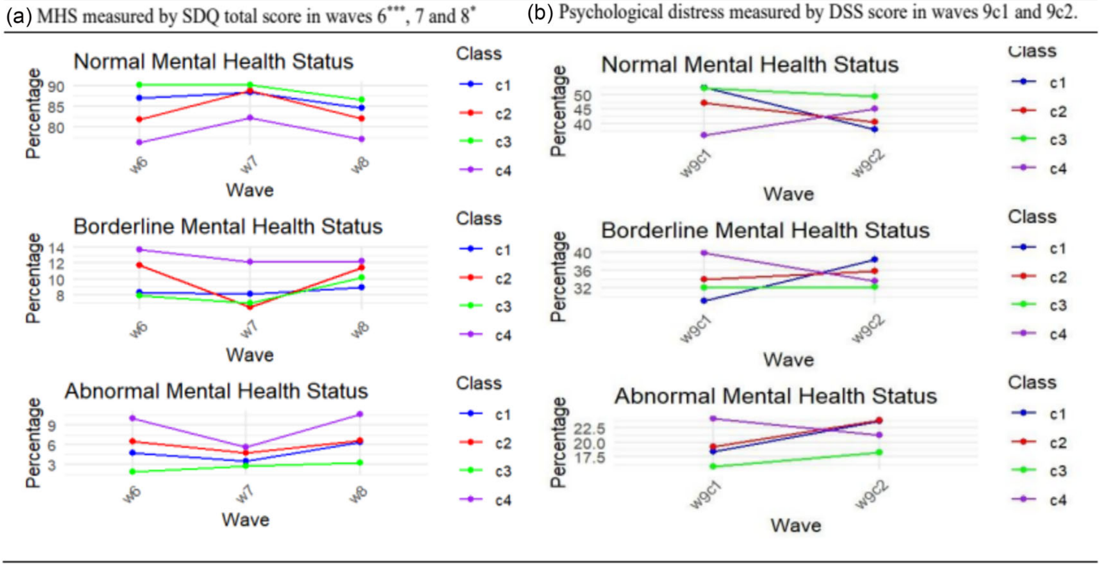

FIGURE 3 Association of children's MHS/psychological distress and latent class membership.

CI:0.35–0.98 in wave 9c2 (for DSS score)) of being classified as having an abnormal level of MHS or psychological distress.

Conversely, PCs in Class 4 demonstrated higher odds of being categorized as having borderline (W6, OR:2.36, 95%CI:1.25–4.45; W7, OR: 2.92, 95%CI: 1.50–5.67) and abnormal levels (W6, OR:4.18, 95%CI:1.82–9.54; W7, OR:3.02, 95%CI: 1.18–7.73; W8, OR: 3.28, 95%CI:1.37–7.84) of psychological distress (measured by DSS score) in waves 6–8 (except for the borderline level in

TABLE 5 Model estimates predicting mental health outcomes (measured by SDQ and DSS score) of waves 6-9c2.

			Class 1 (ref.) Normal (ref.)	Class 2 OR (95% CI)	Class 3 OR (95% CI)	Class 4 OR (95% CI)
MHS measured by SDQ score	Children	Model 1 W6	Border line	1.47 (1.02–2.10)	1.08 (0.65–1.78)	1.75** (1.12-2.73)
			Abnormal	1.25 (0.79–1.99)	0.44* (0.19-1.02)	1.99** (1.17-3.40)
		Model 2 W7	Border line	0.80 (0.53–1.20)	0.77 (0.43–1.37)	1.25 (0.75–2.07)
			Abnormal	1.06 (0.62–1.83)	0.79 (0.35–1.77)	1.36 (0.68–2.71)
		Model 3 W8	Border line	1.20 (0.82–1.76)	1.19 (0.72–1.95)	1.46 (0.90–2.35)
			Abnormal	1.04 (0.66–1.63)	0.50 (0.23–1.08)	1.60 (0.92–2.778)
	Primary carers	Model 4 W6	Border line	1.58 (0.90–2.76)	1.01 (0.45–2.26)	2.36*** (1.25-4.45)
			Abnormal	1.80 (0.83–3.92)	1.06 (0.34–3.26)	4.18*** (1.82–9.54)
		Model 5 W7	Border line	1.07 (0.58–1.96)	1.16 (0.51–2.63)	2.92*** (1.50-5.67)
			Abnormal	1.71 (0.74–3.96)	0.75 (0.19–2.93)	3.02** (1.18-7.73)
		Model 6 W8	Border line	1.08 (0.62–1.90)	0.46 (0.17–1.25)	1.65 (0.82–3.32)
			Abnormal	1.22 (0.54–2.76)	0.79 (0.23–2.65)	3.28** (1.37–7.84)
Psychological distress measured DSS score	Adolescents	Model 1 W9c1	Border line	1.11 (0.74–1.67)	1.01 (0.60–1.72)	1.31 (0.70–2.46)
			Abnormal	0.94 (0.57–1.55)	1.00 (0.52–1.90)	1.19 (0.56–2.53)

TABLE 5 (Continued)

		Class 1 (ref.) Normal (ref.)	Class 2 OR (95% CI)	Class 3 OR (95% CI)	Class 4 OR (95% CI)
	Model 2 W9c2	Border line	1.01 (0.72–1.01)	0.71 (0.46–1.10)	0.85 (0.54–1.35)
		Abnormal	0.96 (0.66–1.41)	0.59* (0.35–0.98)	0.67 (0.39–1.16)
Primary cares	Model 3 W6	Border line	1.44 (0.92–2.25)	1.21 (0.65–2.22)	2.86*** (1.74–4.70)
		Abnormal	1.22 (0.44–3.39)	1.29 (0.34–4.86)	3.21** (1.10–9.33)
	Model 4 W7	Border line	1.11 (0.71–1.73)	1.29 (0.72–2.32)	1.71* (1.01–2.92)
		Abnormal	2.03 (0.69–5.99)	2.07 (0.55–7.86)	2.57 (0.75–8.75)
	Model 5 W8	Border line	1.43 (0.3–2.20)	1.02 (0.52–1.85)	1.93* (1.14–3.27)
		Abnormal	1.82 (0.61–5.41)	1.63 (0.40–6.57)	3.34* (0.99–11.34)
	Model 6 W9c1	Border line	0.97 (0.59–1.59)	0.96 (0.50–1.84)	1.15 (0.55–2.40)
		Abnormal	0.75 (0.24–2.38)	0.98 (0.23–4.27)	4.05* (1.26–13.08)
	Model 7 W9c2	Border line	0.90 (0.59–1.37)	0.91 (0.52–1.58)	1.94** (1.16-3.25)
		Abnormal	1.08 (0.48–2.42)	0.85 (0.28–2.60)	1.97 (0.74–5.27)

Note: OR-Odds ratio; CI-Confidence interval.

*:p < 0.05, **:p < 0.01, and ***:p < 0.001; Adjusted variables: PCs' general health/global health and housing tenure; Children's global health measure for wave 9c1 and 9c2.

Wave 8). In addition, the DSS score of psychological distress of PC showed similar results as the SDQ score in all waves including waves 9c1 and 9c2, with an exception for abnormal level in wave 7.

Using the probability scale, this study examines the marginal effects shown in Figures 4 and 5 to compare all classes with each other, as the odds ratio (OR) only permits comparisons with the reference group. Children (SC_W6_SDQ, SC_W7_SDQ, SC_W8_SDQ, SC_W9c1_DSS), and PCs (PC_W6_SDQ, PC_W7_SDQ, and PC_W8_SDQ in Figure 4; PC_W6_DSS, PC_W7_DSS, PC_W8_DSS, PC_W9c1_DSS, and PC_W9c2_DSS in Figure 5) in Classes 1 and 3 are more likely to fall within the normal level of MHS and psychological distress across all waves (in Figures 4 and 5), except wave 9c2 (SC_W9c2_DSS) for children as illustrated in Figure 5.

The DSS scores of children in Classes 3 and 4 in wave 9c2 indicate a higher tendency toward borderline or abnormal levels of psychological distress, but the association lacks significance.

Conversely, children in Classes 2 and 4 show higher probabilities of borderline or abnormal MHS compared to Classes 1 and 3 during waves 6–8 (Figure 4). Similarly, the SDQ (Figure 4) and DSS (Figure 5) scores of PCs in Classes 2 and 4 consistently demonstrate similar trends across waves 6-9c2, indicating an increased likelihood of falling within borderline or abnormal categories.

DISCUSSION

This study identified socio-demographic clusters among Australian children aged 10–11 and their association with MHS and psychological distress over time using LSAC data from Waves 6-9c2, exploring their impact on both children and PCs. Findings illuminate socio-demographic diversity among Australian children and their PCs, revealing associations with psychological distress and mental health across different socioeconomic and demographic variables (Afroz et al., 2023; Hashmi et al., 2021; Pandia et al., 2021; Shek et al., 2015).

LCA identified four socio-demographic classes, with their association with mental health outcomes analyzed through multinomial logistic regression. Children from disadvantaged and separated families with indigenous status (Class 4), exhibited higher odds of falling into the borderline and abnormal categories of MHS than those in Class 1 (prosperous and stable working families in affluent residential environments) in wave 6 only. However, children in Class 3 (highest parental education, no households in below average SEP) in waves 6 and 9c2 have lower odds of abnormal levels of MHS and psychological distress than Class 1. This supports past findings that children from better socioeconomic backgrounds and higher parental education often have better mental health outcomes (Reiss, 2013; Xiang et al., 2024). Conversely, PCs (in more than 95% of cases, the mother is the PC (Study et al., 2013)), from disadvantaged backgrounds (Class 4) had significantly higher SDQ and DSS scores in waves 6–8 and 6-9c2, respectively, indicating borderline or abnormal levels of MHS and psychological distress compared to Class 1. Children in waves other than 6 and 9c2 lack a significant relationship between their MHS and latent class membership, but this does not imply lower SDQ or DSS scores in those waves. Across all waves and most classes, children consistently demonstrate higher scores in borderline and abnormal categories than in PCs (Figure 6). While no class-wise MHS variation is observed in waves 7-9c1, Classes 2 and 4 consistently display higher scores in borderline and abnormal categories in each wave. Class 4, the underprivileged group, has parents with low education and employment, a high rate of parental separation, and more indigenous children. Additionally, most households in this class have below-average SEP, with the highest income proportion in the 1st quantile, and fewer residents living in highly accessible areas. In past studies (Compton et al., 2019; Hashmi et al., 2021) individuals from lower socioeconomic backgrounds, experiencing unemployment, residing in remote areas, or possessing lower education levels, are negatively associated with mental illness, which is consistent with our current study. Moreover, compared to intact families (two-parent households), non-intact families (single-

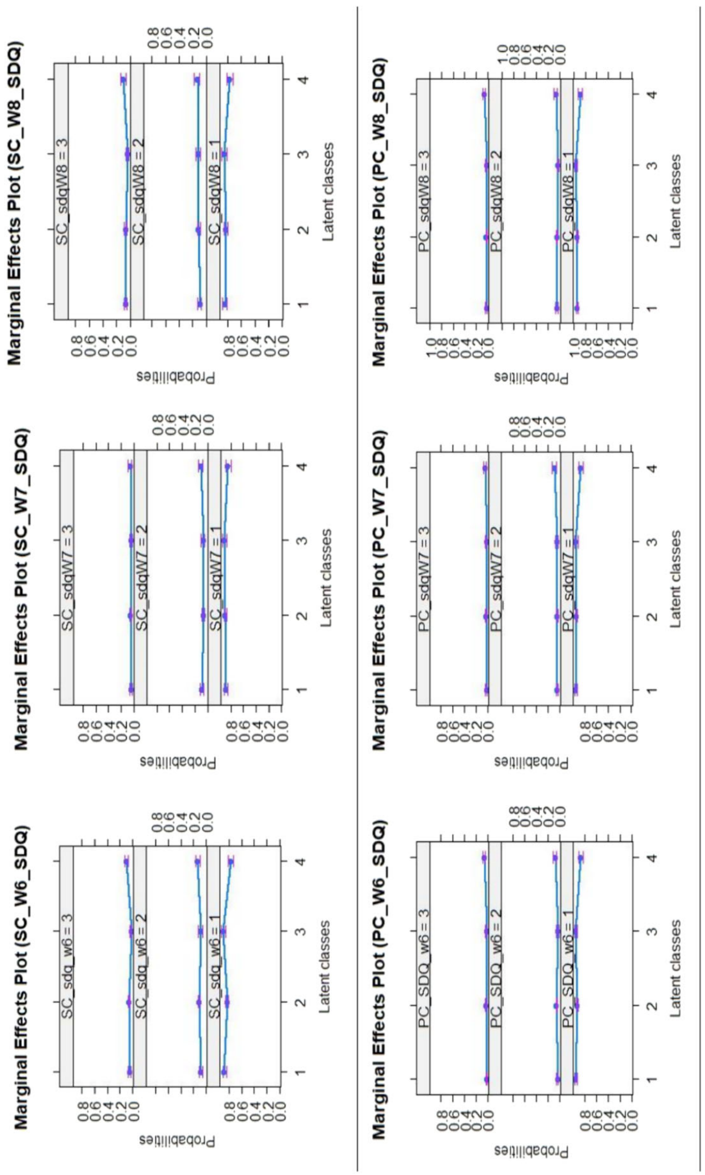

FIGURE 4 Marginal plot of MHS (measured by SDQ score). *Note*: Primary carer (PC) and Study child's (SC) SDQ score for various waves indicate value 1, 2 and 3 for normal, border line and abnormal category respectively; SC_W6_SDQ:SDQ score of SC in wave 6; PC_W6_SDQ: SDQ score of PC in wave 6.

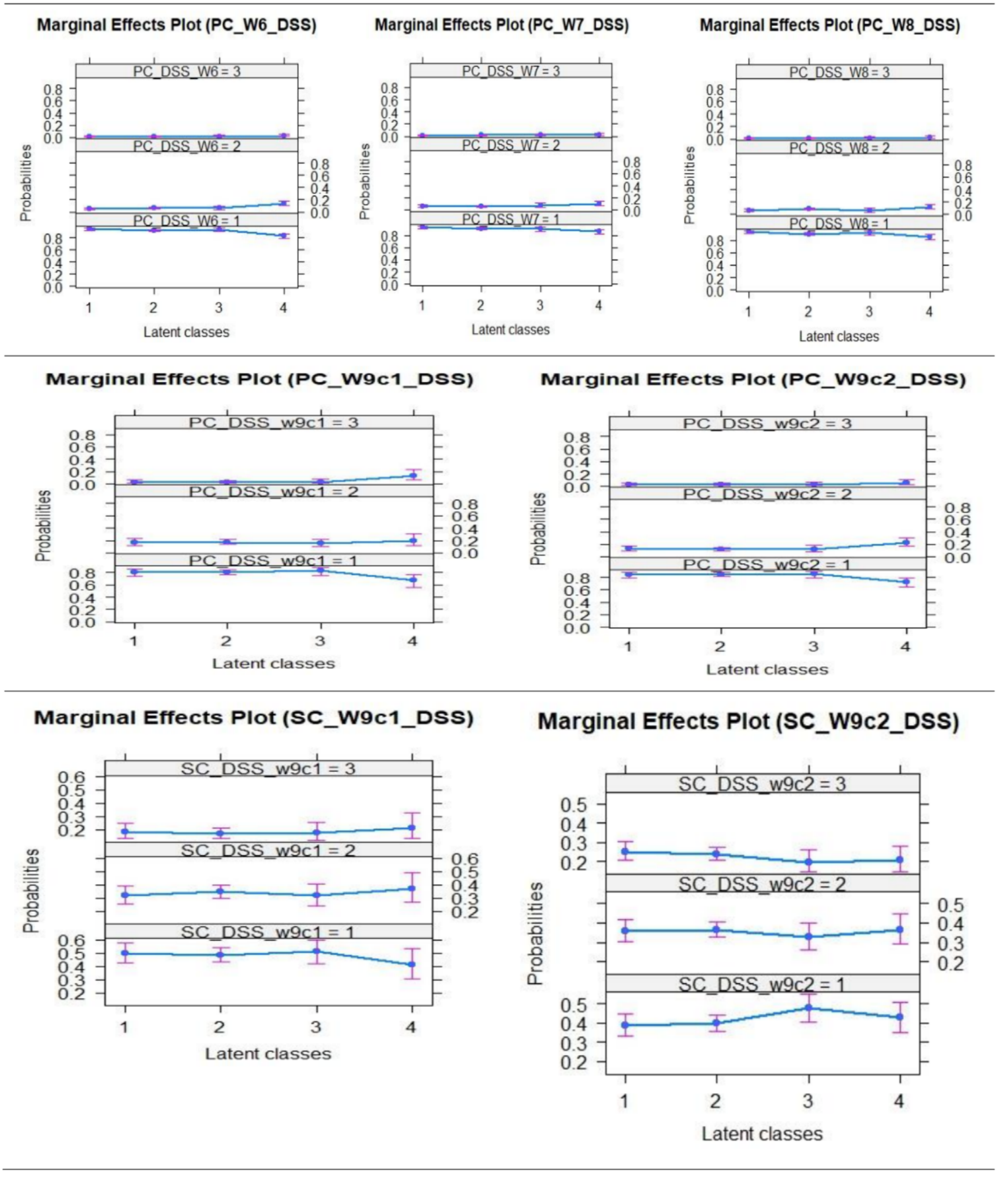

FIGURE 5 Marginal plot of psychological distress (measured by DSS score). *Note*: DSS scores for various waves of Primary Carer's (PC), including W6 to W9c2, and Study Child's (SC), including W9c1 to W9c2, indicate value 1, 2, and 3 for normal, borderline, and abnormal categories respectively; PC_W9c1_DSS: DSS score of PC in wave 9c1; SC_W9c1_DSS: DSS score of SC in wave 9c1.

parent and restructured families) had noticeably greater probabilities of mental health problems such as depression and psychological distress (Park & Lee, 2020). Furthermore, the Australian Institute of Health Service (AIHS) research states that Indigenous people have a higher

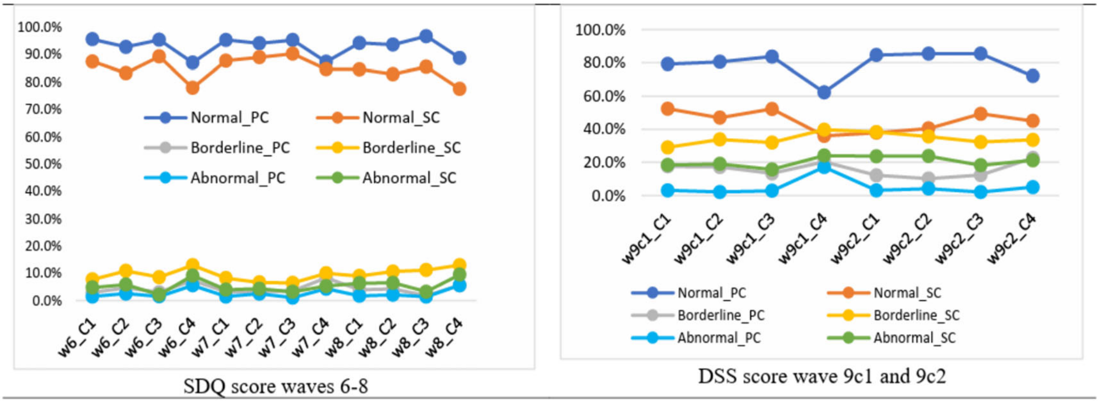

FIGURE 6 Relationship between various levels of MHS/psychological distress of PC and SC. *Note*: PC-primary carer; SC-Study child; w-wave, c1-class 1; c2-class 2; c3-class 3; c4-class 4.

prevalence of mental health problems compared to non-Indigenous Australians (Australian Institute of Health and Welfare (AIHW), 2024b).

The study also explored the marginal effects of the socio-demographic clusters on mental health outcomes that allow for a direct comparison of different classes without the limitation of needing a reference group. Children and PCs in Class 4 have a larger risk of experiencing borderline and abnormal MHS throughout all waves than those in Classes 1, 2, and 3, whereas Class 2 persons are more susceptible to such difficulties than those in Classes 1 and 3. This could be attributed to Class 2's high rate of parental separation, despite most households having average SEP. Parental separation often signifies a non-intact or restructured family structure. Shek et al. (2015) found that adolescents from intact families reported higher levels of parent–child relationship quality and family functioning than adolescents in separated or restructured families (Reiss et al., 2019; Shek et al., 2015). Conversely, in class 3, most parents possess the highest level of education, and no households fall below average socio-economic position. Consequently, adolescents belonging to Class 3 in wave 9c2 demonstrate a notably reduced probability of experiencing abnormal levels of MHS compared to those in Class 1. According to past study, children whose parents hold a university degree are more likely to exhibit enhanced positive mental health compared to children whose parents have non-university education (Padilla-Moledo et al., 2016). PCs in classes 2 and 4 across waves 6-9c2 show elevated risks of borderline and abnormal mental health issues. Children's MHS and distress levels varied with the level of their PC, as depicted in Figure 6, aligning with prior research (Wolicki et al., 2022), although notable class-wise disparities were observed in waves 6 and 9c2.

Policy implications

The study underscores the importance of targeting disadvantaged families through early interventions, such as counseling and co-parenting support, particularly for those facing high parental separation and low socioeconomic position (SEP). Enhancing access to mental health services, especially in remote areas, is crucial for timely intervention. Longitudinal monitoring through routine mental health screenings in schools and healthcare settings can provide ongoing support to vulnerable populations. Additionally, culturally sensitive interventions, including counseling in native languages and traditional healing practices, are essential for addressing mental health challenges in Indigenous communities. These measures are pivotal in mitigating socio-economic disparities and promoting mental well-being among children and primary carers in Australia.

Limitations

This study faces several limitations. Firstly, its reliance on LSAC data may introduce sampling bias, potentially excluding certain demographic groups and limiting the broader applicability of the findings. Secondly, self-reported measures used for assessing MHS and psychological distress may be susceptible to inaccuracies due to biases such as social desirability or recall errors. Thirdly, missing data in certain LSAC waves reduced sample sizes, impacting the robustness and generalizability of the results. Fourthly, the cross-sectional nature of some analyses restricts the ability to establish causal relationships between socio-demographic factors and mental health outcomes over time. Furthermore, while widely used, the SDQ and DSS scores may not fully capture the complexity of mental health issues, potentially overlooking nuances in diagnosis and severity. Fifthly, the study may not fully consider the intricate interactions between socio-demographic variables, possibly overlooking important nuances in how these factors influence mental health outcomes. Lastly, while LCA provides valuable insights, its reliance on probabilistic class assignments introduces methodological limitations, as accurate categorization of individuals into classes cannot be guaranteed. Additionally, although LCA is effective for identifying socio-demographic classes at a single time point and provides a clear basis for examining their longitudinal associations with mental health outcomes, it does not fully exploit the longitudinal nature of the dataset. Future research could extend this work by employing a variety of longitudinal methods to explore the evolution of these classes over time and their long-term impact on mental health outcomes.

CONCLUSIONS

The study identified socio-demographic classes and their impact on mental health outcomes over time. PCs' MHS was significantly associated with socio-demographic classes across time, with Class 4 (disadvantaged and separated families with indigenous children) and Class 2 (employed but separated families in average socioeconomic environments) showing higher odds of borderline and abnormal MHS compared to Class 1 (prosperous and stable working families in affluent residential environments). Though the MHS of PCs influenced children's mental health outcomes in all waves, a significant association between socio-demographic classes and children's mental health outcomes was evident in waves 6 and 9c2. In wave 6, class 4 children had higher odds of mental health issues compared to class 1, while class 3 (in waves 6 and 9c2) children, with educated working mothers, showed lower odds. The study emphasizes targeted interventions to address socio-economic disparities and support intact family structures, crucial for mitigating poor mental health outcomes among vulnerable populations. Understanding longitudinal socio-demographic trajectories is crucial to developing effective policies and interventions promoting mental well-being in children and families.

ACKNOWLEDGMENTS

The data used in this paper are drawn from Waves 6 to 9c2 of the Longitudinal Study of Australian Children (LSAC), which commenced in 2004. The authors extend their gratitude to the Australian Institute of Family Studies for granting access to the LSAC dataset. This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

CONFLICT OF INTEREST STATEMENT

The authors declare that they have no conflicts of interest to disclose.

DATA AVAILABILITY STATEMENT

Data used in this study can be accessed through contacting the Longitudinal Study of Australian Children Dataverse of the National Centre for Longitudinal Data, Australian Government Department of Social Services. One can also email ada@anu.edu.au requesting data access. The principal author was granted permission to the data through an online application from the following web link: https://growingupinaustralia.gov.au/data-and-documentation/accessing-lsac data.

ETHICS STATEMENT

The Australian Institute of Family Studies Ethics Committee granted ethical approval for the LSAC study. The database was accessed by contacting the Longitudinal Study of Australian Children Dataverse of the National Centre for Longitudinal Data. Researchers are permitted to use this dataset in accordance with national regulations, provided that identifiable individual information is not present. Given that the secondary data used in this study did not contain identifiable information, consent for publication is not applicable.

ORCID

Nahida Afroz https://orcid.org/0000-0003-0323-3523
Enamul Kabir https://orcid.org/0000-0002-6157-2753
Khorshed Alam https://orcid.org/0000-0003-2232-0745

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How to cite this article: Afroz, N., Kabir, E., & Alam, K. (2024). Socio-demographic factors and mental health trajectories in Australian children and primary carers: Implications for policy and intervention using latent class analysis. *Applied Psychology: Health and Well-Being*, 1–22. https://doi.org/10.1111/aphw.12584