The current issue and full text archive of this journal is available on Emerald Insight at:
https://www.emerald.com/insight/0263-4503.htm

The dark side of artificial intelligence in marketing: meta-analytics review

Marketing Intelligence & Planning

Mojtaba Barari
Newcastle Business School, The University of Newcastle, Newcastle, Australia
Lars-Erik Casper Ferm
The University of Queensland, Brisbane, Australia
Sara Quach
Department of Marketing, Griffith University - Gold Coast Campus, Southport, Australia
Park Thaichon
University of Southern Queensland, Toowoomba, Australia, and
Liem Ngo
School of Marketing, University of New South Wales, Sydney, Australia

Received 18 September 2023
Revised 2 December 2023
6 February 2024
15 April 2024
2 May 2024
Accepted 12 May 2024

Abstract

Purpose – Artificial intelligence (AI) has become a pivotal technology in both marketing and daily life. Despite extensive research on the benefits of AI, its adverse effects on customers have received limited attention.

Design/methodology/approach – We employed meta-analysis to synthesise effect sizes from 45 studies encompassing 50 independent samples (N = 19,503) to illuminate the negative facets of AI's impact on customer responses.

Findings – Adverse effects of AI, including privacy concern, perceived risks, customer alienation, and uniqueness neglect, have a negative and significant effect on customers' cognitive (perceived benefit, trust), affective (attitude and satisfaction) and behavioural responses (purchase, loyalty, well-being). Additionally, moderators in AI (online versus offline), customer (age, male vs. female), product (hedonic vs. utilitarian, high vs. low involvement), and firm level (service vs. manufacturing) and national level (individualism, power distance, masculinity, uncertainty avoidance, long-term orientation) moderate these relationships.

Practical implications – Our findings inform marketing managers about the drawbacks of utilising AI as part of their value proposition and provide recommendations on how to minimise these effects in different contexts. Additionally, policymakers need to consider the dark side of AI, especially among the vulnerable groups.

Originality/value – This paper is among the first research studies that synthesise previous research on the dark side of AI, providing a comprehensive view of its diminishing impact on customer responses.

Keywords Artificial intelligence, Privacy, Perceived risk, Customer alienation, Uniqueness neglect, Meta-analysis

Paper type Literature review

1. Introduction

Artificial Intelligence (AI) plays a pivotal role in developing marketing strategies that generate value for stakeholders (Gao *et al.*, 2023). AI has become integrated into our daily lives, permeating platforms such as social media (e.g., YouTube and Instagram), voice assistants (e.g., Alexa or Google Home), and Internet of Things (IoT) devices like smart fridges and watches. This has led to the cultivation of a culture orchestrated by algorithms. For example, the Google Photos app employs AI-powered algorithms to identify contextual similarities among photos and videos, facilitating the creation of customised albums (Ferm *et al.*, 2022). Furthermore, ChatGPT, a chatbot developed by the AI research company

Marketing Intelligence & Planning

0263-4503
DOI 10.1108/MIP-09-2023-0494

OpenAI, is utilised to elucidate complex concepts, provide advice to business owners, and aid marketers in content creation (Davenport *et al.*, 2020). Consequently, AI has fundamentally transformed how organisations and customers interact, yielding benefits such as increased efficiency and reduced costs, while research in this domain continues to grow exponentially (Blut *et al.*, 2021) (see Table 1).

While previous research has extensively explored the "bright side" of AI for customers, there is a growing body of research shedding light on its "dark side" (Mou *et al.*, 2023). AI can acquire intimate insights into customers without their knowledge (Grewal *et al.*, 2021). For instance, voice assistants like Alexa have predicted break-ups based on voice recognition, Target informed a father of his daughter's pregnancy before he was aware, and AI systems may impose higher premiums based on demographic characteristics (Davenport *et al.*, 2020). Notably, deepfakes, AI-generated images or videos of individuals, can be misused for criminal activities and inflict psychological harm (Feng *et al.*, 2021). Consequently, the psychological and emotional costs of AI can weigh heavily on customers, as AI may not be perceived as trustworthy (Grewal *et al.*, 2021). Additionally, Longoni *et al.* (2019) suggest that customers often feel neglected by AI, believing it does not consider their uniqueness, ultimately impacting their responses. Moreover, Esmaeilzadeh (2020) studied the impact of factors such as AI-related social and communication barriers, which can negatively affect customer willingness to use AI-based tools.

The study acknowledges the prevailing consensus on the potential negative impact of AI on customer responses. Despite existing research pointing to the negative effects of AI on customer responses, there is a gap in the literature regarding a comprehensive analysis of how the dark side of AI influences these responses. Some studies suggest substantial negative impacts on customer responses (Blut *et al.*, 2021; Feng *et al.*, 2021), while others argue that these effects are negligible when compared to the positive impacts of AI (Mariani *et al.*, 2023). Moreover, the implementation of AI in both online and offline products and services, targeting diverse customer segments, especially different culture adds more complexity to the issue. However, a consensus is lacking on how contextual variables at different levels (AI context, customer, product, firm, and national) may moderate the relationships between the negative aspects of AI and customer responses.

The main objective of the study is to examine the dark side of AI's impact on various customer responses and explore the contextual factors that moderate these relationships in our model. Building on cognitive, effective and behavioural model (Holbrook, 1986), this study utilised meta-analysis to study the impact of dark sides of AI (privacy concerns, perceived risk, customer alienation, and neglect of uniqueness) on customer cognitive (perceived benefit, and trust) and affective (attitude and satisfaction) and behavioural

Table 1. Previous research on the dark side of AI

Darkside of AI	Definition	Representative research
Privacy concern	The extent to which individuals are concerned about how AI-based products and services collect, access, use, and protect their personal information	Han and Yang (2018), Pitardi and Marriott (2021)
Perceived risk	Perceived risk and uncertainty regarding consequences of the use of a retailer, product, technology, or service	Chi *et al.* (2021), Hasan *et al.* (2021)
Customer alienation	The degree to which AI-based products and services may reduce human aspects of relations in customer-firm interaction	Han and Yang (2018), Sung and Jeon (2020)
Uniqueness neglect	The degree to which AI products and services neglect subtle differences between customers	Mou *et al.* (2023), Longoni *et al.* (2019)

Source(s): Created by the authors

responses (purchase intention, loyalty, and well-being). To provide a comprehensive view of boundary conditions in our model, we defined moderators at different levels such as AI, customer, product, firm, and national levels. Including moderators from different levels provides a comprehensive view of contextual factors that influence the depth and direction of relationships between the dark side of AI and customer responses.

The remainder of the paper is structured as follows: First, we present a conceptual framework that underpins our conceptual model and hypotheses. In the method section, we detail the meta-analysis process employed in this research. The data analysis section includes a descriptive analysis of the integration of previous studies and the results of hypothesis testing. Finally, the discussion section delves into the theoretical and practical implications of our findings, while also acknowledging the limitations of the current research and suggesting avenues for future research.

2. Dark side of AI

The dark side of AI includes a range of challenges stemming from AI capabilities and applications (Grewal *et al.*, 2021). One of the primary reasons behind the dark side of AI is its ability to collect, process, and analyse vast amounts of data, leading to concerns about privacy violations (Chen *et al.*, 2023). Individuals are increasingly wary of how AI-based products and services collect, access, use, and protect their personal information, raising significant privacy concerns (Ferm *et al.*, 2022). For instance, Han and Yang (2018) in their research indicate that, besides its positive aspects, privacy risks are barriers to AI-based personal assistance which negatively impact customer satisfaction and consumption. Similarly, Pitardi and Marriott (2021) found that privacy, as a dark side of voice-based AI like Alexa, has a negative impact on customer attitudes, trust, and intention to use.

Furthermore, the perceived risk associated with AI adoption and usage is another component of the dark side of AI. Customers may feel uncertain about the consequences of relying on AI-driven technologies, such as in retail settings, product recommendations, or service delivery (Seo and Lee, 2021). For instance, Chi *et al.* (2021) in their research show that the perceived risk of AI social robots in service delivery influences customer trust. Additionally, Hasan *et al.* (2021) found that perceived risk has a direct impact on customer loyalty for voice-controlled AI such as Siri.

Customer alienation is another aspect of the dark side of AI, where the human aspect of relationships in customer-firm interactions may be diminished (Puntoni *et al.*, 2021). AI-driven systems, while efficient, may reduce the personal and emotional aspects of relationships, leading to a sense of detachment or alienation (Puntoni *et al.*, 2021). In this regard, social attraction is one of the key determinants of AI-based personal assistants, and ignoring the social aspect in designing AI-based personal assistants can have a negative impact on customer response. Additionally, Sung and Jeon (2020) found in their research that the lack of social interaction is one of the key aspects of AI-based Robot Baristas in coffee shops, which can diminish customer attitudes and further response.

Moreover, uniqueness neglect in AI products and services can contribute to customer dissatisfaction. AI algorithms often generalise customer preferences and behaviours, neglecting subtle differences among individuals (Uysal *et al.*, 2022). This neglect of uniqueness can result in impersonalised experiences that fail to satisfy the customer's need for uniqueness. In this regard, (Mou *et al.*, 2023) found in their research that AI's uniqueness neglect increased users' negative response toward AI. Similarly, Longoni *et al.* (2019) indicate that AI's uniqueness neglect is one reason for individuals' negative response toward medical AI.

3. Conceptual framework

The dark side of AI as independent variables in our model refers to the potential negative consequences of its use, such as privacy concerns, perceived risk, customer alienation, and neglect of uniqueness. These variables have been identified in previous research as having a significant impact on customer responses to AI, with at least three studies supporting their effect size. Privacy concerns refer to customers' worries about AI systems' collection, storage, and use of personal data (Quach *et al.*, 2022). Perceived risk refers to the potential negative consequences of AI, such as biased decision-making (Hu *et al.*, 2022). Customer alienation refers to the loss of trust and engagement with a company or brand due to the use of AI. Uniqueness neglect refers to the failure to consider individual customers' unique needs and characteristics when implementing AI-based products and services.

To model customer response to dark side of AI, we utilised cognitive-affect-behaviour (CAB) model (Holbrook, 1986). According to this model, customer responses to marketing activities are categorised into three groups: cognitive, affective, and behavioural responses. The cognitive component pertains to the intellectual and rational aspects of customer responses. In this regard, we include perceived benefits and trust as customer cognitive evaluations of the dark side of AI, reflecting customer cognitive evolution in AI-based products and services (Knoll and Matthes, 2017). The affective component denotes the emotional state in which marketing activities enhance customer liking and preference toward a firm. Thus, we include attitude and satisfaction as customer affective responses to their encounter with the dark side of AI, highlighting the customer's emotional state in using AI-based products and services (Grewal *et al.*, 1997). Lastly, the behavioural component emphasises customer desire and encourages them to purchase firm products and services and engage with the company. Thus, we include customer behavioural responses towards the dark side of AI as part of this construct in our framework (Barari, 2023; Knoll and Matthes, 2017).

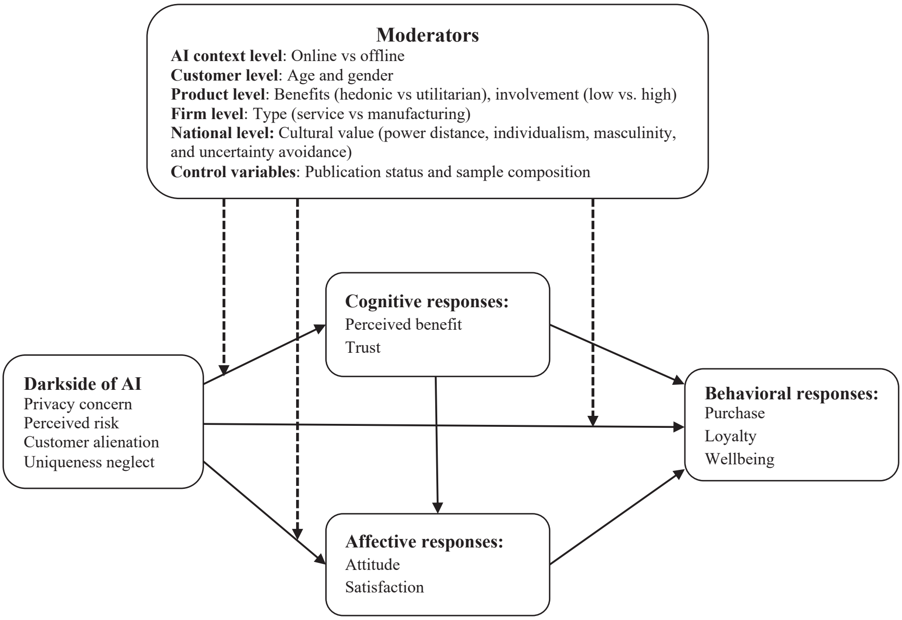
As depicted in our framework (Figure 1) and building on previous research in customer response marketing activities (Dick and Basu, 1994; Holbrook and Batra, 1987), customer cognitive responses include perceived benefits, and trust, and customer affective response includes affective evaluation and behavioural responses include purchase, loyalty, and well-being. In addition, we study that dark side of AI, directly and through cognitive and effective response influence customer behavioural response.

Similar to previous research (Kumar *et al.*, 2023), the moderators were selected based on their identification during data coding and their potential to clarify variations in the relationships between the dark side of AI and customer responses. Consequently, we included moderators at different levels, such as AI, customer, product, and firm and national levels. This diverse set of moderator variables allows us to understand how contextual factors moderate the relationship between the dark side of AI and customer responses. Finally, variables such as publication status and sample composition have been controlled to ensure the variabilities among effect sizes are not because of these variables.

4. Hypothesis development

4.1 Privacy concern

Privacy concerns outline the extent to which customers are concerned about how AI collects, accesses and uses their personal information (Quach *et al.*, 2022). AI-based solutions rely on big data, which help AI algorithms learn from past behaviour to predict or work based on this knowledge (Uysal *et al.*, 2022). However, as the scale of customer data AI uses increases, data breaches and potential cybercrime may also rise, leading to privacy issues (Du and Xie, 2021). These issues include collecting and using customer data (such as financial data) without consent or misusing it which can negatively affect customer perceived benefits of using AI in



Note(s): The hypothesis is developed solely for the direct impact of the dark side of AI on customer responses. However, the complete model has been analysed in the data analysis section

Source(s): Created by the authors

Figure. 1. Research conceptual framework

the firm offering and negate customer evaluation of the firm offering (Esmaeilzadeh, 2020). Additionally, predictive analytics in AI can reveal personal details about an individual based on seemingly harmless information, owing to its ability to analyse large amounts of data and uncover patterns and correlations not immediately apparent to humans. Therefore, privacy concerns can negatively impact customer trust towards a company (Du and Xie, 2021). Furthermore, research has found that AI-based assistants like Alexa raise privacy concerns among users, thereby negatively affecting customers' attitude and satisfaction (Ferm *et al.*, 2022), as well as their behavioural responses towards the firm, such as purchase, loyalty, and well-being (Quach *et al.*, 2022). Thus, we expect:

H1. Privacy concern is negatively related to consumer cognitive responses; (a) perceived benefit and (b) trust.

H2. Privacy concern is negatively related to consumer affective responses; (a) attitude and (b) satisfaction.

H3. Privacy concern is negatively related to consumer conative responses (a) purchase, (b) loyalty, and (c) well-being.

4.2 Perceived risk

Perceived risk highlights the extent to which using AI-based products and services is considered risky (Hu *et al.*, 2022). AI-based solutions can pose various risks to customers, including physical, functional, financial, and psychological risks (Song *et al.*, 2022).

For example, customers may be concerned about the potential for AI to malfunction and not effectively address their needs. However, the perceived risk is not always because of the inherent danger of using these technologies. The failure of firms to communicate how AI products work can exacerbate these perceived risks, leading to concerns about potential benefits of AI based solution and subsequently customer evaluation of them (Song *et al.*, 2022). In addition, AI based solution such self-driving cars are heavily based on AI technology to replace humans as drivers and customers may be concerned about the safety of a self-driving car and have negative impact of customer trust to AI based solution. This perceived risk not only leads to negative affective response toward AI-based products (Barari *et al.*, 2022b) but also causes negative behavioural responses among customers (Seo and Lee, 2021). In this regard, previous research indicate that perceived risk as integral part of AI based solution can negatively impact customer purchase and loyalty which can deteriorate their well-being as well (Esmaeilzadeh, 2020; Quach *et al.*, 2022). Thus, we expect:

H4. Perceived risk is negatively related to consumer cognitive responses; (a) perceived benefit and (b) trust.

H5. Perceived risk is negatively related to consumer affective responses; (a) attitude and (b) satisfaction.

H6. Perceived risk is negatively related to consumer conative responses (a) purchase, (b) loyalty, and (c) well-being.

4.3 Customer alienation

Customer alienation indicates customer's tendency to prefer human interactions, such as with a salesperson, instead of interacting with AI to receive products and services (Puntoni *et al.*, 2021). Although AI helps firms deliver products and services to customers innovatively and efficiently, it lacks human touch. Although new generations of AI-based products and services aim to enhance the human appearance and interactive capability of the technology (Puntoni *et al.*, 2021), AI still cannot replace humans (Esmaeilzadeh, 2020). Research indicates that the value derived from customer-employee interaction is not limited to hedonic and utilitarian value but also social value, which AI lacks (Grewal *et al.*, 2021). Research in AI indicates that customer alienation can result in a negative evaluation of their interaction with AI, even humanised AI, which negatively impacts customer perceived benefits of using AI and negate their evaluation of firm offering (Puntoni *et al.*, 2021). Beside that AI's failure to interact with customers reduces the human aspect of interactions between customers and service providers and negatively impacts customers trust towards firm (Esmaeilzadeh, 2020). In addition, customers may feel alienated when interacting with an AI-powered customer service agent if the agent does not understand their problem or seems apathetic, negatively impacting customer affective responses such as attitude and satisfaction (Puntoni *et al.*, 2021), as well as influencing purchasing behaviour and reducing the likelihood of using the company's products or services (Puntoni *et al.*, 2021). Similarly, customer alienation can diminish customer well-being, as the social value of interaction with humans, as opposed to AI, can have a profound impact on customer well-being (Puntoni *et al.*, 2021). Thus, we expect:

H7. Customer alienation is negatively related to consumer cognitive responses; (a) perceived benefit and (b) trust.

H8. Customer alienation is negatively related to consumer affective responses; (a) attitude and (b) satisfaction.

H9. Customer alienation is negatively related to consumer conative responses (a) purchase, (b) loyalty, and (c) well-being.

4.4 Uniqueness neglect

Uniqueness neglect indicates that AI technology may fails to account for customer individuality or specific needs (Mou *et al.*, 2023). For example, recommendation systems in retail suggest products based on customers' historical data and machine learning. However, customers may feel irritation as AI cannot consider a customer's unique characteristics and circumstances (Longoni *et al.*, 2019). While personalisation is a promising area for AI, neglecting customers' uniqueness can diminish the perceived benefits of using AI-based products and services and trust towards this kind of product and service (Longoni *et al.*, 2019). In addition, when customers perceive that their uniqueness is neglected, it may lead to scepticism and reduced trust in the AI's ability to provide reliable and personalised solutions (Grewal *et al.*, 2021). Besides its impact on customer cognitive responses, as customers perceive themselves as unique and requiring unique products or services, it can influence their emotional response such as their attitude and satisfaction in using AI-based products and services (Kallel *et al.*, 2024). Furthermore, previous research indicates that uniqueness neglect can negatively affect customer behavioural responses as well. For example, Longoni *et al.* (2019) found that compared to human-based healthcare, AI-based services can neglect the uniqueness of customers, leading to negative customer purchases and a tendency to stay with the firm (Uysal *et al.*, 2022). Also, AI systems providing generic recommendations or solutions that do not align with customers' specific needs or circumstances can lead to a negative attitude, dissatisfaction, and frustration, thereby negatively influencing the well-being of customers (Quach *et al.*, 2022). Thus, we expect:

H10. Uniqueness neglect is negatively related to consumer cognitive responses; (a) perceived benefit and (b) trust.

H11. Uniqueness neglect is negatively related to consumer affective responses; (a) attitude and (b) satisfaction.

H12. Uniqueness neglect is negatively related to consumer conative responses (a) purchase, (b) loyalty, and (c) well-being.

4.5 AI context level (online vs offline)

New technologies, such as AI, enable firms to develop products and services for online and offline contexts to enrich customer experience (Eisingerich *et al.*, 2019). For instance, restaurants are using AI based robot to serve customers (AI in offline context) or firms are using chatbot to respond to customer common questions (AI in online context). Besides its benefits for customers, AI causes several concerns and issues for the customer as well. While the moderating role of technology context on customer responses has not received enough attention in AI literature (Blut *et al.*, 2021), the differences between these two contexts (online vs. offline) can significantly impact the negative effects of AI and customer responses. For example, Okazaki *et al.* (2020) found that compared to physical retail channels, the online channel poses a higher level of risk for customers. Therefore, the AI context (e.g., in a physical store vs. online store) can moderate the relationship between risk and customer cognitive, affective, attitudinal, and behavioural responses. In this context, the impact of perceived risk on customer responses is higher online than offline (Blut *et al.*, 2021). Similarly, there are differences between customers in the requirement for interaction with human employees and the level of personalisation, especially in online versus offline contexts such as a physical store (Barari *et al.*, 2022b). Consequently, the relationship between customer alienation and uniqueness neglect and customer response can differ in online and offline contexts. Thus, we expect:

H13. AI context (online vs. offline) moderate the direct relationship between the dark sides of AI and all customer responses.

4.6 Customer level (age and gender)

Demographic factors, such as age and gender, can significantly impact customer evaluations and responses towards AI based products and services are essential moderators in marketing models. For instance, Kozlenkova *et al.* (2021) point out that people of different ages and gender have diverse attitudes towards technology, influencing their evaluation and responses. Previous research indicates that younger generation is more open to AI-based products and services than the older generation (Blut *et al.*, 2021). This is because the older generation is more cautious about AI's dark side during and after their shopping experience. Therefore, age may positively moderate the relationship between the dark side of AI and customer cognitive, affective and behavioural responses. Research suggests that males and females tend to have different data processing approaches during their shopping journey, with females being more comprehensive and detail-oriented and males being more selective (Arcand *et al.*, 2011). This difference in data processing led to different responses toward the dark side of AI. Compared to males, females tend to be more sceptical about using AI in their decision-making due to its drawbacks, and it has a more significant impact on their evaluation and behavioural responses towards the firm (Blut *et al.*, 2021). Thus, we expect:

H14. Age moderates the direct relationship between the dark sides of AI, and all customer responses.

H15. Gender moderates the direct relationship between the dark sides of AI, and all customer responses.

4.7 Product level (hedonic vs utilitarian)

Product type (i.e., utilitarian vs hedonic) moderates the relationship between the dark side of AI and customer responses (Dhar and Wertenbroch, 2000). Utilitarian products, such as banking products and services, are mostly functional and instrumental, while hedonic products, such as theme parks, have experiential and sensorial value (Babin *et al.*, 1994). There is limited research on the moderating role of product type in the relationship between the dark side of AI and customer responses. However, some studies suggest that the nature of the product being evaluated can play a role in how customers respond to AI (Feng *et al.*, 2021). Hedonic products, such as luxury goods, are often based on intangible attributes such as brand image and emotional appeal. Due to their intangible nature, these products may pose more challenges for customers in evaluating the product, leading to a higher level of negative cognitive, affective, and behavioural responses to the dark side of AI (Kumar, 2022). On the other hand, utilitarian products, such as appliances or tools, have a more practical function and are typically based on tangible attributes such as price, features, and functionality. These products may lead to less negative customer responses when evaluated by AI (Bakpayev *et al.*, 2022). Thus, we expect:

H16. Product types (hedonic vs utilitarian) moderate the direct relationship between dark sides of AI and all customer responses.

4.8 Product level (high vs low involvement)

Product involvement signifies a customer's perception of a product and service, particularly in terms of alignment with their needs, value, and interests (Quester and Lin Lim, 2003). It also serves as a reflection of a customer's assessment of a product's importance and associated risks (Mehta *et al.*, 2022). In the context of high-involvement products, customers tend to allocate more time and effort to the decision-making process, engaging in thorough analysis to inform their choices (Quester and Lin Lim, 2003). Previous research has not explicitly delved into the moderating role of product involvement in the relationship between the dark side of AI and customer responses. However, it is notable that product involvement could exert a substantial influence on shaping customers' cognitive, affective, and behavioural responses to the negative aspects of AI (Wedel *et al.*, 2020). Customers highly involved with products are more inclined to evaluate a product or service holistically, taking into account both positive and negative aspects. Therefore, customer the impact of dark side of AI on both customer evaluative and behavioural responses are stronger in high involvement product than low product involvement. Thus, we expect:

H17. Product involvement (high vs low) moderate the direct relationship between dark sides of AI and all customer responses.

4.9 Firm level (service vs manufacturing)

Firm type is a crucial moderator in the relationship between the dark side of AI and customer responses (Barari *et al.*, 2022a). Service firms, unlike those in the manufacturing industry, have intangible products requiring higher customer involvement in production and delivery process (Kumar *et al.*, 2019). This intangibility increases customer risk related to buying and consuming AI-based products and services (Puntoni *et al.*, 2021). For example, customers can physically interact with a washing machine before purchasing, but they may not have the same level of opportunity to evaluate a service-based product, such as a robo-advisor solution. This lack of pre-purchase evaluation can lead to higher negative customer cognitive, affective and behavioural responses to the dark side of AI in service-based industries (Kumar *et al.*, 2019). Therefore, industry type can moderate the relationship between the dark side of AI and customer negative evaluation and behavioural response, with service-based industries experiencing a higher impact than manufacturing industries (Puntoni *et al.*, 2021). Thus, we expect:

H18. Industry type (service vs manufacturing) moderates the direct relationship between the dark sides of AI, and all customer responses.

4.10 National level (cultural values)

Culture has been identified as an important moderator that significantly influences customer attitudes and behaviour towards marketing activities. As such, it is considered an essential variable to consider in meta-analyses of marketing models (Barari *et al.*, 2021), which seek to capture cultural differences in customer responses. Despite the significance of culture in explaining customer differences in response to firm marketing strategies, the role of culture has not received sufficient attention in the customer response to dark side of AI (Kumar, 2022). However, previous research indicates that customers from different cultures exhibit distinct cognitive and affective responses toward technologies, shaping their behavioural responses to both the positive and negative aspects of technology (Barari *et al.*, 2022a). For example, research indicates that the impact of risk related to the sharing economy on customer responses is higher among cultures with a higher level of power distance and uncertainty avoidance (Barari *et al.*, 2022a). While there are various approaches to studying cross-cultural differences, Hofstede *et al.* (2005) framework is the most widely used in previous meta-analyses to study the role of culture (Grewal *et al.*, 2018). Therefore, this study adopts Hofstede *et al.* (2005) five dimensions - individualism, power distance, masculinity, uncertainty avoidance, and long-term orientation - as moderators between dark side of AI and customer evaluative and behavioural response. Thus, we expect:

H19. Cultural values (i.e., individualism, power distance, masculinity, uncertainty avoidance, and long-term orientation) moderates the direct relationship between the dark sides of AI, and all customer responses.

5. Method

A comprehensive strategy was followed in this data collection process to ensure all related publications were identified and included in the data analysis process. In the first step, we used key terms such as "artificial intelligence", "AI", and "Intelligent" with "robots", "chatbot", "assistant", "agent", "bot" in combination with "dark side", "risk", "privacy", "alienation", and "uniqueness neglect". Popular databases include Business Source Complete, ProQuest Digital Dissertations, SSRN, Emerald, Springer, ISI Web of Science, Taylor & Francis, ABI/INFORM Global, and Scopus. Finally, 565 publications were included in our database for further analysis.

For the next step, several critical inclusions have been defined to only include related publications for the analysis section. First, we only considered empirical research, which has enough information to extract effect size. In addition, we included empirical research in which correlation coefficient or other statistical information was provided to calculate the effect size. Moreover, we only included publications in the English language. The final dataset includes 45 publications, providing 50 independent sample sizes and 19,503 sample sizes (Appendix 1). For data coding, we first developed the coding manual for both research construct and moderatos (Appendix 2 and Appendix 3).

Most of the research in our database were surveys and reported correlation coefficients; thus, our analysis uses correlation as effect size. For publications that did not report correlation, we used data available, such as standardised regression coefficients or t-test values, to calculate an effect size. The next step corrected the correlation coefficient for measurement error. Also, we calculate the 95% confidence intervals to determine the statistical significance of effect size. In addition, Hedges's Q statistic was used to test effect size homogeneity. Significant Q-statistics indicate variance in effect size distribution and point to the necessity for moderation analysis (Appendix 4).

To test the research conceptual model and hypotheses, we utilised Meta-Analytic Structural Equation Modelling (MASEM) in R with the SEM package. We chose MASEM over other methods, such as network meta-analysis and Bayesian meta-analysis. This choice was based on the methods capability to effectively examine complex relationships within a conceptual model (Paul and Barari, 2022). Therefore, the correlation matrix from each study was aggregated into a single matrix, serving as input for structural equation modelling. In addition, meta-regression approach was employed to test the role of moderators in our conceptual model. We employed a random effects regression model to study the role of moderators. Hence, reliability-adjusted and sample size-weighted correlations are considered as dependent variables and moderator variables as independent variables to explain the variability in the effect sizes.

6. Results

The results of the testing of the research conceptual model and hypotheses are provided in Table 2. Overall, except for the effects of customer alienation ($\beta = -0.03$, $p < 0.05$) and uniqueness neglect ($\beta = -0.02$, $p < 0.05$) on loyalty, the rest of the hypotheses are supported in our model. Additionally, our results indicate a negative and significant effect of the dark sides of AI on most dependent variables in our model, with the exceptions of customer alienation ($\beta = -0.34$, $p < 0.05$) and uniqueness neglect ($\beta = -0.34$, $p < 0.05$) with loyalty.

Moreover, the results indicate that among the components of the dark side of AI, perceived risk has the highest effect on perceived benefits ($\beta = -0.27$, $p < 0.05$), trust ($\beta = -0.29$, $p < 0.05$), evaluation ($\beta = -0.37$, $p < 0.05$), and purchase ($\beta = -0.40$, $p < 0.05$), but privacy concern has the highest relationships with customer loyalty ($\beta = -0.26$, $p < 0.05$) and well-being ($\beta = -0.12$, $p < 0.05$). For most relationships, customer alienation and uniqueness neglect have the lowest relationships with both customer evaluative and behavioural

Hypothesis	Relationship	β -value	Result
H1a	Privacy concern → Perceived benefits	−0.12*	Supported
H1b	Privacy concern → Trust	−0.23*	Supported
H2a	Privacy concern → Attitude	−0.17*	Supported
H2b	Privacy concern → Satisfaction	−0.19*	Supported
H3a	Privacy concern → Purchase	−0.23*	Supported
H3b	Privacy concern → Loyalty	−0.26*	Supported
H3c	Privacy concern → Well-being	−0.12*	Supported
H4a	Perceived risk → Perceived benefits	−0.27*	Supported
H4b	Perceived risk → Trust	−0.29*	Supported
H5a	Perceived risk → Attitude	−0.34*	Supported
H5b	Perceived risk → Satisfaction	−0.37*	Supported
H6a	Perceived risk → Purchase	−0.40*	Supported
H6b	Perceived risk → Loyalty	−0.22*	Supported
H6c	Perceived risk → Well-being	−0.10*	Supported
H7a	Customer alienation → Perceived benefits	−0.14*	Supported
H7b	Customer alienation → Trust	−0.09*	Supported
H8a	Customer alienation → Attitude	−0.09*	Supported
H8b	Customer alienation → Satisfaction	−0.10*	Supported
H9a	Customer alienation → Purchase	−0.14*	Supported
H9b	Customer alienation → Loyalty	−0.03	Rejected
H10a	Uniqueness neglect → Perceived benefits	−0.10*	Supported
H10b	Uniqueness neglect → Trust	−0.09*	Supported
H11a	Uniqueness neglect → Attitude	−0.09*	Supported
H11b	Uniqueness neglect → Satisfaction	−0.10*	Supported
H12a	Uniqueness neglect → Purchase	−0.10*	Supported
H12b	Uniqueness neglect → Loyalty	−0.02	Rejected
–	Perceived benefits → Attitude	0.45*	–
–	Perceived benefits → Satisfaction	0.48*	–
–	Trust → Attitude	0.50*	–
–	Trust → Satisfaction	0.52*	–
–	Perceived benefits → Purchase	0.43*	–
–	Perceived benefits → Loyalty	0.40*	–
–	Perceived benefits → Well-being	0.39*	–
–	Trust → Purchase	0.44*	–
–	Trust → Loyalty	0.44*	–
–	Trust → Well-being	0.42*	–
–	Attitude → Purchase	0.51*	–
–	Attitude → Loyalty	0.50*	–
–	Attitude → Well-being	0.49*	–
–	Satisfaction → Purchase	0.55*	–
–	Satisfaction → Loyalty	0.53*	–
–	Satisfaction → Well-being	0.50*	–

Note(s): There were not affect sizes for H9c and H12c thus there are not reported in the current table; * <0.05
Source(s): Created by the authors

Table 2. Result of testing research conceptual model

responses. Additionally, the relationships between customer alienation ($\beta = -0.03, p > 0.05$) and uniqueness neglect ($\beta = -0.02, p > 0.05$) are not significant."

Table 3 presents the outcomes of the moderator analysis, revealing substantial moderation effects between the components of the dark side of AI and customer responses. The results underscore that the majority of moderator variables specified in our analysis significantly influence the relationship between the dark side of AI and both evaluative and behavioural customer responses.

Table 3.
Results of moderator analysis

Moderated relationships	Online (vs. offline)	Age	Female (vs. male)	Hedonic (vs. utilitarian)	High (vs. low involvement)	Services (vs. manufacturing)	Individualism	Power distance	Masculinity	Uncertainty avoidance	Long-term orientation
Privacy → Benefits	0.132**	0.031	0.053*	−0.003	0.069*	0.113**	0.059*	0.023	0.010	0.067*	0.019
Risk → Benefits	0.106**	0.010	0.060*	0.010	0.076*	0.210**	0.061*	0.021	0.011	0.009	0.016
Alienation → Benefits	−0.046*	0.004	0.044*	0.004	0.001	0.114**	−0.046*	0.005	−0.016	−0.011	0.011
Uniqueness → Trust	–	–	–	–	–	–	–	–	–	–	–
Privacy → Trust	0.242**	0.199**	0.101*	0.051*	0.98*	0.091*	0.148**	0.128**	0.048*	0.163**	0.148**
Risk → Trust	0.212**	0.201**	0.99*	0.087*	0.104*	0.097*	0.113**	0.102*	0.012	0.196**	0.112**
Alienation → Trust	0.009	0.134**	−0.011	0.001	0.009	0.061*	−0.064*	0.012	0.006	−0.019	0.056*
Uniqueness → Trust	−0.010	−0.011	0.014	0.005	0.023	0.016	0.023	−0.030	−0.070	0.019	−0.010
Privacy → Attitude	0.082*	0.094*	0.099*	0.069*	0.91*	0.100*	0.050*	0.066*	0.011	0.060*	0.007
Risk → Attitude	0.114**	0.121**	0.110*	0.066*	0.106*	0.139**	0.049*	0.059*	0.021	0.077*	0.069*
Alienation → Attitude	−0.070*	0.009	0.080*	−0.011	0.021	0.014	−0.011	0.019	0.011	0.060*	0.049*
Uniqueness → Attitude	−0.040*	−0.101**	0.017	−0.010	0.012	−0.019	0.015	−0.009	0.011	−0.023	0.009
Privacy → Satisfaction	0.094*	0.105*	0.103*	0.088*	0.91*	0.103*	0.051*	0.066*	0.021	0.065*	0.024
Risk → Satisfaction	0.129**	0.125**	0.109*	0.075*	0.101*	0.143**	0.046*	0.052*	0.016	0.088**	0.073*
Alienation → Satisfaction	−0.073*	0.030	0.085*	−0.006	0.012	0.015	−0.011	0.017	0.009	0.075*	0.043*
Uniqueness → Satisfaction	−0.049*	−0.115**	0.019	−0.009	0.011	−0.016	0.018	−0.008	0.012	−0.025	0.005
Privacy → Purchase	0.106*	0.209**	0.089*	0.057*	0.107*	0.134**	0.056*	0.002	−0.006	0.055*	0.021
Risk → Purchase	0.226**	0.211**	0.111*	0.061*	0.121*	0.201**	0.053*	0.019	0.011	0.061*	0.016

(*continued*)

Table 3.

Moderated relationships	Online (vs. offline)	Age	Female (vs. male)	Hedonic (vs. utilitarian)	High (vs. low involvement)	Services (vs. manufacturing)	Individualism	Power distance	Masculinity	Uncertainty avoidance	Long-term orientation
Alienation → Purchase	0.002	0.094*	0.004	0.010	0.002	−0.013	−0.001	0.007	0.001	−0.011	−0.002
Uniqueness → Purchase	−0.012	0.012	−0.002	−0.004	0.008	0.008	0.010	−0.006	−0.004	0.009	−0.001
Privacy → Loyalty	0.007	−0.014	−0.024	0.012	0.014	0.024	0.023	0.016	0.021	−0.003	0.011
Risk → Loyalty	−0.012	0.021	0.011	−0.001	0.059*	0.016	0.016	0.019	0.013	0.011	0.015
Uniqueness → Loyalty	–	–	–	–	–	–	–	–	–	–	–
Alienation → Loyalty	0.003	−0.009	0.039*	0.019	0.019	0.014	0.004	0.009	0.014	−0.012	0.015
Privacy → Well-being	0.019	0.011	0.007	−0.021	0.008	0.013	−0.001	−0.002	−0.001	−0.007	−0.011
Risk → Well-being	–	–	–	–	–	–	–	–	–	–	–
Uniqueness → Well-being	–	–	–	–	–	–	–	–	–	–	–
Alienation → Well-being	–	–	–	–	–	–	–	–	–	–	–

Note(s): We did not perform a moderator analysis if the value of a binary moderator was based on fewer than five effect sizes or three studies; $^{*}p < 0.05$, $^{**}p < 0.01$
Source(s): Created by the authors

7. General discussion

Overall, our result indicate that AI can have a negative effect on customer responses. Through the review and coding of these selected empirical research, we developed our research framework underpinned by the CAB model. This framework highlights that dark side AI components, including privacy concerns, perceived risks, customer alienation, and uniqueness neglect, negatively and significantly affect customer evaluative responses (perceived benefit, positive evaluations, trust) and behavioural responses (purchase, loyalty, well-being). Additionally, based on available data, we identified moderators at five levels: AI context, customer, product, firm, and national level. The results of these analyses indicate that the role of the dark side of AI in customer responses is higher in the online context compared to the offline context, except for alienation and uniqueness neglect. Moreover, age positively moderates the relationship between the dark side of AI and customer response, except for uniqueness neglect. The impact of the dark side of AI on customer response is higher among hedonic (vs. utilitarian) and high involvement (vs. low involvement) products. Furthermore, the negative impact of dark side AI on customer response is higher in service than manufacturing firms. Finally, our results indicate that the impact of the dark side of AI on customer responses is higher in individualistic, high-power distance, uncertainty avoidance, and long-term orientation cultures.

7.1 Theoretical implications

Analysing our conceptual model enables us to provide several theoretical contributions to the dark side of AI literature. Firstly, while priors research has examined the negative effects of the dark side of AI on various customer responses (Mou *et al.*, 2023), our findings contribute by identifying privacy concerns and perceived risk as two key negative aspects of the dark side of AI. These aspects significantly impact a broad spectrum of customer evaluative and behavioural responses. Notably, privacy concern and risk are recognised in previous research as crucial elements of the dark side of AI, affecting customer adoption of AI technologies such as chatbots, bots, and robots (Barari *et al.*, 2022b; Mariani *et al.*, 2023).

Moreover, our results highlight that AI's reliance on customer personal data, while beneficial, can be viewed negatively due to perceived unauthorised access and utilisation of customer information (Chen *et al.*, 2023). The (mis)use of customer data by AI significantly influences both evaluative and behavioural customer responses (Ferm *et al.*, 2022). Additionally, perceived risk emerges as the second dark side of AI, creating uncertainty about the consequences of AI usage and influencing various customer responses, encompassing physical, financial, and psychological aspects (Hasan *et al.*, 2021).

Beyond privacy concerns and perceived risks, our study reveals a third adverse aspect: customer alienation from AI, emphasising the importance of social value to customers. The absence of humanised interaction provided by AI contributes to negative customer reactions (Gao *et al.*, 2023). This finding underscores the multidimensional nature of customer expectations, where the lack of human interaction adversely impacts responses (Quach *et al.*, 2022). Furthermore, our results indicate that while AI promises customisation based on customer needs, it falls short in satisfying customers' desire for uniqueness. AI's customisation based on historical data neglects the individuality of customers, negatively impacting responses (Mou *et al.*, 2023).

Moderator analysis reveals important findings about how different factors affect customer responses to AI. In online situations, people worry more about privacy and risks due to increased reliance on customer data. Conversely, in offline settings, customers may feel more neglected and alienated, diminishing their overall evaluation and perceived benefits. Age plays a role, with increasing age amplifying customer scepticism towards AI-based products and services, resulting in more negative responses (Blut *et al.*, 2021). Additionally, the relationship between the dark side of AI and customer responses is stronger among females than males, aligning with existing research (Goswami and Sraboni, 2015).

From a product perspective, certain aspects of the dark side of AI, particularly privacy concerns and perceived risk, exhibit a stronger negative relationship with customer responses in hedonic products compared to utilitarian products. This emphasises the subjective and intangible nature of hedonic products, making them more susceptible to the impact of AI. The negative impact of AI is also more pronounced in high-involvement products, characterised by extensive decision-making processes, exacerbating the negative effect on customer responses. Additionally, services experience a greater negative impact compared to manufacturing, given their intangible nature, making it harder for customers to evaluate before consumption (Mariani *et al.*, 2023; Longoni *et al.*, 2019; Wedel *et al.*, 2020).

Finally, our study addresses an under-researched area by examining the role of cultural values in moderating the relationship between the dark side of AI and customer responses. Cultural values such as individualism, power distance, uncertainty avoidance, and long-term orientation positively moderate the relationship between the dark side of AI, especially privacy concerns and perceived risk, and customer responses. However, exceptions exist, such as individualism negatively moderating the impact of the dark side of AI on certain customer responses, like benefits and trust (Nam and Kannan, 2020).

7.2 Managerial implications

In addition to its theoretical contributions, our model emphasises important factors for marketing managers when incorporating AI into their offerings. While AI can boost profits, it can also damage relationships with customers and affect their behaviour, like buying decisions or loyalty to the company. To reduce perceived risks and privacy concerns, past studies show that being transparent about a company's privacy practices can improve customer responses (Chen *et al.*, 2023). For instance, Apple's App Tracking Transparency (ATT) feature introduced in iOS 14 allows users to control which apps can track their activity across other apps and websites (Kollnig *et al.*, 2022). This practice empowers customers to make informed decisions about their privacy and mitigate the negative impact of the dark side of AI on customer response.

Moreover, while using AI instead of employees can save costs for a company, it might not fully meet customers' specific needs and social preferences. AI aims for personalised solutions through customer input and machine learning but often leads to mass customisation. For customers who value personalised service, we suggest that companies gather extra information to create a truly unique experience. Netflix is a good example of this; they encourage customers to share more information for a more personalised service. Even though Amazon is mainly online, they understand the importance of customer service and offer various support options. For those who prefer human interaction, Amazon provides a customer service hotline where individuals can talk to a representative about enquiries, concerns, or issues.

Additionally, marketing managers who work across product and service domains should carefully consider how to use AI in different contexts, such as online and offline environments, and for various customer groups. Our research shows that online and offline settings pose unique challenges for AI that managers should take into account when creating AI-based products and services. For example, AI-based offerings can sometimes make customers feel disconnected because they expect a more personal touch in their interactions with the company. To address this, we recommend that managers combine AI with human employees or include human-like features in their design to make interactions feel more personal. One example of this is using chatbots in online customer service with conversational features that mimic human interaction, improving the overall customer experience. Similarly, regarding different customer groups, our research suggests that females and older generations are more affected by the negative aspects of AI. Managers should be cautious when collecting personal data from these groups for personalised experiences, as it could lead to negative reactions. Also, as AI replaces human workers in service-focused companies, managers should offer choices to customers. Implementing self-service technologies gives customers the option to interact with AI or choose human interactions, meeting varying preferences.

From a public policy standpoint, it's important to acknowledge the significant impact of AI's negative side on customer responses. Our study emphasises the negative effects of privacy concerns and perceived risks related to AI, influencing customer evaluations and behaviours. Practical strategies should prioritise transparent and ethical AI practices, handling customer data responsibly with clear consent. Combating customer alienation from AI by adding human-like elements or offering human interaction options in AI services is key to improving overall customer satisfaction. A balanced and responsible approach to AI implementation, considering both benefits and drawbacks, is crucial for practical implications in AI marketing.

7.3 Limitations and further research

Like many previous meta-analysis studies (Kumar *et al.*, 2023), our analysis has its limitations. Our model primarily relies on existing AI literature, which predominantly emphasises the positive impact of AI on customer responses. Consequently, we found insufficient data to explore the relationships between the darker side of AI, including perceived risk, customer alienation, and neglect of uniqueness, with customer responses. This limitation opens the door for future research to delve into how AI-based products and services might affect customer well-being. Additionally, there's a noticeable scarcity of research addressing the negative aspects of AI, hindering our ability to construct a more complex model that considers mediation mechanisms. Thus, exploring the underlying mechanisms in the relationship between AI-based products and services and customer responses holds great potential for future research. Finally, the emergence of technologies like Generative AI creates a new era of AI's dark side, a realm previously unexplored in traditional AI. These advancements bring forth unique challenges and ethical considerations that demand thorough investigation in future studies.

References

Arcand, M., Nantel, J. and Sénécal, S. (2011), "The effects of sex and Internet usage on search efficiency and effectiveness", *International Journal of Computer Information Systems and Industrial Management Applications*, Vol. 3, pp. 663-670.

Babin, B.J., Darden, W.R. and Griffin, M. (1994), "Work and/or fun: measuring hedonic and utilitarian shopping value", *Journal of Consumer Research*, Vol. 20 No. 4, pp. 644-656, doi: 10.1086/209376.

Bakpayev, M., Baek, T.H., van Esch, P. and Yoon, S. (2022), "Programmatic creative: AI can think but it cannot feel", *Australasian Marketing Journal*, Vol. 30 No. 1, pp. 90-95, doi: 10.1016/j.ausmj.2020.04.002.

Barari, M., Paul, J., Ross, M., Thaichon, S. and Surachartkumtonkun, J. (2022a), "Relationships among actors within the sharing economy: meta-analytics review", *International Journal of Hospitality Management*, Vol. 103, 103215, doi: 10.1016/j.ijhm.2022.103215.

Barari, M., Quach, S. and Thaichon, P. (2022b), "New developments in artificial intelligence (AI)-powered products in marketing", *Artificial Intelligence for Marketing Management*, Routledge, Chicago, pp. 55-75.

Barari, M. (2023), "Unveiling the dark side of influencer marketing: how social media influencers (human vs virtual) diminish followers' well-being", *Marketing Intelligence & Planning*, Vol. 41 No. 8, pp. 1162-1177, doi: 10.1108/mip-05-2023-0191.

Barari, M., Ross, M., Thaichon, S. and Surachartkumtonkun, J. (2021), "A meta-analysis of customer engagement behaviour", *International Journal of Consumer Studies*, Vol. 45 No. 5, pp. 457-477.

Blut, M., Wang, C., Wünderlich, N.V. and Brock, C. (2021), "Understanding anthropomorphism in service provision: a meta-analysis of physical robots, chatbots, and other AI", *Journal of the Academy of Marketing Science*, Vol. 49 No. 4, pp. 632-658, doi: 10.1007/s11747-020-00762-y.

Chen, S.J., Tran, K.T., Xia, Z.R., Waseem, D., Zhang, J.A. and Potdar, B. (2023), "The double-edged effects of data privacy practices on customer responses", *International Journal of Information Management*, Vol. 69, 102600, doi: 10.1016/j.ijinfomgt.2022.102600.

Chi, O.H., Jia, S., Li, Y. and Gursoy, D. (2021), "Developing a formative scale to measure consumers' trust toward interaction with artificially intelligent (AI) social robots in service delivery", *Computers in Human Behavior*, Vol. 118, 106700, doi: 10.1016/j.chb.2021.106700.

Davenport, T., Guha, A., Grewal, D. and Bressgott, T. (2020), "How artificial intelligence will change the future of marketing", *Journal of the Academy of Marketing Science*, Vol. 48 No. 1, pp. 24-42, doi: 10.1007/s11747-019-00696-0.

Dhar, R. and Wertenbroch, K. (2000), "Consumer choice between hedonic and utilitarian goods", *Journal of Marketing Research*, Vol. 37 No. 1, pp. 60-71, doi: 10.1509/jmkr.37.1.60.18718.

Dick, A.S. and Basu, K. (1994), "Customer loyalty: toward an integrated conceptual framework", *Journal of the Academy of Marketing Science*, Vol. 22 No. 2, pp. 99-113, doi: 10.1177/0092070394222001.

Du, S. and Xie, C. (2021), "Paradoxes of artificial intelligence in consumer markets: ethical challenges and opportunities", *Journal of Business Research*, Vol. 129, pp. 961-974, doi: 10.1016/j.jbusres.2020.08.024.

Eisingerich, A.B., Marchand, A., Fritze, M.P. and Dong, L. (2019), "Hook vs. hope: how to enhance customer engagement through gamification", *International Journal of Research in Marketing*, Vol. 36 No. 2, pp. 200-215, doi: 10.1016/j.ijresmar.2019.02.003.

Esmaeilzadeh, P. (2020), "Use of AI-based tools for healthcare purposes: a survey study from consumers' perspectives", *BMC Medical Informatics and Decision Making*, Vol. 20 No. 1, pp. 1-19, doi: 10.1186/s12911-020-01191-1.

Evanschitzky, H., Ramaseshan, B., Woisetschläger, D., Richelsen, V., Blut, M. and Backhaus, C. (2012), "Consequences of customer loyalty to the loyalty program and to the company", *Journal of the Academy of Marketing Science*, Vol. 40, pp. 625-638.

Feng, C.M., Park, A., Pitt, L., Kietzmann, J. and Northey, G. (2021), "Artificial intelligence in marketing: a bibliographic perspective", *Australasian Marketing Journal*, Vol. 29 No. 3, pp. 252-263, doi: 10.1016/j.ausmj.2020.07.006.

Ferm, L.-E.C., Quach, S. and Thaichon, P. (2022), "Data privacy and artificial intelligence (AI): how AI collects data and its impact on data privacy", *Artificial Intelligence for Marketing Management*, Routledge, pp. 163-174, doi: 10.4324/9781003280392-13.

Gao, L., Li, G., Tsai, F., Gao, C., Zhu, M. and Qu, X. (2023), "The impact of artificial intelligence stimuli on customer engagement and value co-creation: the moderating role of customer ability readiness", *Journal of Research in Interactive Marketing*, Vol. 17 No. 2, pp. 317-333, doi: 10.1108/jrim-10-2021-0260.

Grewal, D., Kavanoor, S., Fern, E.F., Costley, C. and Barnes, J. (1997), "Comparative versus noncomparative advertising: a meta-analysis", *Journal of Marketing*, Vol. 61 No. 4, pp. 1-15, doi: 10.1177/002224299706100401.

Grewal, D., Puccinelli, N. and Monroe, K.B. (2018), "Meta-analysis: integrating accumulated knowledge", *Journal of the Academy of Marketing Science*, Vol. 46 No. 1, pp. 9-30, doi: 10.1007/s11747-017-0570-5.

Goswami, A. and Sraboni, D. (2015), "Gender differences in technology usage—a literature review", *Open Journal of Business and Management*, Vol. 4 No. 1, pp. 51-59.

Grewal, D., Guha, A., Satornino, C.B. and Schweiger, E.B. (2021), "Artificial intelligence: the light and the darkness", *Journal of Business Research*, Vol. 136, pp. 229-236, doi: 10.1016/j.jbusres.2021.07.043.

Han, S. and Yang, H. (2018), "Understanding adoption of intelligent personal assistants: a parasocial relationship perspective", *Industrial Management & Data Systems*, Vol. 118 No. 3, pp. 618-636, doi: 10.1108/imds-05-2017-0214.

Hasan, R., Shams, R. and Rahman, M. (2021), "Consumer trust and perceived risk for voice-controlled artificial intelligence: the case of Siri", *Journal of Business Research*, Vol. 131, pp. 591-597, doi: 10.1016/j.jbusres.2020.12.012.

Hofstede, G., Hofstede, G.J. and Minkov, M. (2005), *Cultures and Organizations: Software of the Mind*, McGraw-Hill, New York.

Holbrook, M.B. (1986), "Emotion in the consumption experience: toward a new model of the human consumer", *The Role of Affect in Consumer Behavior: Emerging Theories and Applications*, Vol. 6 No. 23, pp. 17-52.

Holbrook, M.B. and Batra, R. (1987), "Assessing the role of emotions as mediators of consumer responses to advertising", *Journal of Consumer Research*, Vol. 14 No. 3, pp. 404-420, doi: 10.1086/209123.

Hu, P., Lu, Y. and Wang, B. (2022), "Experiencing power over AI: the fit effect of perceived power and desire for power on consumers' choice for voice shopping", *Computers in Human Behavior*, Vol. 128, 107091, doi: 10.1016/j.chb.2021.107091.

Kallel, A., Ben Dahmane Mouelhi, N., Chaouali, W. and Danks, N.P. (2024), "Hey chatbot, why do you treat me like other people? The role of uniqueness neglect in human-chatbot interactions", *Journal of Strategic Marketing*, Vol. 32 No. 2, pp. 170-186, doi: 10.1080/0965254x.2023.2175020.

Knoll, J. and Matthes, J. (2017), "The effectiveness of celebrity endorsements: a meta-analysis", *Journal of the Academy of Marketing Science*, Vol. 45 No. 1, pp. 55-75, doi: 10.1007/s11747-016-0503-8.

Kollnig, K., Shuba, A., Van Kleek, M., Binns, R. and Shadbolt, N. (2022), "Goodbye tracking? Impact of iOS app tracking transparency and privacy labels", *Proceedings of the 2022 ACM Conference on Fairness, Accountability, and Transparency*. doi: 10.1145/3531146.3533116.

Kozlenkova, I.V., Lee, J.-Y., Xiang, D. and Palmatier, R.W. (2021), "Sharing economy: international marketing strategies", *Journal of International Business Studies*, Vol. 52 No. 8, pp. 1-29, doi: 10.1057/s41267-020-00393-z.

Kumar, H. (2022), "Augmented reality in online retailing: a systematic review and research agenda", *International Journal of Retail & Distribution Management*, Vol. 50 No. 4, pp. 537-559, doi: 10.1108/ijrdm-06-2021-0287.

Kumar, V., Rajan, B., Gupta, S. and Pozza, I.D. (2019), "Customer engagement in service", *Journal of the Academy of Marketing Science*, Vol. 47 No. 1, pp. 138-160, doi: 10.1007/s11747-017-0565-2.

Kumar, H., Gupta, P. and Chauhan, S. (2023), "Meta-analysis of augmented reality marketing", *Marketing Intelligence & Planning*, Vol. 41 No. 1, pp. 110-123, doi: 10.1108/mip-06-2022-0221.

Longoni, C., Bonezzi, A. and Morewedge, C.K. (2019), "Resistance to medical artificial intelligence", *Journal of Consumer Research*, Vol. 46 No. 4, pp. 629-650, doi: 10.1093/jcr/ucz013.

Mariani, M.M., Hashemi, N. and Wirtz, J. (2023), "Artificial intelligence empowered conversational agents: a systematic literature review and research agenda", *Journal of Business Research*, Vol. 161, 113838, doi: 10.1016/j.jbusres.2023.113838.

Mehta, P., Jebarajakirthy, C., Maseeh, H.I., Anubha, A., Saha, R. and Dhanda, K. (2022), "Artificial intelligence in marketing: a meta-analytic review", *Psychology & Marketing*, Vol. 39 No. 11, pp. 2013-2038, doi: 10.1002/mar.21716.

Mou, Y., Xu, T. and Hu, Y. (2023), "Uniqueness neglect on consumer resistance to AI", *Marketing Intelligence & Planning*, Vol. 41 No. 6, pp. 669-689, doi: 10.1108/mip-11-2022-0505.

Nam, H. and Kannan, P.K. (2020), "Digital environment in global markets: cross-cultural implications for evolving customer journeys", *Journal of International Marketing*, Vol. 28 No. 1, pp. 28-47.

Nghia, H.T., Olsen, S.O. and Nguyen, T.M.T. (2020), "Shopping value, trust, and online shopping well-being: a duality approach", *Marketing Intelligence and Planning*, Vol. 38 No. 5, pp. 545-558.

Okazaki, S., Eisend, M., Plangger, K., de Ruyter, K. and Grewal, D. (2020), "Understanding the strategic consequences of customer privacy concerns: a meta-analytic review", *Journal of Retailing*, Vol. 96 No. 4, pp. 458-473, doi: 10.1016/j.jretai.2020.05.007.

Paul, J. and Barari, M. (2022), "Meta-analysis and traditional systematic literature reviews—what, why, when, where, and how?", *Psychology & Marketing*, Vol. 39 No. 6, pp. 1099-1115, doi: 10.1002/mar.21657.

Pitardi, V. and Marriott, H.R. (2021), "Alexa, she's not human but… Unveiling the drivers of consumers' trust in voice-based artificial intelligence", *Psychology & Marketing*, Vol. 38 No. 4, pp. 626-642, doi: 10.1002/mar.21457.

Puntoni, S., Reczek, R.W., Giesler, M. and Botti, S. (2021), "Consumers and artificial intelligence: an experiential perspective", *Journal of Marketing*, Vol. 85 No. 1, pp. 131-151, doi: 10.1177/0022242920953847.

Quach, S., Thaichon, P., Martin, K.D., Weaven, S. and Palmatier, R.W. (2022), "Digital technologies: tensions in privacy and data", *Journal of the Academy of Marketing Science*, Vol. 50 No. 6, pp. 1299-1323, doi: 10.1007/s11747-022-00845-y.

Quester, P. and Lin Lim, A. (2003), "Product involvement/brand loyalty: is there a link?", *Journal of Product & Brand Management*, Vol. 12 No. 1, pp. 22-38, doi: 10.1108/10610420310463117.

Seo, K.H. and Lee, J.H. (2021), "The emergence of service robots at restaurants: integrating trust, perceived risk, and satisfaction", *Sustainability*, Vol. 13 No. 8, p. 4431, doi: 10.3390/su13084431.

Song, M., Xing, X., Duan, Y., Cohen, J. and Mou, J. (2022), "Will artificial intelligence replace human customer service? The impact of communication quality and privacy risks on adoption intention", *Journal of Retailing and Consumer Services*, Vol. 66, 102900, doi: 10.1016/j.jretconser.2021.102900.

Sung, H.J. and Jeon, H.M. (2020), "Untact: customer's acceptance intention toward robot barista in coffee shop", *Sustainability*, Vol. 12 No. 20, p. 8598, doi: 10.3390/su12208598.

Uysal, E., Alavi, S. and Bezençon, V. (2022), "Trojan horse or useful helper? A relationship perspective on artificial intelligence assistants with humanlike features", *Journal of the Academy of Marketing Science*, Vol. 50 No. 6, pp. 1153-1175, doi: 10.1007/s11747-022-00856-9.

Wedel, M., Bigné, E. and Zhang, J. (2020), "Virtual and augmented reality: advancing research in consumer marketing", *International Journal of Research in Marketing*, Vol. 37 No. 3, pp. 443-465, doi: 10.1016/j.ijresmar.2020.04.004.

Appendix 1
Papers Included in the Meta-Analysis

Ameen, N., Hosany, S., & Paul, J. (2022). The personalisation-privacy paradox: Consumer interaction with smart technologies and shopping mall loyalty. *Computers in Human Behavior*, *126*, 106976.

Ameen, N., Tarhini, A., Reppel, A., & Anand, A. (2021). Customer experiences in the age of artificial intelligence. *Computers in Human Behavior*, *114*, 106548.

Bawack, R. E., Wamba, S. F., & Carillo, K. D. A. (2021). Exploring the role of personality, trust, and privacy in customer experience performance during voice shopping: Evidence from SEM and fuzzy set qualitative comparative analysis. *International Journal of Information Management*, *58*, 102309.

Benlian, A., Klumpe, J., & Hinz, O. (2020). Mitigating the intrusive effects of smart home assistants by using anthropomorphic design features: A multimethod investigation. *Information Systems Journal*, *30*(6), 1010-1042.

Berge, S. H. (2018). *Rise of the Chatbots: Trust in Artificial Intelligence During Extreme Weather Events*

Cabrera-Sánchez, J.-P., Ramos-de-Luna, I., Carvajal-Trujillo, E., & Villarejo-Ramos, Á. F. (2020). Online recommendation systems: Factors influencing use in e-commerce. *Sustainability*, *12*(21), 8888.

Cabrera-Sánchez, J.-P., Villarejo-Ramos, Á. F., Liébana-Cabanillas, F., & Shaikh, A. A. (2021). Identifying relevant segments of AI applications adopters–Expanding the UTAUT2's variables. *Telematics and Informatics*, *58*, 101529.

Casidy, R., Claudy, M., Heidenreich, S., & Camurdan, E. (2021). The role of brand in overcoming consumer resistance to autonomous vehicles. *Psychology & Marketing*, *38*(7), 1101-1121.

Cavus, N., Mohammed, Y. B., & Yakubu, M. N. (2021). An artificial intelligence-based model for prediction of parameters affecting sustainable growth of mobile banking apps. *Sustainability*, *13*(11), 6206.

Chatterjee, S., Ghosh, S. K., Chaudhuri, R., & Chaudhuri, S. (2021). Adoption of AI-integrated CRM system by Indian industry: from security and privacy perspective. *Information & Computer Security*, *29*(1), 1-24.

Cheng, Y., & Jiang, H. (2020). How do AI-driven chatbots impact user experience? Examining gratifications, perceived privacy risk, satisfaction, loyalty, and continued use. *Journal of Broadcasting & Electronic Media*, *64*(4), 592-614.

Chi, O. H., Jia, S., Li, Y., & Gursoy, D. (2021). Developing a formative scale to measure consumers' trust toward interaction with artificially intelligent (AI) social robots in service delivery. *Computers in Human Behavior*, *118*, 106700.

Chuah, S. H.-W., Aw, E. C.-X., & Yee, D. (2021). Unveiling the complexity of consumers' intention to use service robots: An fsQCA approach. *Computers in Human Behavior*, *123*, 106870.

De Graaf, M. M., & Allouch, S. B. (2013). Exploring influencing variables for the acceptance of social robots. *Robotics and autonomous systems*, *61*(12), 1476-1486.

Esmaeilzadeh, P. (2020). Use of AI-based tools for healthcare purposes: a survey study from consumers' perspectives. *BMC medical informatics and decision making*, *20*(1), 1-19.

Fan, H., Han, B., & Gao, W. (2022). (Im) Balanced customer-oriented behaviours and AI chatbots' Efficiency–Flexibility performance: The moderating role of customers' rational choices. *Journal of Retailing and Consumer Services*, *66*, 102937.

Fan, H., Han, B., Gao, W., & Li, W. (2022). How AI chatbots have reshaped the frontline interface in China: examining the role of sales–service ambidexterity and the personalisation–privacy paradox. *International Journal of Emerging Markets*, *17*(4), 967-986.

Granulo, A., Fuchs, C., & Puntoni, S. (2021). Preference for human (vs. robotic) labour is stronger in symbolic consumption contexts. *Journal of Consumer Psychology*, *31*(1), 72-80.

Han, S., & Yang, H. (2018). Understanding adoption of intelligent personal assistants: A parasocial relationship perspective. *Industrial Management & Data Systems*, *118*(3), 618-636.

Hasan, R., Shams, R., & Rahman, M. (2021). Consumer trust and perceived risk for voice-controlled artificial intelligence: The case of Siri. *Journal of Business Research*, *131*, 591-597.

Ho, C.-C., & MacDorman, K. F. (2010). Revisiting the uncanny valley theory: Developing and validating an alternative to the Godspeed indices. *Computers in Human Behavior*, *26*(6), 1508-1518.

Hu, P., Lu, Y., & Wang, B. (2022). Experiencing power over AI: The fit effect of perceived power and desire for power on consumers' choice for voice shopping. *Computers in Human Behavior*, *128*, 107091.

Huang, Y., & Qian, L. (2021). Understanding the potential adoption of autonomous vehicles in China: The perspective of behavioural reasoning theory. *Psychology & Marketing*, *38*(4), 669-690.

Kamide, H., Takubo, T., Ohara, K., Mae, Y., & Arai, T. (2014). Impressions of humanoids: The development of a measure for evaluating a humanoid. *International Journal of Social Robotics*, *6*, 33-44.

Lehto, X. Y., Park, S., Mohamed, M. E., & Lehto, M. R. (2023). Traveller attitudes toward biometric data-enabled hotel services: Can risk education play a role? *Cornell Hospitality Quarterly*, *64*(1), 74-94.

Longoni, C., Bonezzi, A., & Morewedge, C. K. (2019). Resistance to medical artificial intelligence. *Journal of Consumer Research*, *46*(4), 629-650.

McLean, G., Osei-Frimpong, K., & Barhorst, J. (2021). Alexa, do voice assistants influence consumer brand engagement?–Examining the role of AI powered voice assistants in influencing consumer brand engagement. *Journal of Business Research*, *124*, 312-328.

Mende, M., Scott, M. L., van Doorn, J., Grewal, D., & Shanks, I. (2019). Service robots rising: How humanoid robots influence service experiences and elicit compensatory consumer responses. *Journal of marketing research*, *56*(4), 535-556.

Meyer-Waarden, L., & Cloarec, J. (2022). "Baby, you can drive my car": Psychological antecedents that drive consumers' adoption of AI-powered autonomous vehicles. *Technovation*, *109*, 102348.

Olk, S., Tscheulin, D. K., & Zogaj, A. (2020). Crisis communication via COVID-19 Chatbots - Effects of communication style on public management objectives [Article]. *Krisenkommunikation mittels COVID-19 Chatbot - Auswirkungen des Kommunikationsstils auf die Ziele der öffentlichen Verwaltung.*, *29*(1), 419-434. https://doi.org/10.5771/0344-9777-2020-4-419

Pal, D., Roy, P., Arpnikanondt, C., & Thapliyal, H. (2022). The effect of trust and its antecedents towards determining users' behavioural intention with voice-based consumer electronic devices. *Heliyon*, *8*(4).

Pillai, R., & Sivathanu, B. (2020). Adoption of AI-based chatbots for hospitality and tourism. *International Journal of Contemporary Hospitality Management*, *32*(10), 3199-3226.

Piotrowski, D. (2022). Consumer perceived ethicality of banks in the era of digitalisation: The case of Poland. *Economics and Business Review*, *8*(1), 90-114.

Pitardi, V., & Marriott, H. R. (2021). Alexa, she's not human but... Unveiling the drivers of consumers' trust in voice-based artificial intelligence. *Psychology & Marketing*, *38*(4), 626-642.

Rajaobelina, L., Prom Tep, S., Arcand, M., & Ricard, L. (2021). Creepiness: Its antecedents and impact on loyalty when interacting with a chatbot. *Psychology & Marketing*, *38*(12), 2339-2356.

Ribeiro, M. A., Gursoy, D., & Chi, O. H. (2022). Customer acceptance of autonomous vehicles in travel and tourism. *Journal of Travel Research*, *61*(3), 620-636.

Seo, K. H., & Lee, J. H. (2021). The emergence of service robots at restaurants: Integrating trust, perceived risk, and satisfaction. *Sustainability*, *13*(8), 4431.

Song, M., Xing, X., Duan, Y., Cohen, J., & Mou, J. (2022). Will artificial intelligence replace human customer service? The impact of communication quality and privacy risks on adoption intention. *Journal of Retailing and Consumer Services*, *66*, 102900.

Sung, H. J., & Jeon, H. M. (2020). Untact: Customer's acceptance intention toward robot barista in coffee shop. *Sustainability*, *12*(20), 8598.

Uysal, E., Alavi, S., & Bezençon, V. (2022). Trojan horse or useful helper? A relationship perspective on artificial intelligence assistants with humanlike features. *Journal of the Academy of Marketing Science*, *50*(6), 1153-1175.

Vimalkumar, M., Sharma, S. K., Singh, J. B., & Dwivedi, Y. K. (2021). 'Okay google, what about my privacy?': User's privacy perceptions and acceptance of voice based digital assistants. *Computers in Human Behavior*, *120*, 106763.

Wang, I.-C., Liao, C.-W., Lin, K.-P., Wang, C.-H., & Tsai, C.-L. (2021). Evaluate the consumer acceptance of aiot-based unmanned convenience stores based on perceived risks and technological acceptance models. *Mathematical Problems in Engineering*, *2021*, 1-12.

Yeo, S. F., Tan, C. L., Kumar, A., Tan, K. H., & Wong, J. K. (2022). Investigating the impact of AI-powered technologies on Instagrammers' purchase decisions in digitalisation era–A study of the fashion and apparel industry. *Technological Forecasting and Social Change*, *177*, 121551.

Zhang, W., Sun, L., Wang, X., & Wu, A. (2022). The influence of AI word-of-mouth system on consumers' purchase behaviour: The mediating effect of risk perception. *Systems Research and Behavioral Science*, *39*(3), 516-530.

Appendix 2

Responses variable	Definition	Common aliases
Perceived benefits	The extent of a belief that a retailer, product, technology, or service will help perform a task (Grewal *et al.*, 2021)	Perceived usefulness, informativeness, perceived value
Trust	Confidence in the reliability and integrity of a service provider (Seo and Lee, 2021)	Trustworthiness, credibility, benevolence, honesty
Attitude	Consumers' overall attitude toward the product, service and firm (Dick and Basu, 1994)	Attitude towards AI, attitude toward firm
Satisfaction	The positive affective or emotional state resulting from the appraisal of the firm offering (Okazaki *et al.*, 2020)	Positive emotion, satisfaction
Purchase	Intention to purchase or actual purchase of firm products and services (Okazaki *et al.*, 2020)	Purchase intention, willingness to purchase, purchase behaviour
Loyalty	A collection of attitudes aligned with a series of behaviours that systematically favour one entity over competing entities (Evanschitzky *et al.*, 2012)	Brand loyalty, attitudinal loyalty
Well-being	Customer emotional and cognitive evaluation of their personal life satisfaction (Nghia *et al.*, 2020)	Customer well-being, subjective well-being

Source(s): Created by the authors

Table A2.
Research constructs definitions and aliases

Appendix 3

Moderator	Operationalisation	Coding
AI context	Whether the AI-based solution presented is in an online context (e.g., a service bot on an online website) rather than an offline context (e.g., a robot in a restaurant)	1 = online (31) vs. 0 = offline (19)
Gender	Whether the percentage of females in the study sample was greater than males	1 = Female (33) vs. 0 = Male (17)
Age	The average age of the sample in each study	Continuous variable (Average age = 38.2)
Product type	Whether the benefits of using the AI based solution for customers is hedonic (e.g., virtual wardrobe) rather than utilitarian (e.g., AI based financial adviser)	1 = Hedonic (27) vs. 0 = Utilitarian (28)
Product involvement	Whether the level of customer involvement with AI based solution is high (e.g., AI based self-diagnostic) rather than low (e.g., recommendation system)	1 = High (30) vs. 0 = Low (20)
Industry type	Whether the AI-based solution is provided by a service (e.g., service robot in a restaurant) company rather than a manufacturing company (e.g., self-drive car)	1 = Service (37) vs. 0 = Manufacturing (13)
Cultural context	Cultural values of the sample in a study, including power distance, individualism, masculinity, and uncertainty avoidance	Continuous variable ranging from 1 to 100

Source(s): Created by the authors

Table A3.
Moderator variables definition, operationalisation and coding

Appendix 4

Relationship	k	*N*	r_{cw}	LCI	UCI
Privacy concern ↔ Perceived benefits	13	6,034	−0.12*	−0.08	−0.16
Privacy concern ↔ Trust	14	6,612	−0.23*	−0.15	−0.34
Privacy concern ↔ Attitude	13	6,021	−0.17*	−0.12	−0.20
Privacy concern ↔ Satisfaction	15	6,510	−0.19*	−0.14	−0.23
Privacy concern ↔ Purchase	10	4,130	−0.23*	−0.08	−0.37
Privacy concern ↔ Loyalty	8	4,137	−0.26*	−0.05	−0.51
Privacy concern ↔ Well-being	5	3,123	−0.12*	−0.06	−0.18
Perceived risk ↔ Perceived benefits	18	7,983	−0.27*	−0.18	−0.36
Perceived risk ↔ Trust	14	6,200	−0.29*	−0.18	−0.39
Perceived risk ↔ Attitude	10	4,853	−0.34*	−0.14	−0.53
Perceived risk ↔ Satisfaction	13	5,817	−0.37*	−0.15	−0.59
Perceived risk ↔ Purchase	19	8,828	−0.40*	0.20	0.55
Perceived risk ↔ Loyalty	7	3,964	−0.22*	−0.11	−0.32
Perceived risk ↔ Well-being	4	2,675	−0.10*	−0.04	−0.20
Customer alienation ↔ Perceived benefits	5	1987	−0.14*	−0.03	−0.26
Customer alienation ↔ Trust	5	2,995	−0.09*	−0.02	−0.15
Customer alienation ↔ Attitude	6	3,420	−0.09*	−0.02	−0.15
Customer alienation ↔ Satisfaction	7	3,765	−0.10*	−0.03	−0.16
Customer alienation ↔ Purchase	5	2,786	−0.14*	0.03	0.26
Customer alienation ↔ Loyalty	5	2,388	−0.03	−0.03	0.09
Customer alienation ↔ Well-being	–	–	–	–	–
Uniqueness neglect ↔ Perceived benefits	4	1,465	−0.10*	−0.01	−0.27
Uniqueness neglect ↔ Trust	4	2,476	−0.09*	−0.01	−0.18
Uniqueness neglect ↔ Attitude	4	2,675	−0.09*	−0.01	−0.15
Uniqueness neglect ↔ Satisfaction	5	2,675	−0.10*	−0.04	−0.17
Uniqueness neglect ↔ Purchase	5	2,765	−0.10*	−0.04	−0.29
Uniqueness neglect ↔ Loyalty	4	2011	−0.02	−0.05	0.011
Uniqueness neglect ↔ Well-being	–	–	–	–	–

Note(s): K: number of effect sizes; ***N***: cumulative sample size; $\mathbf{r}_{cw}$: reliability adjusted and sample size weighted correlation; **LCI**: 95%- lower confidence interval; **UCI**: 95%-upper confidence interval. *$p < 0.01$; we did not include pair relationships that had less than three effect sizes
Source(s): Created by the authors

Table A4. Result of the relationship between the dark sides of AI and customer responses

Corresponding author
Mojtaba Barari can be contacted at: moji.barari@newcastle.edu.au