

# **The Dark side of Artificial intelligence in Marketing: Meta-Analytics Review**

**Mojtaba Barari** (*Corresponding author*)

Newcastle Business School, University of Newcastle, Newcastle, Australia

*moji.barari@newcastle.edu.au*

**Lars-Erik Casper Ferm**

UQ Business School, Australia

*l.ferm@business.uq.edu.au*

**Sara Quach**

Department of Marketing, Griffith Business School, Griffith University, Australia

*s.quach@griffith.edu.au*

**Park Thaichon**

Faculty of Business Education, Law and Arts, School of Business, University of Southern  
Queensland, Australia

*park.thaichon@gmail.com*

**Liem Viet Ngo**

UNSW Business School, UNSW Sydney, Australia

*liem.ngo@unsw.edu.au*

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## 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 synthesize 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 utilizing AI as part of their value proposition and provide recommendations on how to minimize 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 synthesize 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

## 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 customized albums (Ferm et al., 2022). Furthermore, ChatGPT, a chatbot developed by the AI research company OpenAI, is utilized 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 organizations 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).

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, Esmailzadeh (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 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.

Table 1. Previous research on the dark side of AI

<b>Darkside of AI</b>	<b>Definition</b>	<b>Representative research</b>
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 & Yang, 2018); (Pitardi & 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 & Yang, 2018); (Sung & 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)

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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 & 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 generalize customer preferences and behaviours, neglecting subtle differences among individuals (Uysal et al., 2022). This neglect of uniqueness can result in impersonalized 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.

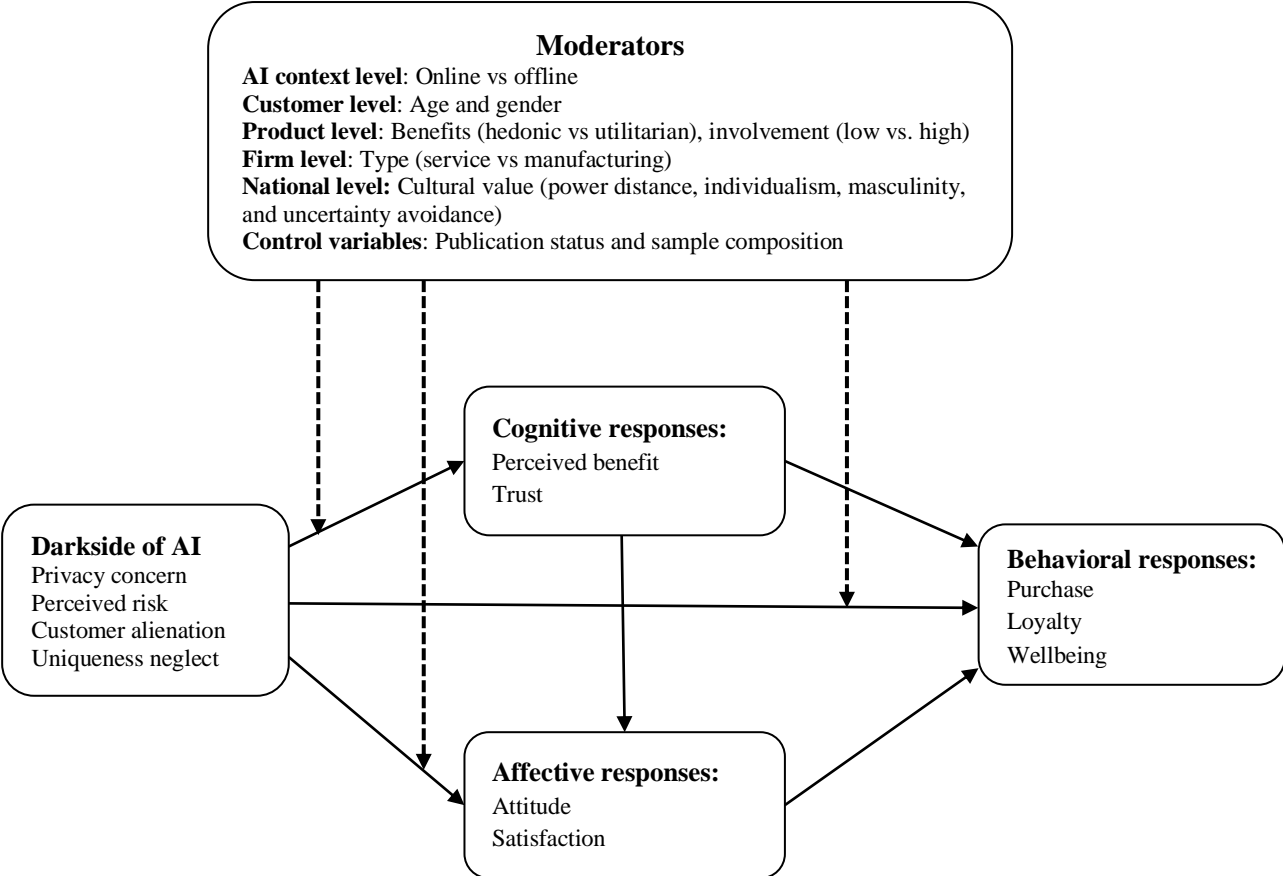
## **2. Conceptual framework**

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 utilized cognitive-affect-behaviour (CAB) model (Holbrook, 1986). According to this model, customer responses to marketing activities are categorized 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 & 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 emphasizes 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 & Matthes, 2017).

As depicted in our framework (Figure 1) and building on previous research in customer response marketing activities (Dick & Basu, 1994; Holbrook & 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.



**Note:** 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.

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Figure. 1: Research conceptual framework

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.

### **3. Hypothesis development**

#### **3.1 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 & 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 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 & 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:

**H<sub>1</sub>**: Privacy concern is negatively related to consumer cognitive responses; (a) perceived benefit and (b) trust.

**H<sub>2</sub>**: Privacy concern is negatively related to consumer affective responses; (a) attitude and (b) satisfaction.



**H<sub>3</sub>:** Privacy concern is negatively related to consumer conative responses (a) purchase, (b) loyalty, and (c) wellbeing.

### **3.2 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, Quach, et al., 2022) but also causes negative behavioural responses among customers (Seo & 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:

**H<sub>4</sub>:** Perceived risk is negatively related to consumer cognitive responses; (a) perceived benefit and (b) trust.

**H<sub>5</sub>:** Perceived risk is negatively related to consumer affective responses; (a) attitude and (b) satisfaction.

**H<sub>6</sub>:** Perceived risk is negatively related to consumer conative responses (a) purchase, (b) loyalty, and (c) wellbeing.

### **3.3 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 (Esmailzadeh, 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 (Gremmler et al., 2020). 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 (Esmailzadeh, 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) wellbeing.

### **3.4 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 personalization 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 personalized 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:

**H<sub>10</sub>:** Uniqueness neglect is negatively related to consumer cognitive responses; (a) perceived benefit and (b) trust.

**H<sub>11</sub>:** Uniqueness neglect is negatively related to consumer affective responses; (a) attitude and (b) satisfaction.

**H<sub>12</sub>:** Uniqueness neglect is negatively related to consumer conative responses (a) purchase, (b) loyalty, and (c) wellbeing.

### **3.5 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 personalization, especially in online versus offline contexts such as a physical store (Barari, Quach, et al., 2022). Consequently, the relationship between customer alienation and uniqueness neglect and customer response can differ in online and offline contexts. Thus, we expect:

**H<sub>13</sub>:** AI context (online vs. offline) moderate the direct relationship between the dark sides of AI and all customer responses.

### **3.6 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:

**H<sub>14</sub>:** Age moderates the direct relationship between the dark sides of AI, and all customer responses.

**H<sub>15</sub>:** Gender moderates the direct relationship between the dark sides of AI, and all customer responses.

### **3.7 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 & 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:

**H<sub>16</sub>:** Product types (hedonic vs utilitarian) moderate the direct relationship between dark sides of AI and all customer responses.

### **3.8 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 & 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 & 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:

**H<sub>17</sub>:** Product involvement (high vs low) moderate the direct relationship between dark sides of AI and all customer responses.

### **3.9 Firm level (service vs manufacturing)**

Firm type is a crucial moderator in the relationship between the dark side of AI and customer responses (Barari, Paul, et al., 2022). 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:

**H<sub>18</sub>:** Industry type (service vs manufacturing) moderates the direct relationship between the dark sides of AI, and all customer responses.

### **3.10 National level (Cultural values)**

Culture has been identified as an important moderator that significantly influences customer attitudes and behavior towards marketing activities (Palmatier et al., 2006). 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, 2021). However, previous research indicates that customers from different cultures exhibit distinct cognitive and affective responses toward technologies,

shaping their behavioral responses to both the positive and negative aspects of technology (Barari, Paul, et al., 2022). 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, Paul, et al., 2022). While there are various approaches to studying cross-cultural differences, Hofstede et al. (2010) 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.'s (2010) five dimensions - individualism, power distance, masculinity, uncertainty avoidance, and long-term orientation - as moderators between dark side of AI and customer evaluative and behavioral response. Thus, we expect:

**H<sub>19</sub>:** 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.

#### **4. 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 moderators (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 utilized 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 & 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.

## 5. 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 ( $\beta = -.03$ ,  $p < .05$ ) and uniqueness neglect ( $\beta = -.02$ ,  $p < .05$ ) 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 ( $\beta = -.34$ ,  $p < .05$ ) and uniqueness neglect ( $\beta = -.34$ ,  $p < .05$ ) 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 ( $\beta = -.27$ ,  $p < .05$ ), trust ( $\beta = -.29$ ,  $p < .05$ ), evaluation ( $\beta = -.37$ ,  $p < .05$ ), and purchase ( $\beta = -.40$ ,  $p < .05$ ), but privacy concern has the highest relationships with customer loyalty ( $\beta = -.26$ ,  $p < .05$ ) and wellbeing ( $\beta = -.12$ ,  $p < .05$ ). For most relationships, customer alienation and uniqueness neglect have the lowest relationships with both customer evaluative and behavioural responses. Additionally, the relationships between customer alienation ( $\beta = -.03$ ,  $p > .05$ ) and uniqueness neglect ( $\beta = -.02$ ,  $p > .05$ ) are not significant."



Table 2. Result of testing research conceptual model

Hypothesis	Relationship	$\beta$ -value	Result
H1a	Privacy concern → Perceived benefits	-.12*	Supported
H1b	Privacy concern → Trust	-.23*	Supported
H2a	Privacy concern → Attitude	-.17*	Supported
H2b	Privacy concern → Satisfaction	-.19*	Supported
H3a	Privacy concern → Purchase	-.23*	Supported
H3b	Privacy concern → Loyalty	-.26*	Supported
H3c	Privacy concern → Wellbeing	-.12*	Supported
H4a	Perceived risk → Perceived benefits	-.27*	Supported
H4b	Perceived risk → Trust	-.29*	Supported
H5a	Perceived risk → Attitude	-.34*	Supported
H5b	Perceived risk → Satisfaction	-.37*	Supported
H6a	Perceived risk → Purchase	-.40*	Supported
H6b	Perceived risk → Loyalty	-.22*	Supported
H6c	Perceived risk → Wellbeing	-.10*	Supported
H7a	Customer alienation → Perceived benefits	-.14*	Supported
H7b	Customer alienation → Trust	-.09*	Supported
H8a	Customer alienation → Attitude	-.09*	Supported
H8b	Customer alienation → Satisfaction	-.10*	Supported
H9a	Customer alienation → Purchase	-.14*	Supported
H9b	Customer alienation → Loyalty	-.03	Rejected
H10a	Uniqueness neglect → Perceived benefits	-.10*	Supported
H10b	Uniqueness neglect → Trust	-.09*	Supported
H11a	Uniqueness neglect → Attitude	-.09*	Supported
H11b	Uniqueness neglect → Satisfaction	-.10*	Supported
H12a	Uniqueness neglect → Purchase	-.10*	Supported
H12b	Uniqueness neglect → Loyalty	-.02	Rejected
-	Perceived benefits → Attitude	.45*	-
-	Perceived benefits → Satisfaction	.48*	-
-	Trust → Attitude	.50*	-
-	Trust → Satisfaction	.52*	-
-	Perceived benefits → Purchase	.43*	-
-	Perceived benefits → Loyalty	.40*	-
-	Perceived benefits → Wellbeing	.39*	-
-	Trust → Purchase	.44*	-
-	Trust → Loyalty	.44*	-
-	Trust → Wellbeing	.42*	-
-	Attitude → Purchase	.51*	-
-	Attitude → Loyalty	.50*	-
-	Attitude → Wellbeing	.49*	-

-	Satisfaction → Purchase	.55*	-
-	Satisfaction → Loyalty	.53*	-
-	Satisfaction → Wellbeing	.50*	-

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Note: There were not affect sizes for H9c and H12c thus there are not reported in the current table; \* <.05

**Source(s):** Created by the authors

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	.132**	.031	.053*	-.003	.069*	.113**	.059*	.023	.010	.067*	.019
Risk → Benefits	.106**	.010	.060*	.010	.076*	.210**	.061*	.021	.011	.009	.016
Alienation → Benefits	-.046*	.004	.044*	.004	.001	.114**	-.046*	.005	-.016	-.011	.011
Uniqueness → Trust	-	-	-	-	-	-	-	-	-	-	-
Privacy → Trust	.242**	.199**	.101*	.051*	.98*	.091*	.148**	.128**	.048*	.163**	.148**
Risk → Trust	.212**	.201**	.99*	.087*	.104*	.097*	.113**	.102*	.012	.196**	.112**
Alienation → Trust	.009	.134**	-.011	.001	.009	.061*	-.064*	.012	.006	-.019	.056*
Uniqueness → Trust	-.010	-.011	.014	.005	.023	.016	.023	-.030	-.070	.019	-.010
Privacy → Attitude	.082*	.094*	.099*	.069*	.91*	.100*	.050*	.066*	.011	.060*	.007
Risk → Attitude	.114**	.121**	.110*	.066*	.106*	.139**	.049*	.059*	.021	.077*	.069*
Alienation → Attitude	-.070*	.009	.080*	-.011	.021	.014	-.011	.019	.011	.060*	.049*
Uniqueness → Attitude	-.040*	-.101**	.017	-.010	.012	-.019	.015	-.009	.011	-.023	.009
Privacy → Satisfaction	.094*	.105*	.103*	.088*	.91*	.103*	.051*	.066*	.021	.065*	.024
Risk → Satisfaction	.129**	.125**	.109*	.075*	.101*	.143**	.046*	.052*	.016	.088**	.073*
Alienation → Satisfaction	-.073*	.030	.085*	-.006	.012	.015	-.011	.017	.009	.075*	.043*
Uniqueness → Satisfaction	-.049*	-.115**	.019	-.009	.011	-.016	.018	-.008	.012	-.025	.005
Privacy → Purchase	.106*	.209**	.089*	.057*	.107*	.134**	.056*	.002	-.006	.055*	.021
Risk → Purchase	.226**	.211**	.111*	.061*	.121*	.201**	.053*	.019	.011	.061*	.016
Alienation → Purchase	.002	.094*	.004	.010	.002	-.013	-.001	.007	.001	-.011	-.002
Uniqueness → Purchase	-.012	.012	-.002	-.004	.008	.008	.010	-.006	-.004	.009	-.001
Privacy → Loyalty	.007	-.014	-.024	.012	.014	.024	.023	.016	.021	-.003	.011
Risk → Loyalty	-.012	.021	.011	-.001	.059*	.016	.016	.019	.013	.011	.015
Uniqueness → Loyalty	-	-	-	-	-	-	-	-	-	-	-
Alienation → Loyalty	.003	-.009	.039*	.019	.019	.014	.004	.009	.014	-.012	.015
Privacy → Wellbeing	.019	.011	.007	-.021	.008	.013	-.001	-.002	-.001	-.007	-.011
Risk → Wellbeing	-	-	-	-	-	-	-	-	-	-	-
Uniqueness → Wellbeing	-	-	-	-	-	-	-	-	-	-	-
Alienation → Wellbeing	-	-	-	-	-	-	-	-	-	-	-

Note: 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 < .05, \*\*p < .01.

Source(s): Created by the authors

## 6. General discussion

Overall, our results 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.

### 6.1 Theoretical implications

Analysing our conceptual model enables us to provide several theoretical contributions to the dark side of AI literature. Firstly, while previous research has examined the negative effects of the dark side of AI on various customer responses (Chaturvedi & Verma, 2023; 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 recognized 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, Quach, et al., 2022; 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 unauthorized access and utilization 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, emphasizing the importance of social value to customers. The absence of humanized 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 customization based on customer needs, it falls short in satisfying customers' desire for uniqueness. AI's customization 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 & Dutta, 2016).

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 emphasizes 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, characterized 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 & Cian, 2022; 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 & Kannan, 2020).

## *6.2 Managerial Implications*

In addition to its theoretical contributions, our model emphasizes 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 personalized solutions through customer input and machine learning but often leads to mass customization. For customers who value personalized 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 personalized 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 inquiries, 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 personalized 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 emphasizes the negative effects of privacy concerns and perceived risks related to AI, influencing customer evaluations and behaviors. Practical strategies should prioritize 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.

### *6.3 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 emphasizes 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.

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