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The Influence of Benefits and Trust on Consumers' Attitudes towards Artificial Intelligence: The Moderating Role of Threats

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Background/Purpose: This article explores consumers' perception of the benefits of intelligent service robots (ISR) in the purchasing process, their trust in artificial intelligence (AI), their perception of AI-related threats, and the impact of these variables on consumer attitudes toward AI. Additionally, the study examines the moderating effect of perceived AI-related threats on the relationship between perceived benefits and trust on one side and the formation of consumer attitudes toward AI on the other.
Methods: The research was conducted in the first half of 2024 on a judgmental sample of 224 employed consumers in the Republic of Slovenia. Data were collected through a structured online questionnaire. For the empirical analysis, a non-parametric approach using SEM-PLS modelling was applied to examine relationships between the studied research constructs.
Results: The findings indicate that perceived benefits of ISR have a strong and positive impact on consumer attitudes toward AI, while perceived AI-related threats strongly and negatively influence these attitudes. Moreover, the results reveal that perceived AI-related threats significantly and negatively moderate the effect of consumers' perceived trust in AI on the formation of their attitudes toward AI.
Conclusion: The results of this study contribute significantly to the theoretical understanding of employed consumers' attitudes toward AI. They also provide practical implications for companies in developing predictive models of consumer behaviour and defining effective marketing strategies to encourage AI adoption in the purchasing process.

Keywords: *Artificial intelligence (AI), Consumer attitudes, Perceived AI-related threats, Perceived benefits of intelligent service robots (ISR), Perceived consumer trust*

JEL Classification: M21, M31

1 Introduction

Artificial intelligence (AI) refers to technologies capable of performing tasks that typically require human intelligence (Stein et al., 2024), such as visual perception, speech recognition, decision-making, and natural language processing. AI systems are designed to learn from experience and improve over time using algorithms and statistical models (Ahmad et al., 2023; Russell & Norvig, 2010). Consequently, AI has a transformative impact on how we live and work (Lockey et al., 2021), enhancing efficiency, accuracy, and decision-making.

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AI has numerous applications across various fields and industries, including healthcare, finance, retail, transportation, education, and marketing (Cavallo, 2019; Cao, 2022; Bughin et al., 2018; Bharadiya, 2023; Özüdoğru & Cakir, 2021; Huang & Rust, 2018).

The marketing industry, in particular, has widely adopted AI, streamlining various market exchange processes such as customer segmentation and personalized advertising. AI can analyse customer data to identify behavioural patterns and provide personalized recommendations and advertisements based on customer preferences and purchase history (Basha, 2023). It supports the evolution of marketing toward automated, data-driven value creation, optimizing operations by automating tasks and enabling precise marketing strategies (Kirova & Boneva, 2024; Martinez-Lopez & Casillas, 2013). Additionally, it enhances product and service customization by analysing consumer purchases and interests (Trawnih et al., 2022; Shank et al., 2019).

AI is transforming the way companies interact with customers, leading to improved customer experiences and satisfaction. AI technologies, such as chatbots, virtual assistants, and predictive analytics, offer numerous benefits to consumers by enhancing service quality, personalizing experiences, and increasing purchasing efficiency (Aksu & Sener, 2024; Trawnih et al., 2022; Xu et al., 2021). As a result, the rapid adoption of AI is reshaping the consumer buying process and significantly influencing consumer behaviour, including attitudes toward AI (Mendez-Suarez et al., 2024).

Recent research indicates that AI has a significant impact on consumer trust (Chi & Vu, 2022). Studies have observed a positive relationship between empathetic AI responses and consumer trust, as they improve communication quality between AI systems and consumers, fostering AI acceptance as a service agent (Chi & Vu, 2022; Huang & Rust, 2018). Previous research has primarily focused on factors such as transparency, explainability, accuracy, reliability, automation, anthropomorphism, and mass data extraction as key antecedents and challenges of trust in AI technology (Lockey et al., 2021; Hasan et al., 2021; Zarifis & Cheng, 2022). However, there is a lack of detailed research examining consumer trust and the benefits of AI as key factors influencing consumer attitudes toward AI.

On the other hand, the adoption of AI technologies has raised concerns regarding privacy, security, and job displacement (Mirbabaie et al., 2022). Therefore, it is essential to understand consumers' perceived experiences with AI, both in the buying process and in general, as these perceptions shape their attitudes toward AI and influence their willingness to engage with AI technologies (Kieslich et al., 2021). Negative attitudes toward AI may lead to skepticism regarding its capabilities, concerns about potential risks and ethical implications, and ultimately, reduced adoption (Ikkatai et al., 2022). Additionally, some consumers exhibit significant hesitation and fear toward autonomous systems (Hinks, 2020).

We argue that consumer attitudes toward AI technologies are a crucial factor strongly influencing behavioural patterns and the willingness to adopt AI in the buying process. While consumers recognize the benefits of AI and trust its capabilities, they also perceive potential threats, such as job displacement, changes in work tasks, ethical and security dilemmas, and other possible negative consequences of AI implementation in different environments. However, research exploring this "dual role" of consumers—both recognizing the advantages and perceiving threats of AI—remains limited.

This study contributes to the theoretical understanding of consumer attitudes toward AI and the factors influencing their formation by focusing on employed consumers. This approach provides a more comprehensive assessment of attitudes toward AI, exploring the interplay between the perceived benefits of AI in the purchasing process, general trust in AI, and perceived risks of AI both in the purchasing process and the workplace.

To address the identified gaps in the literature, we formulated the following research questions:

(a) How do the potential benefits of AI for consumers, consumer trust in AI, and perceived threats of AI influence consumer attitudes toward AI?

(b) Do perceived threats moderate the relationship between perceived benefits, trust, and consumer attitudes toward AI?

Furthermore, the findings of this research are expected to provide valuable insights for policymakers and companies, helping them design and market AI-based products and services that address consumer concerns and preferences, mitigate perceived threats, and overcome adoption barriers to improve consumer attitudes toward AI.

2 Literature Review and Hypothesis Development

2.1 Consumers' benefits of AI

To fully exploit the economic and societal advantages of AI technologies, it is vital for companies to comprehend and quantify their benefits for consumers (Ahmad et al., 2023) in order to know how do they feel about their AI products to market them better (Haleem et al., 2022). Perceived benefits are beliefs about the positive outcomes associated with a cognitive, affective or behaviour response of consumers to a real or perceived threat (Chandon et al., 2000; Liu et al., 2012). Grewal et. al (2021) suggest that realized and anticipated benefits of AI for consumers based on customized offers achieved through data-led personalization, optimization, and innovation.

According to the majority of researchers, there are a few benefits of AI for consumers: enhances decision-making and problem solving (Sivarajah et al., 2017; Topol, 2019; Bastani et al., 2021; Chen et al., 2019), increases efficiency and productivity, customization (Grewal et al., 2021) as well as enhances consumers' experience (Trawnih et al., 2024), which is relating to the interactions between the consumer and the company during the consumer' journey, and encompasses multiple dimensions: emotional, cognitive, behavioural, sensorial, and social (Puntoni et al., 2021; Lemon and Verhoef, 2016; Brakus et al., 2009).

From the marketing point of view, last mentioned benefit of AI, i.e. enhanced consumer experience, significantly reshapes exchanging processes by enhancing customer engagement through interaction and increasing efficiency (Xu et al., 2021). By analysing customer data, AI can create a detailed profile of each consumer and use this information to provide customized recommendations and offers (Kadambi et al., 2018). The data capture experience provides benefits to consumers because it can make them feel as if they are served by the AI: the provision of personal data allows consumers access to customized services, information, and entertainment, often for free (Puntoni et al., 2021).

Consumers in buying process often face with intelligent customer service robots (i.e. chatbots and virtual assistants), which can significantly influence their experience with AI. Chatbots are automated software programs that can simulate conversation with human users. They can be used to provide customer support, answer common questions, and provide recommendations. Virtual assistants are similar to chatbots but are designed to provide more personalized assistance to users (Jenkins, 2021) by offering quick and efficient support and reducing wait times. They can also be available 24/7, providing consumers with access to support outside of regular business hours.

Consequently, companies can improve consumer satisfaction and loyalty, leading to increased revenue and consumer retention. Chatbots and virtual assistants can also reduce the need for human support staff, leading to cost savings for companies. Predictive analytics can be used to identify trends and patterns in consumer behaviour, which can be used to develop targeted marketing campaigns and identify new opportunities for growth (Mariani et al., 2023).

Despite of a number of researches on specific elements of consumers' benefits of AI, and factors through which we can explain cognitive, affective and behavioural reactions of consumers in relation to implementation of AI technology, there is still a research gap.

To fill this gap, our research tries to contribute to more comprehensive insight into different viewpoints of consumers' benefits of specific manifestation of AI (i.e. intelligent consumer service robots), and a potential impact of these benefits on consumers' attitudes towards AI.

Suggested by Gao et al. (2022), potential consumers' stimuli of AI can fall into five groups: perceived interactivity of consumers, perceived personalization of consumers, consumers' engagement, consumers' value co-creation, and consumers' ability readiness. In our opinion, first four groups of stimuli, suggested by Gao et al. (2022), have the characteristics of consumers' benefits of AI as well.

Perceived interactivity and personalization are two of the most critical stimuli, with the former relating to consumers' subjective assessment of their interaction with AI technology overall (Scardamalia and Bereiter, 2014; Gao et al., 2022) and the latter relating to the potential of AI technology to provide consumers with customized and personalized services (Neuhofer et al., 2015; Gao et al., 2022). AI based devices with high levels of interactivity not only enable consumers to engage, but also provide them with opportunities to share information and emotional support with others (Roy et al., 2019; Gao et al., 2022). In addition to these, high levels of personalized offerings provide consumers with customized suggestions or solutions through algorithmic analysis to satisfy their personal preferences and needs (Heer, 2019; Gao et al. 2022).

Consumers engagement is mental state of consumers who are creating experiences with a company in a specific service relationship (Brodie et al., 2011). AI systems are only useful if consumers recognize the suggestions provided by AI before they can accept the AI itself (Gao et al., 2022).

Among the actors involved in the value co-creation process, consumers have been identified as a particularly significant contributor that companies can effectively exploit (Tran and Vu, 2021). According to Zhang and Chen (2008), companies focus on co-creation with consumers can help to gain new competences, and to achieve a more competitive advantage for them. On the other side, consumers' cooperation with companies and their empowerment in process of creating a new product (AI technology) influence their level of perceived benefits, received from the AI, and their level of satisfaction as well.

In our opinion such framework can offer a good starting point to hypothesize:

Hypothesis 1: Consumers' perceived benefits of intelligent consumer service robots (ICSRs) have a positive and significant effect on consumers' attitudes towards AI technology.

2.2 Consumers' trust in AI

Although there is no universally accepted scholarly definition of this concept, we can define trust as 'a belief by one party in a relationship that the other party will not act against his or her interests, where this belief is held without undue doubt or suspicion and in the absence of detailed information about the actions of the other party'

(Tomkins, 2001; Laaksonen et al., 2008). One party may trust the other party's benevolence (a belief that on party acts in the interests of the other), honesty (a belief that the other party's word is reliable and credible), and competence (a belief that the other party has the necessary expertise to per-form as required) (Buttle, 2010).

Therefore, trust is a vital aspect of consumers' behaviour, influencing the attitudes and decision-making processes of consumers towards products and services (Rousseau et al., 1998) and is linked to consumers' expectation of services provided by companies (Chi and Vu, 2022), namely the two components of trust are the intention to accept vulnerability based on positive expectations of consumers (Lockey et al., 2021).

In the context of AI, trust can be defined as the willingness of individuals to rely on AI systems and accept their recommendations or decisions. Trust in AI can be influenced by various factors, including the perceived reliability, competence, and ethical standards of the system and its operators (Mayer et al., 1995). Deeper understanding of consumers' trust based on AI system features to consumers' motivation and responses has yet to be reached. From this perspective, consumers' trust in AI is defined as a common ground of belief from consumers to AI devices (Chi and Vu, 2022).

As AI technologies are increasingly integrated into various aspects of daily life, the importance of trust in AI is growing (Wang et al., 2019). Trust plays a crucial role in ensuring the safe and effective use of AI, as well as promoting public acceptance of these technologies. Some researchers have shown that consumers are more likely to adopt and use new technologies when they trust the technology and its providers (Riegelsberger et al., 2003). On the other hand, lack of trust in technology can lead to resistance and reluctance to use it. Therefore, building and maintaining trust is essential for the successful adoption and integration of AI technologies into every day' buying processes of consumers (Komiak and Benbasat, 2006).

However, building trust in AI is not always easy, as AI systems often operate in complex and opaque ways, making it difficult for consumers to understand how decisions are made (Lu et al., 2025). Additionally, concerns about privacy, security, and bias can erode trust in AI systems (Kaplan and Haenlein, 2019). As a result, there is a need for greater transparency and accountability in AI systems to increase trust and confidence in their use (European Commission, 2020).

Another challenge to building trust in AI is the lack of regulation and standardization in the industry. As AI technologies continue to evolve and develop, there is a need for clear guidelines and standards to ensure the ethical and responsible use of AI. This will not only help build trust among consumers but also promote innovation and growth in the industry (Floridi et al., 2018).

The adoption of new technologies by the public is strongly influenced by the level of trust that individuals have in those technologies (Siau and Wang, 2018). This is especially true for AI technologies, which are often viewed as complex and potentially dangerous. Research has shown that trust is a key factor in the adoption of AI technologies, and that lack of trust can be a significant barrier to adoption (Hasan et al., 2021; Venkatesh et al., 2003).

One of the main reasons why trust is important for the adoption of new technologies is that it reduces uncertainty and perceived risk. When individuals are uncertain about the potential risks and benefits of a new technology, they may be hesitant to adopt it. Trust helps to reduce this uncertainty by providing individuals with a sense of confidence that the technology will perform as expected and that their personal information will be protected (Zarifis and Cheng, 2022; Morgan and Hunt, 1994).

Another important factor in the role of trust in the adoption of AI technologies is the social influence of trust. Consumers are often influenced by the opinions and behaviours of others when making decisions about new technologies. If individuals perceive that others trust a new technology, they are more likely to adopt it themselves. On the other hand, if there is a lack of trust in a new technology, this can lead to a negative perception and reduced adoption (Lockey et al., 2021; Luhmann, 1988).

In our opinion, trust plays a crucial role in consumers' adoption of AI technologies. To promote the adoption of AI, it is important for developers of AI and policymakers to prioritize building trust with the consumers by addressing concerns related to transparency, ethics, and security. By building trust, AI technologies can be adopted more widely and effectively, leading to their potential benefits and positive consumers' attitudes towards AI. Hence, our hypothesis is proposed as follows:

Hypothesis 2: Consumers' trust in AI has a positive and significant effect on consumers' attitudes towards AI technology.

2.3 Consumers' perceived threats of AI

Consumers as general public (outside the buying process) show, despite of perceived benefits of AI, some considerable restraint when it comes to the broad societal diffusion of AI applications that might even border on actual fear of such technology (Kieslich et al., 2021; Hinks, 2020; McClure, 2018; Liang, 2017). Understanding both, benefits and threats, enables companies a more comprehensive approach to threats assessment (Ahmad et al., 2023; Tepylo et al., 2023). If companies' know how people feel about their AI products, they can market them better (Ahmad et al., 2023; Haleem et al., 2022).

There are numerous articles discussing the threats of AI tools for general public. The majority of researchers define the following reasons of threats: job displacement

(Mirbabaie et al., 2022), economic inequality (Brynjolfsson and McAfee, 2014), ethical and legal reasons (Huang et al., 2023; Wach et al., 2023; Kieslich et al., 2021), lack of transparency (Jones, 2018), potential for different types of bias (Buolamwini and Gebru, 2018), and risk of potential misuse and abuse (Tufekci, 2018).

AI has the potential to automate many tasks that are currently performed by humans, which may lead to job loss and unemployment. Recent research has suggested that up to 47% of US jobs are at risk of automation in the next few decades (Frey and Osborne, 2017). While some new jobs may be created by the development of AI, the displacement of jobs is likely to have a significant impact on the labour market and may disproportionately affect low-skilled workers and those in industries that are most susceptible to automation, such as manufacturing and transportation (Mirbabaie et al., 2022; Autor, 2015).

The displacement of jobs can also lead to economic inequality. Those who are most impacted by job loss may not have the skills or resources to adapt to new jobs or industries, which can lead to long-term unemployment and reduced income. This may exacerbate existing economic inequalities and create a widening gap between the rich and poor (Brynjolfsson and McAfee, 2014). In addition, the development of AI may create a new class of "winner-takes-all" industries, where a few companies and individuals benefit greatly from the advances in AI technology, while others are left behind (Brynjolfsson and McAfee, 2014).

As AI technology continues to advance, there are growing concerns about its ethical and legal implications. One of the main ethical concerns surrounding AI is the potential for the technology to be used in ways that violate privacy and human rights. Facial recognition technology has been criticized for its potential use in mass surveillance and tracking of individuals without their consent (Huang et al., 2023; Wach et al., 2023; Kieslich et al., 2021; Crawford and Calo, 2016). The possibility for AI to be prejudiced or racist is yet another ethical worry. Because AI systems are trained on historical data, they may learn and perpetuate existing biases and inequalities. This might result in unfairness in the recruiting, financing, and criminal justice systems.

In addition, the lack of diversity in the tech industry may contribute to biased AI systems, as the people designing and developing these systems may not represent the diversity of the population they are intended to serve (O'Neil, 2016). There are also legal concerns surrounding AI, particularly in the area of liability. As AI systems become more autonomous and make decisions that impact human lives, questions arise about who is responsible if something goes wrong (Mirbabaie et al., 2022; Calo, 2015).

One of the major challenges with AI systems is their lack of transparency and potential for bias. AI systems can be very complex, and it can be difficult to understand how they make decisions. This lack of transparency can make it difficult to identify errors or biases in the system, which can have significant consequences (Jones, 2018).

One way in which bias can manifest in AI systems is through biased data. AI systems learn from the data they are trained on, and if that data is biased, the system can learn to make biased decisions. Specifically, if a facial recognition system is trained on a dataset that is predominantly male and white, the system may not perform as well on images of women or people with darker skin tones. This can have serious implications for areas such as law enforcement or hiring decisions (Buolamwini and Gebru, 2018). In addition to biased data, AI systems can also perpetuate and amplify existing social biases. If an AI system is trained on data that reflects existing gender or racial biases, the system may learn to perpetuate these biases in its decisions. This can lead to discrimination and exacerbate existing inequalities (O'Neil, 2016).

While AI has the potential to bring significant benefits to consumers, there is also a risk of potential misuse and abuse. This can occur in a variety of ways, such as the use of AI for malicious purposes (cyberattacks or the spread of misinformation) (Ye et al., 2016), or the unintended consequences of AI systems (perpetuation of biases or the amplification of harmful behaviours) (O'Neil, 2016). This can lead to discriminatory outcomes, such as biased hiring decisions or the denial of access to services for certain groups of people. AI systems can amplify harmful behaviours, such as the spread of hate speech or the promotion of extremist content, by prioritizing engagement over accuracy or truth (Tufekci, 2018).

According to some previous researches, threats of AI are at first processed cognitively (Kieslich et al., 2021; Witte, 1992) and, therefore, can shape consumers' attitudes towards AI. Consequently, we hypothesize:

Hypothesis 3: Consumers' perceived threats of AI have a negative and significant effect on consumers' attitudes towards AI technology.

2.4 Consumers' Attitudes towards AI

According to Eagly and Chaiken (1993), attitudes are described as "evaluative judgments about objects, people, or events that are expressed by positive or negative affect, cognition, or behaviour". Positive, negative, or neutral attitudes as evaluations can be communicated with affective, cognitive, and behavioural reactions (Fishbein and Ajzen, 1975).

There are a number of factors that affect how attitudes are formed, i.e. personal beliefs, social influence, as well as cognitive processes, such as perception and learning. Personal beliefs refer to an individual's thoughts and convictions about an object or issue. Experiences, socialization, and media exposure can all have an impact on these beliefs (Ajzen and Fishbein, 1980). Social influence refers to the impact that others have on individual's attitudes and behaviour. It can take many forms, including conformity, social comparison, and persuasion (Cialdini and Goldstein, 2004). In order to make sense of their surroundings, people organize and interpret sensory data through a process known as perception. Contrarily, learning describes the process by which people pick up new facts and understanding about a subject. Both, perception and learning can shape an individual's attitudes towards an object or issue (Petty and Cacioppo, 1986).

To successfully design, develop, launch, communicate, and promote new AI-intensive products, companies must first understand their consumers' attitudes towards AI, as current consumer perceptions appear to be divided (Mendez-Suarez et al., 2024). It is essential to understand consumers' views on AI; thus, reducing perceived risks, enhancing potential benefits, strengthen their trust, and diminish perceived threats. Consumers with more favourable attitudes towards AI are more likely to hold positive views of AI and more receptive attitude toward AI in marketing communications (Lobera et. Al., 2020; Chen et al., 2022; Mendez-Suarez et al., 2024).

Several theoretical frameworks have been proposed to explain how individuals form attitudes towards new technologies such as AI. Technology Acceptance Model (TAM) developed by Davis (1989) posits that perceived usefulness and perceived ease of use are the primary determinants of an individual's intention to use a technology. This model has been used to study public attitudes towards a wide range of technologies, including AI (Venkatesh et al., 2003).

Another relevant theoretical framework is the Social Cognitive Theory (SCT) developed by Bandura (1986). According to SCT, individuals learn attitudes and behaviours through observation and modelling of others, as well as through their own experiences (Bandura, 1986). In the context of AI, SCT could be applied to understand how individuals form attitudes towards AI based on their exposure to AI technologies and their perceptions of AI in the media.

The Technology Risk Framework (TRF) developed by Slovic (1999) is another relevant framework. The TRF suggests that public attitudes towards technologies are influenced by three main factors: dread risk, unknown risk, and personal control. Dread risk refers to the perceived potential for a technology to cause catastrophic harm, unknown risk refers to uncertainties surrounding the technology, and personal control refers to the perceived ability of an individual to control the risks associated with the technology (Slovic, 1999).

Attitude-Behavioural Intention (ABI) model developed by Moon and Kim (2001) suggests that attitudes towards AI are influenced by perceived usefulness, perceived ease of use, and perceived risks associated with AI. These attitudes, in turn, influence an individual's intention to use or not use AI.

Another relevant model is the Cognitive-Affective-Conative (CAC) model proposed by Cacioppo et al. (2007). This model suggests that attitudes towards AI are formed through cognitive (i.e. beliefs about AI), affective (i.e. emotions towards AI), and conative (i.e. behavioural processes). This model has been used to study attitudes of individuals towards a range of technologies, including AI (Kraus, 2017; Stein et al. 2024).

While theoretical frameworks and models provide a useful starting point for understanding consumers' attitudes towards AI, empirical studies are necessary to gain a more comprehensive and nuanced understanding of these attitudes. Nevertheless, a growing body of research has explored consumers' attitudes towards AI, examining factors such as trust, risk perception, benefits, drawbacks, and ethical considerations, there are still gaps and limitations in the literature that need to be addressed, if we investigate consumers' attitudes towards AI. Therefore, it seems to be a good platform for empirical research.

2.5 The moderating role of consumers' perceived threats of AI

In order to get comprehensive insight into consumers' attitudes towards AI as a consequence of their perceived benefits of AI and perceived trust in AI, it is of great importance not to overlook consumers' perceived threats of AI. Although consumers evaluate specified benefits of AI and develop a particular level of trust in it during the buying process, they inevitable face different threats of AI in every day' life, which are not necessarily derived as a consequence of their interaction and experiences in the buying process. Such threats can arise as a result of different factors, as for example: personal opinion, their readiness to adopt AI devices, and a huge number of influences from external environment (i.e. social, economic, cultural, technological, educational etc.).

Therefore, we posit that consumers' perceived threats of AI may moderate, i.e. effect strength of the impact of consumers' potential benefits of AI and consumers' perceived trust in AI. Thus, our study proposes:

Hypothesis 4: Consumers' perceived threats of AI negatively and significantly moderates the effect of consumers' perceived benefits of AI on consumers' attitudes towards AI.

Hypothesis 5: Consumers' perceived threats of AI negatively and significantly moderates the effect of consumers' perceived trust in AI on consumers' attitudes towards AI.

3 Research Methodology and Results

3.1 Sample and collection of data

The data for the empirical research was collected through a highly structured online questionnaire from January 2024 to June 2024. The respondents were employed consumers aged 18 to 64 in the Republic of Slovenia who had used intelligent consumer service robots (ICSRs) in their purchasing process.

In the first step, the questionnaire was distributed to a convenient sample of 600 respondents, using filter questions regarding their age range, employment status, and experience with ICSRs in the purchasing process. In the second step, a non-random judgmental sampling method was applied to select valid responses based on the required respondent parameters for our research. Among the received questionnaires, 224 were deemed valid.

A chi-square test of early and late respondents showed no significant differences ($p > 0.05$) in gender, age, years of employment, or monthly income. Therefore, the possibility of non-response bias was ruled out. The characteristics of the respondents in terms of gender, age, years of employment, and monthly income are presented in Table 1.

3.2 Analysis of data

The research is quantitative using non-parametric approach to SEM-PLS modelling of relations between the main research constructs: consumers' perceived benefits of ICSRs, consumers' perceived trust in AI, and consumers' perceived threats of AI as independent research constructs on one side, as well as consumers' attitudes towards AI as dependent research construct. In addition to these, the moderating impact of consumers' perceived threats of AI was analysed. Figure 1 shows to us the conceptual framework developed.

Table 1: Respondents' demographic characteristics

Criteria	Frequency	%
Gender		
Male	123	54,9
Female	101	45,1
Age		
18 – 24 years old	58	25,9
25 – 34 years old	76	33,9
35 – 49 years old	72	32,1
50 – 64 years old	18	8,1
Working years		
Below 3 years	37	16,5
3 – 5 years	55	24,6
5 – 10 years	51	22,8
Above 10 years	81	36,1
Monthly income		
Below 1000 euro	39	17,4
1000 – 1500 euro	78	34,8
1501 – 2000 euro	67	29,9
Above 2000 euro	40	17,9

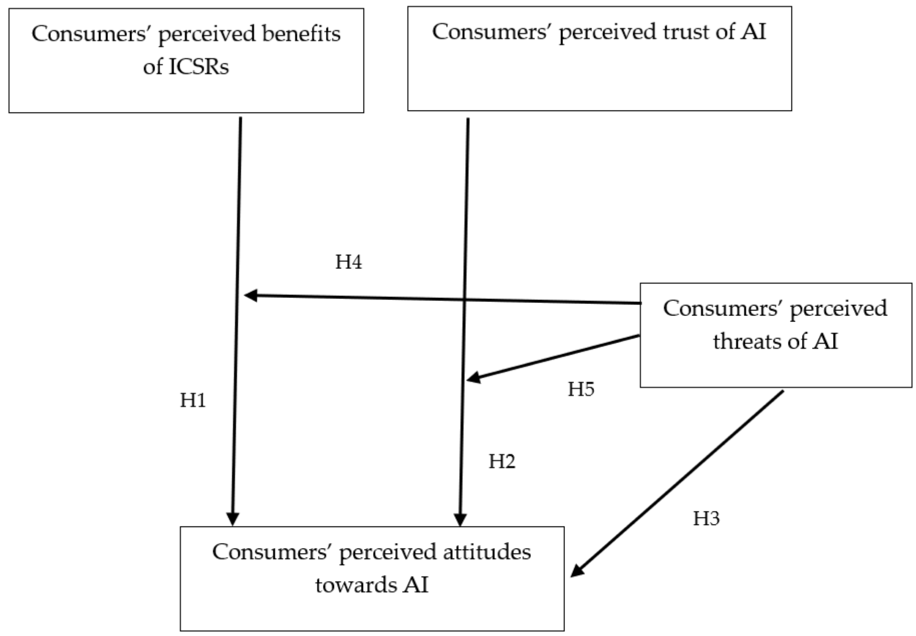

Figure 1: Conceptual framework

3.2.1 Measurement model

All the items for main constructs that we have used in our empirical study have been collected by the relevant authors, who empirically investigated the constructs analysed in our research, and have been measured by five-point Likert scale (5 – strongly agree to 1 – strongly disagree).

The items of consumers’ perceived benefits of intelligence consumer service robots (ICSRs) scale were generated by literature reviews. Finally, we derived from S-O-R framework, suggested by Jacoby (2002), Koo and Ju (2010) and modified by Gao et al. (2022), which covers different aspects of possible consumers’ stimuli appearing as possible consumers’ benefits. They act as external stimuli (S), can affect consumers’ internal cognitions and emotions (O), and eventually drive their behaviour responses (R). According to such comprehensive definition, perceived consumers’ benefits of intelligent consumer service robots (ICSRs) may fall into four groups of benefits: perceived interactivity, perceived personalization, customer engagement, and value co-creation (Gao et al., 2022) with 19 items.

Consumers’ perceived trust in AI have been measured by six items, which are validated by Pelau et al. (2021) and implemented by Chi and Vu (2022), who have investigated the impact of anthropomorphism, empathy response, and interaction on the customer trust in AI. Therefore, such measurement may fit our research objectives too.

The items for measuring consumers’ perceived threats of AI, adapted for our empirical research, derived from psychometric instrument to measure threats, suggested and conducted by Ahmad et al. (2023) and encompass 14 items.

Consumers’ attitudes towards AI have been measured by ATTARI-12 Scale of attitudes, suggested by Stein et al. (2024), which incorporates 12 items with the psychological trichotomy of cognition, emotion, and behaviour as the main components of attitude as well as captures both positive and negative aspects of the attitude towards AI. Therefore, by opinion of the authors, it eliminates some weaknesses of other known scales for attitudes measurement, i.e. General Attitudes Towards Artificial Intelligence Scale – GAAIS (Schepman and Rodway, 2020), the Attitudes Towards Artificial Intelligence Scale – ATAI (Sindermann et al., 2020), AI Anxiety Scale – AIAS (Wang and Wang, 2019), and the Threats of Artificial Intelligence Scale – TAI (Kieslich et al., 2021).

First of all, we tested the convergent validity of research constructs using item loadings, Cronbach alpha coefficient (CA), average variance extracted (AVE), and composite reliability (CR).

The results of PLS analysis show to us that all research constructs and items indicated satisfactory average variance extracted (AVE), Cronbach’s alpha coefficient (CA), composite reliability (CR) and item loadings (all loadings are higher than 0.65 for the sample size n = 224). Therefore, we can conclude that they demonstrate overall satisfactory discriminant validity and reliability and satisfactory convergent validity. Detail list of all construct items, means, standard deviations, Cronbach's alpha, AVE as well as CR values and item loadings are provided in table 2.

The validity of research constructs in our reflective measurement model and individual items was tested also by exploratory factor analysis in order to estimate the convergent validity. All items of our research constructs possess main item loadings above 0.65, while side loadings are below 0.3 (Fornell and Larcker, 1981). According to such results, we can conclude that convergent validity is satisfactory.

In addition to these, we tested the research constructs and items by HTMT criterion (Hetrotrait-Monotrait) to assess discriminant validity and indicate the research constructs' correlations, which is suggested by Henseler et al. (2015) and Kline (2015). The results in the table 3 show to us that the criterion for discriminant validity for all research constructs is achieved, because all values are lower than 0.85.

Table 2: Construct items, means (M), standard deviations (SD), Cronbach's alpha (CA), average variance extraction (AVE), composite reliability (CR), and item loadings

Research Constructs	Items	M	SD	Item loadings	CA	CR	AVE
Consumers' perceived benefits of ICSRs		2.88	0.80		0.71	0.85	0.66
	CPB1	2.31	0.73	0.81			
	CPB2	3.85	0.76	0.86			
	CPB3	3.90	0.85	0.84			
	CPB4	2.21	0.71	0.79			
	CPB5	3.08	0.66	0.77			
	CPB6	2.14	0.89	0.75			
	CPB7	2.87	0.45	0.67			
	CPB8	3.18	0.76	0.68			
	CPB9	2.06	0.64	0.66			
	CPB10	4.02	1.05	0.78			
	CPB11	3.15	0.78	0.69			
	CPB12	2.85	0.62	0.81			
	CPB13	2.76	0.89	0.74			
	CPB14	3.10	0.98	0.68			
	CPB15	2.23	0.56	0.71			
	CPB16	2.06	1.04	0.72			
	CPB17	2.89	1.19	0.66			
	CPB18	3.15	0.93	0.71			
	CPB19	2.85	0.65	0.79			
Consumers' perceived trust in AI		3.96	0.75		0.68	0.73	0.66
	CPT1	4.05	0.60	0.71			
	CPT2	4.14	0.71	0.67			
	CPT3	3.65	0.75	0.66			
	CPT4	4.17	0.79	0.68			
	CPT5	3.90	0.94	0.69			
	CPT6	3.86	0.72	0.79			

Table 2: Construct items, means (M), standard deviations (SD), Cronbach's alpha (CA), average variance extraction (AVE), composite reliability (CR), and item loadings (continue)

Research Constructs	Items	M	SD	Item loadings	CA	CR	AVE
Consumers' perceived threats of AI		3.50	0.85		0.81	0.85	0.77
	CPTH1	3.61	1.13	0.74			
	CPTH2	4.05	1.39	0.66			
	CPTH3	3.55	0.92	0.67			
	CPTH4	4.08	0.95	0.73			
	CPTH5	4.16	0.69	0.69			
	CPTH6	4.03	0.77	0.70			
	CPTH7	3.78	0.62	0.68			
	CPTH8	3.32	0.96	0.79			
	CPTH9	3.09	0.74	0.67			
	CPTH10	2.92	1.13	0.84			
	CPTH11	3.01	0.60	0.74			
	CPTH12	3.45	0.73	0.78			
	CPTH13	2.88	0.61	0.67			
	CPTH14	3.14	0.71	0.66			
Consumers' attitudes towards AI		3.75	0.77		0.77	0.89	0.85
	CA1	4.03	0.78	0.71			
	CA2	4.15	0.82	0.73			
	CA3	3.87	0.75	0.69			
	CA4	3.94	0.63	0.72			
	CA5	3.85	0.96	0.79			
	CA6	4.06	0.88	0.78			
	CA7	3.67	0.65	0.67			
	CA8	3.05	0.89	0.66			
	CA9	3.15	0.92	0.66			
	CA10	4.02	0.77	0.81			
	CA11	3.55	0.62	0.82			
	CA12	3.67	0.61	0.67			

Table 3: HTMT ratio for discriminant validity assessment

Research constructs	1	2	3	4
1 Consumers' perceived benefits of ICSRs				
2 Consumers' perceived trust in AI	0.812			
3 Consumers' attitudes towards AI	0.797	0.774		
4 Consumers' perceived threats of AI	0.841	0.816	0.825	

3.2.2 Structural Research Model Assessment and Results

In the next step of our analysis we tested the structural research model, which is derived from the measurement model explained in the previous step, and tested research hypotheses. Suggested by Hair et al. (2018), we had to assess the proportion of variance explained in order to determine the accuracy of the model's predictions. In our research, the structural model explains 27% of the variance of consumers' attitudes towards AI ($R2 = 0.27$). Next, the Stone-Geisser cross-validated redundancy (Q2) was calculated, which gives us the information about the quality of model prediction. Because in our study $Q2 = 0.81$, the perceived result fits the recommended range between 0 and 1. Thus, we can confirm the predictive relevance of our research.

In the table 4, we present the results of hypotheses testing, including path coefficients (β), t-value, p-value, and final results.

The results in table 4 reveal that the impact of consumers' perceived benefits of ICSRs on consumers' attitudes towards AI is positive and statistically significant, while the consumers' perceived trust in AI has a positive but statistically non-significant impact on consumers' attitudes towards AI. In addition to these, the impact of consumers' perceived threats of AI on consumers' attitudes towards AI is negatively and statistically significant. Therefore, we can confirm the research hypotheses H1 and H3, but we cannot support the research hypothesis H2.

The results of moderation effect of consumers' perceived threats of AI on the impact of consumers' perceived benefits of AI on consumers' attitudes towards AI is not significant. On the other hand, the consumers' perceived threats of AI significantly moderate the impact of consumers' perceived trust in AI on consumers' attitudes towards AI. Therefore, we can confirm research hypothesis H5, while the research hypothesis H4 is not supported.

4 Discussion

4.1 Theoretical and managerial implications

In a world shaped by AI that are supposed to make human life safer, healthier, and more convenient, it is important to understand how people (and particularly consumers) evaluate the very notion of AI – and to identify factors that account for notable variance in this regard (Stein et el., 2024). Therefore, their perception of AI become of great importance. Thus, a comprehensive insight in their attitudes (i.e. cognitive, affective, and behavioural component) towards AI significantly contribute to the knowledge of how do they feel and what are their possible reactions (usage of AI in buying processes as well in general in every day' life).

This research has provided comprehensive insights into the multifaceted landscape of consumers' attitudes towards AI and factors that shape these attitudes. It constructs an integrated analysis framework and research model of three independent research constructs to measure their impact on consumers' attitudes towards AI, during which we explored a moderating influence one of them. The research, therefore, systematically expands the analyses of factors and their multi-collinearity that influence consumers' attitudes towards AI in previous studies. In addition to this, the implementation of specific measurement framework for individual research constructs, based on previous studies and used for other purposes, strongly supported our research objectives and added to the value of our empirical study.

The study researched five fundamental hypotheses, providing a deep understanding of the complex relations between consumers' perception of benefits of ICSRs, trust in AI, threats of AI, and, consequently, their attitudes towards AI. In our opinion, the key findings of our research may significantly contribute to the highly growing field of consumers' perception of AI.

Table 4: Hypotheses testing results

Research hypotheses		β	t-value	p-value	Results
H1	Benefits - Attitudes	0.39	1.64	<0,001	Supported
H2	Trust - Attitudes	0.08	3.23	>0,01	Not-Supported
H3	Threats - Attitudes	- 0.38	2.81	<0.001	Supported
H4	Benefits - Threats - Attitudes	- 0.09	0.87	>0.01	Not supported
H5	Trust - Threats - Attitudes	- 0.22	2.35	<0,01	Supported

Although a huge number of previous researches investigated the role of different research constructs and variables, including benefits and trust, influence customers in the process of shaping their attitudes towards AI (Lobera et al., 2020; Stein et al., 2024; Bergdahl et al., 2023; Gerlich, 2023; Sartori and Bocca, 2023; Aksu and Sener, 2024), there is no previous research that has been focused on moderating role of consumers' perceived threats of AI and their inter-relations with consumers' perceived benefits and trust, which may shape their attitudes towards AI.

In line with our hypothesis H3, it has been affirmed that consumers, who perceive AI as a threat, manifest more negative attitudes towards AI. Our research showed a significantly negative correlation ($\beta = -0.39$, $p < 0.001$) between their concerns about AI threats and their attitudes towards AI. This fact underlines the importance of dealing with consumers concern regarding how AI might affect different fields of their life, as it is essential for encouraging more positive attitude.

However, according to our hypothesis H4, it is important to emphasize that a negative influence of perceived threats of AI does not reduce a positive and strong relation between consumers' perceived benefits of a specific tool of AI (ICSRs), and their attitudes towards AI ($\beta = 0.045$, $p < 0.001$). This finding held particular relevance for chief marketing officers of companies, who care for their AI technology in buying processes as they shed light on the possible negative influences of consumers' perceived threats of AI on their AI adoption. Thus, companies, which enable a use of AI technology for consumers in their process of selling, should strengthen a bundle of benefits of AI perceived by consumers, because perceived benefits, despite of possible threats, significantly impact consumers' attitudes towards AI.

By examining the impact of consumers' perceived trust on their attitudes towards AI (hypothesis H2), the research offers a comprehensive understanding of consumers' perceived threats as a moderator (hypothesis H5). Namely, there exists statistically non-significant positive impact of consumers' perceived trust on their attitudes towards AI ($\beta = 0.10$). However, consumers' perceived threats of AI statistically significantly and negatively moderate the relationship between consumers' perceived trust and their attitudes towards AI ($\beta = -0.22$, $p < 0.01$). The results, obviously, have shown that AI providers should take into the consideration an important negative role of consumers' perceived threats in shaping their attitudes of AI and try to eliminate an influence of such threats in consumers' perception. Consequently, AI developers and policymakers should focus on specific threats perceived by consumers and adopt personalized approaches to effectively address them.

In addition to these, the results of our research enable companies to better understand all three components of the customers' attitude towards AI in the exchange process (i.e. cognitive, affective and behavioural component). Consumers' experiences improved through AI-driven marketing activities can enhance effectiveness and efficiency of exchange processes between the companies and consumers. Hence, knowledge about the factors which influence customers' attitude may support the companies in the process of establishing predictive models of consumers' behaviour, defining efficient marketing strategy aimed to encouraging adoption of AI technology in buying process (Hicham et al., 2023; Verma et al. 2021).

4.2 Research limitations and directions for future research

Despite its contributions to understanding consumers' attitudes towards AI, this research has several limitations. Firstly, the study focused only on non-random judgmental sample of consumers who use AI-related product (i.e. intelligent consumer service robots), which may introduce sample bias and not fully represent the broader population. The reliability of results depends on respondents providing honest and consistent answers, but self-reported data can be influenced by social desirability bias and limited understanding of AI concepts. Second, since data for both endogenous and exogenous research constructs were collected from the same respondents in the same location at the same time, there is a potential for research bias, such as common method bias (MacKenzie and Podsakoff, 2012). Third, the study was conducted over a limited period, affecting the depth of data collection and analysis. A more extensive study with a larger and more diverse sample size could provide deeper insights. Solely relying on surveys might benefit from including other methods like interviews or focus groups to enhance findings. Limited demographic information about respondents may hinder analysis of how factors such as age, gender, income, and working years influence attitudes toward AI. Finally, the rapidly evolving field of AI means consumers' perceptions may change over time, and this research represents a snapshot of their answers at a particular moment. These limitations should be considered when interpreting the findings.

Considering these limitations, future research in this field can benefit from the following suggestions: longitudinal studies which should track changes in consumers' attitudes over time to identify evolving trends and shifts as AI technology progresses; cross-cultural studies by examining AI attitudes across different cultures can reveal unique concerns and expectations as well as offering a more nuanced understanding of global perceptions; in-depth qualitative research, such as interviews and focus groups in combination with quantitative surveys will help uncover the deeper reasons behind consumers' attitudes that surveys alone might miss; contextual analysis with investigating how various applications and contexts of

AI impact consumers' responses can provide insights into specific areas of concern.

Analysing consumers' attitudes toward AI applications in different industries will help address sector-specific concerns.

Furthermore, some ethical considerations should be considered, because research into the ethical aspects of AI, including the development of ethical frameworks, is essential for responsible AI development. Exploring factors that contribute to trust in AI, such as transparency and accountability, can guide the creation of more trustworthy AI systems. As AI technology continues to evolve, understanding and shaping consumers' attitudes remains an ongoing process. Following the suggested areas for future research and addressing individual concerns and ethical issues can help provide clearer and more balanced perspectives on AI. This approach aims to benefit both the industry and society. As AI impacts various aspects of life, establishing a transparent and responsible relationship between AI and the public (not only consumers in buying process) is crucial. This research offers foundational insights that can guide future developments and improve the integration of AI into society.

4.3 Conclusion

Understanding consumer attitudes towards AI is crucial for several reasons. First, it helps companies tailor their products and services to meet consumer expectations. The perceived benefits of AI, such as increased efficiency and personalized experiences, play a significant role in shaping these attitudes. Consumers who recognize the advantages of AI are more likely to embrace it in their daily lives. However, the level of trust that consumers have in AI technologies can significantly influence their acceptance. Building this trust requires transparency, accountability, and ethical considerations by AI developers.

Moreover, consumers' perceived threats associated with AI cannot be overlooked. Concerns about privacy and data security often deter individuals from fully adopting AI solutions. It is essential for companies to address these threats through clear communication and robust security measures. The balance between perceived benefits and threats they recognize ultimately determines consumer sentiment. Companies need to ensure that their AI applications enhance user experience without compromising personal safety.

Finally, understanding consumer attitudes also enables policymakers to create regulations that protect users. By listening to consumer concerns, regulations can enhance trust in AI technologies, setting the groundwork for wider adoption. Therefore, comprehensively understanding consumer perceptions of AI—its benefits and threats, and the importance of trust—is essential for successful integration into society. This understanding ultimately drives innovation while ensuring that AI development remains aligned with public values and expectations.

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Appendix: Scales of measurement

Consumers' perceived benefits of intelligent consumer service robots-ICSRs (5-point Likert scale ranging from strongly agree - 5 to strongly disagree - 1)

Perceived interactivity

ICSRs can accurately provide me with the information I need.

When I encounter a problem, ISR can provide me with a solution.

ICSRs can effectively collect consumer feedback.

ICSRs can effectively promote two-way communication with a seller.

Perceived personalization

ICSRs store my preferences and offer me extra services based on my preferences.

ICSRs do a pretty good job guessing what kinds of things I might want and making suggestions.

ICSRs know what I want.

ICSR setup can be personalized to my needs.

The service provided by ICSRs is customized exactly to my question.

Consumers' engagement

I feel like I can be myself when using ICSRs.

The things I did with the ICSRs are in line with what I really wanted to do.

Using ICSRs has become a part of my daily consumption.

I think I have a strong emotional connection with ICSRs.

Value co-creation

I actively responded to the questions of the ICSRs so that the company can understand my needs.

I participated in the solicitation or evaluation of new product/service ideas proposed by the ICSRs.

I participated in the experience or promotion of new products recommended by the ICSRs.

I actively gave feedback about my experience, questions, improvement suggestions to the ICSRs.

I actively recommended that others use ICSRs to purchase products/services.

I actively help other consumers solve their problems.

Consumers' perceived trust in AI (5-point Likert scale ranging from strongly agree - 5 to strongly disagree - 1)

I trust that AI will take care of me.

I trust that people are safe when interacting with AI.

I trust that AI will deliver the best services.

I trust that AI will recommend the best services for my needs and demands.

I trust that AI will offer more efficient services than human beings.

I trust that AI will offer a modern look to service firms.

Consumers' perceived threats of AI (5-point Likert scale ranging from strongly agree - 5 to strongly disagree - 1)

AI causes a lack of human interaction.

AI causes some legal issue problems.

AI decreases creativity and critical thinking.

AI tools do not replace classical off-line buying process.

AI causes some security concerns.

AI causes some technical issue problems.

AI causes over-reliance on technology.

AI causes some ethical dilemmas.

Use of AI tools requires constantly need for Internet.

Difficulty in handling complex task in buying process.

Risk of acquire inaccurate / incorrect or biased information.

Over-detailed, redundant, excessive content.

Using AI tools will reduce some skills and abilities of person who use it.

I see AI tools as a threat to human ethics.

Consumers' attitudes towards AI (5-point Likert scale ranging from strongly agree - 5 to strongly disagree - 1)

AI will make the world a better place. (Cognitive)

I have strong positive emotions about AI. (Affective)

I want to use technologies that rely on AI. (Behavioural)

AI has more advantages than disadvantages. (Cognitive)

I look forward to future AI developments. (Affective)
AI offers solutions to many world problems. (Cognitive)
I prefer technologies that feature AI. (Behavioural)
I am not afraid of AI. (Affective)
I would rather choose a technology with AI than one without it. (Behavioural)
AI solves problems rather than creates them. (Cognitive)
When I think about AI, I have mostly positive feelings. (Affective)
I would not avoid technologies that are based on AI. (Behavioural)