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Why should I trust you? Influence of explanation design on consumer behavior in AI-based services

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Abstract

Purpose: This study explores how the format of explanations used in AI-based services affects consumer behavior, specifically the effects of explanation detail (low vs. high) and consumer control (automatic vs. on demand) on trust and acceptance. The aim is to provide service providers with insights into how to optimize the format of explanations to enhance consumer evaluations of AI-based services.

Design/methodology/approach: Drawing on the literature on explainable AI (XAI) and information overload theory, a conceptual model is developed. To empirically test the conceptual model, two between-subjects experiments were conducted wherein the level of detail and level of control were manipulated, taking AI-based recommendations as a use case. The data were analyzed via partial least squares (PLS) regressions.

Findings: The results reveal significant positive correlations between level of detail and perceived understanding and between level of detail and perceived assurance. The level of control negatively moderates the relationship between the level of detail and perceived understanding. Further analyses revealed that the perceived competence and perceived integrity of AI systems positively and significantly influence the acceptance and purchase intentions of AI-based services.

Originality/value: This article elucidates the nuanced interplay between the level of detail and control over explanations for nonexpert consumers in high-credence service sectors. The findings offer insights for the design of more consumer-centric explanations to increase the acceptance of AI-based services.

Practical implications: This research offers service providers key insights into how tailored explanations and maintaining a balance between detail and control build consumer trust and enhance AI-based service outcomes.

1. Introduction

Artificial intelligence (AI), which is intended to replicate human intelligence in tasks such as learning and problem solving (De Bruyn *et al.*, 2020), has become integral to modern life. This is particularly true for AI-based services, which affect individuals, businesses, and institutions (Davenport *et al.*, 2020; Huang and Rust, 2022). More specifically, consumers interact with AI-based systems to obtain a service. However, when providing AI-based services, companies encounter challenges in gaining consumer trust and acceptance due to their persistent concerns related to algorithmic decision-making processes (Longoni *et al.*, 2019; Longoni and Cian, 2022) and a lack of understanding among nonexpert consumers (Ribeiro *et al.*, 2016).

In response to these challenges, eXplainable Artificial Intelligence (XAI) has surfaced as a strategy to demystify the AI-based decision-making process. It consists of a set of processes and methods that allow consumers to understand the rationale behind decisions and forecasts made by AI-based systems (Arrieta *et al.*, 2020; Miller, 2019). Specifically, XAI includes diverse explanatory methods, such as text explanations and visual diagrams, which are typically provided with AI outputs to facilitate understanding of system behavior. However, the effectiveness of these explanations hinges on consumer comprehension, which requires tailored approaches for nonexpert consumers (Kim *et al.*, 2023). This reflects the need to bridge the gap between developers' intentions and consumers' interpretations of explanations (Dazeley *et al.*, 2021). Service providers seek to strategically design explanation attributes, such as the level of detail and the level of consumer control over the way explanations are presented, to enhance comprehension and foster trust (Fan and Poole, 2006; Haque *et al.*, 2023; Kim *et al.*, 2023). However, it remains unclear whether their actions have the desired results. Thus, further research is needed to investigate the effects of the explanation format on consumer behavior in the context of AI-based services. Specifically, the following research question is posed: "How does the level of detail of explanations (low vs. high) and consumer control (automatic vs. on-demand) affect consumers' trust in and acceptance of AI-based services? ".

The managerial imperative to provide understandable explanations arises from various factors, including a decline in consumer trust, as emphasized by IBM's report (IBM Institute for Business Value, 2023), or regulatory demands for comprehensible AI-based systems to ensure that the benefits outweigh the risks (Grennan *et al.*, 2022). Regulatory frameworks such as the EU's AI Act also highlight the growing importance of explainability (EU Artificial Intelligence Act, 2024), especially in service sectors such as banking, insurance, and healthcare, where the accountability and transparency of AI-based systems are crucial.

Despite fragmented investigations on the existence of different XAI format elements, limited research exists on consumers' perceptions of the XAI format and consequent service impacts (Chen *et al*., 2024; Guo *et al*., 2024). Two main research gaps appear in the literature. First, there is a lack of understanding of how different formats of explanations affect consumer psychological responses, particularly in terms of perceived understanding and assurance, which are necessary for enhanced services (Chen, 2024; Wysocki *et al*., 2023). Specifically, the interplay between the level of detail provided in explanations and the degree of control consumers have over explanations and its influence on trust and acceptance has not been thoroughly addressed (Guesmi *et al*., 2021b; Khan and Mishra, 2024). This study seeks to address this gap by examining how consumers process explanations, especially with respect to information load (Roetzel, 2019), to provide insights for service managers on optimizing the explanation format for improved consumer trust and acceptance.

Second, existing research does not adequately address the application of XAI in high-credence AI-based service sectors, such as insurance and healthcare, where the stakes of trust and acceptance are particularly high (Eisingerich and Bell, 2007; Longo *et al.*, 2024). These services are perceived to involve greater risks, as attribute information is not easily obtainable (Girard and Dion, 2010; Longoni *et al.*, 2019), while it is difficult to evaluate in terms of service quality (Park *et al.*, 2021). This study addresses this gap by focusing on these sectors to provide actionable insights for service managers, emphasizing the critical role of the explanation format in shaping consumer perceptions and behaviors when interacting with an AI-based system to obtain a service (EU Artificial Intelligence Act, 2024; Grennan *et al.*, 2022). This study aims to determine the effects of XAI on consumers and the conditions under which XAI improves consumers' trust in the system and acceptance of high-credence AI-based services, considering AI-based recommender systems as a use case (Wien and Peluso, 2021; Zhang and Chen, 2020).

The subsequent sections of the article are structured as follows. A conceptual model is developed by examining the relevant literature on explanations for AI-based services on the basis of information overload theory to answer the research questions. The methodology is subsequently presented in addition to the outcomes of the experimental studies, which aim to investigate the effects of the format of explanations on consumers' perceptions and behavioral outcomes. Finally, theoretical advances, managerial contributions, and potential avenues for further research are discussed.

2. Theoretical background

2.1. Lacking trust and resistance to AI-based service

When interacting with an AI-based system for a service, consumers tend to be skeptical about its ability to assist in decision-making and accurately infer their preferences (Gaczek *et al.*, 2023;

Longoni *et al.*, 2019; Schmidt *et al.*, 2020). Their resistance stems from concerns about the perceived loss of autonomy in their decisions (Husairi and Rossi, 2024) and the perceived opacity of AI-based systems (European Data Protection Supervisor, 2023; Grewal *et al.*, 2021). This skepticism, especially among nonexpert consumers, limits the effectiveness of AI-based services (Hair and Sarstedt, 2021; Hasan *et al.*, 2021; Osburg *et al.*, 2022), particularly in high-credence service sectors where additional information is needed to evaluate service quality but is often unavailable (Girard and Dion, 2010).

Recent studies underscore the pivotal role of trust in fostering consumers' acceptance of AI-based services (Frank *et al.*, 2023). Trust in technology entails the willingness to make oneself vulnerable on the basis of a feeling of confidence or assurance in the trusted party (Gefen, 2002). Mayer *et al.*'s (1995) trust theory delineates three fundamental dimensions: competence, benevolence, and integrity. Competence pertains to the perceived capability and effectiveness of the trustee in fulfilling his or her responsibilities. Benevolence reflects the "extent to which a trustee is believed to want to do good to the trustor, aside from an egocentric profit motive" (Mayer *et al.*, 1995, p.718). Finally, integrity involves the trustor's belief in the trustee's honesty, fairness, and adherence to ethical principles.

2.2. Explainable artificial intelligence

The emergence of XAI addresses the challenge of making AI-based systems understandable to consumers by providing accessible explanations for their decisions (Rai, 2020), thus enhancing decision-making processes (Coussement *et al.*, 2024). Drawing from various fields, such as computer science (Dwivedi *et al.*, 2023), psychology and cognitive science (Miller, 2019; Shin, 2021), and marketing and services (Chen, 2024; Rai, 2020), XAI provides insight into how data inputs are processed and how AI outcomes, such as predictions or recommendations, are generated

(Dwivedi *et al.*, 2023; Chen *et al*., 2024). The literature highlights five main objectives of XAI: increasing confidence, fairness, accessibility, interactivity, and confidentiality/privacy (Masialeti *et al*., 2024). Many studies investigate XAI from a broad perspective (Longo *et al*., 2024), including discussions on XAI design (Schoonderwoerd *et al*., 2021; Wang *et al*., 2019) and considerations from a consumer perspective (Haque *et al*., 2023; Mohseni *et al*., 2021) (see Web Appendix A). However, the literature on XAI in service management is limited (Chen, 2024; Guo *et al*., 2024) (see Web Appendix B). While these studies address XAI broadly, they do not thoroughly explore the impact of explanation format attributes on consumers and the associated cognitive load. Furthermore, research on XAI in high-credence services is scarce, despite these services being a compelling context for examining how XAI design affects consumer behavior due to the information asymmetry between the service provider and consumer (Du and Xie, 2021).

When crafting explanations for nonexpert consumers, a pivotal focus is their "human-centered" nature (Kim *et al*., 2023) and alignment with consumer needs and expertise (Guesmi *et al*., 2021a; Rai, 2020) to ensure effectiveness and persuasion (Kim *et al*., 2023). The design strategies employed in crafting and visualizing these explanations, such as offering additional details and granting consumers greater control, can significantly influence consumers' perceptions of a service (Haque *et al*., 2023). First, explanations can contain more or less detail (i.e., the amount of information revealed in an explanation presented to a consumer) (Haque *et al*., 2023) depending on the target consumers and their need for information. The literature reflects an ambiguous discussion of the level of detail that should be provided to consumers (Gregor and Benbasat, 1999; Mehmood *et al*., 2023). While providing more detailed information may help consumers understand the reasoning behind AI-based decisions and recommendations (Chatti *et al*., 2022), excessive information can lead to confusion and information overload (Zhao *et al*., 2019). Second, consumers' level of control over how explanations are presented reflects their active demand for information (Guesmi *et al.*, 2021b; Kim *et al.*, 2024; Millecamp *et al.*, 2019). They may encounter automatically displayed explanations, relinquish control (Fan and Poole, 2006), or opt for greater control by actively requesting explanations while engaging in their decision-making journey. In this case, explanations are provided on demand (Haque *et al.*, 2023), and the most recent information on any decision or prediction may be included in the explanation (Wang *et al.*, 2019). Although the concept of the level of control has been discussed briefly in the literature, there is a lack of in-depth research in the context of XAI, supporting the need for additional investigations. This study seeks to reduce ambiguity regarding the level of detail and to explore the level of control over the way explanations are presented. Specifically, this study aims to test the effects and understand how and under which conditions the design strategies of explanations affect consumer behavior when consumers interact with AI-based systems to obtain a service.

3. Hypothesis development

3.1. Level of detail

In the context of XAI, where demystifying algorithmic decisions is paramount, explanations serve as a potent tool for enhancing consumers' perceived understanding of AI-based systems (Rai, 2020). Perceived understanding refers to consumers' subjective self-assessment of their own comprehension of the system's behavior and how well the provided explanations assist in decision-making (Chromik *et al*., 2021). Explanations can contain more or less detail to adjust to consumers' needs and expectations (Haque *et al.*, 2023). However, the literature reveals a nuanced relationship between the level of explanation detail and consumers' understanding, particularly among consumers who are not experts in AI. Consumers can be confused by insufficient information, especially when it is ambiguous, and require additional cognitive effort to understand the system's outcomes (Puntoni *et al*., 2021). Conversely, providing too much detail can lead to information overload and confusion (Guesmi *et al*., 2021a; Zhao *et al*., 2019), resulting in decision-making difficulties and cognitive strain (Hu *et al*., 2019; Phillips-Wren and Adya, 2020). Consumers with limited AI expertise seem to expect less detailed explanations to better understand the reasoning process of AI-based systems (Chatti *et al.*, 2022; Mohseni *et al.*, 2021; Rai, 2020). Simplified explanations effectively bridge the gap between complex algorithms and consumer understanding by providing clear and accessible information (Arrieta *et al*., 2020).

H1. The level of detail is negatively associated with consumers' perceived understanding.

In a context characterized by consumer uncertainty and skepticism, clarity and understanding become paramount (Arrieta *et al.*, 2020; Yue and Li, 2023). This comprehension facilitates a shift in perception from a state of apprehension to one of assurance (Longoni *et al.*, 2019), particularly as the complexity and novelty of AI-based systems increase, making assurance crucial for informed decision-making (Israelsen and Ahmed, 2019). When interacting with an AI-based system to obtain a service, consumers seek assurance that the system considers their preferences and interests, aligning its outputs with their expectations (Shin, 2020). Concise explanations can serve as powerful tools for providing this assurance by instilling confidence in system performance and unbiased outcomes (Lee *et al.*, 2019). By presenting information in an easily digestible manner, explanations with a low level of detail prevent information overload and help consumers grasp the rationale behind AI-based outcomes (Orth and Wirtz, 2014; Yang *et al.*, 2020). Furthermore, the impact of explanations with low detail extends beyond mere comprehension to influence consumers' emotional responses and foster a sense of comfort and certainty in their decision-making journey (Shin, 2021). This finding aligns with research indicating that consumers prefer simpler, easily digestible explanations when interacting with AI-based systems to obtain services, seeking assurance through straightforward information (Wysocki *et al*., 2023).

H2. The level of detail is negatively associated with consumers' perceived assurance.

3.2. Moderating effects of the level of control

As AI-based systems increasingly impact consumers, there is a pressing need for greater transparency and consumer control through accessible information to ensure their responsible integration into society (Westphal *et al.*, 2023). Consumers' level of control over the display of explanations is expected to influence how they perceive and understand the system (Guesmi *et al.*, 2021b; Kim *et al.*, 2024). Allowing consumers to tailor the level of control in explanations caters to their cognitive preferences and styles of information processing, potentially influencing their subsequent understanding (Zhao *et al.*, 2019). Providing consumers with the ability to request on-demand explanations can give them a sense of control and ownership over their interactions with the AI system (Millecamp *et al.*, 2019). This allows for tailored information delivery, which promotes informed decision-making and reduces uncertainty (Haque *et al.*, 2023). Research by Oh *et al.* (2018) suggests that consumers require information on demand rather than automatic explanations because they need to lead the task. Similarly, findings from André *et al.* (2018) indicate that when consumers control the flow of information and tailor explanations to their needs, they are likely to gain a deeper understanding of the system. Therefore, the following hypothesis is proposed:

H3. The level of control positively moderates the relationship between the level of detail and consumers' perceived understanding.

The relationship between the level of detail and consumers' perceived assurance is also expected to be influenced by the level of control because of the way consumers employ this control to navigate the presented explanations (Millecamp *et al.*, 2019). It can be hypothesized that providing explanations with a low level of detail positively impacts consumers' perceived assurance and that the level of control over the display of explanations moderates this relationship: "The value of information provision should not be reduced to the value of the informational content itself but that it lies in the relational function of the communicative action of the information provision" (Felzmann *et al.*, 2019, p.9). Hence, the following hypothesis is proposed:

H4. The level of control positively moderates the relationship between the level of detail and consumers' perceived assurance.

3.3. Mediating roles of perceived understanding and perceived assurance

When consumers receive explanations, they are likely to understand the underlying rationale, which enhances their perception of assurance in the system's intended functionality (Ostinelli *et al.*, 2024; Shin, 2021). Wu *et al.* (2010) define perceived assurance as consumers' perceptions of the efforts companies make to address privacy, security, and transaction integrity concerns in the online environment. This assurance is crucial for alleviating consumers' apprehensions or uncertainties regarding the relevance of AI-based outcomes.

This alignment between perceived understanding and assurance highlights the crucial roles of transparency and clarity in shaping consumers' perceptions and attitudes toward the AI-based system and, consequently, the service itself (Shin, 2021). Therefore, the following hypothesis is proposed:

H5. A positive association exists between consumers' perceived understanding and perceived assurance.

3.4. Trust in AI-based systems

Effective explanations help consumers understand the reasoning behind AI-based outcomes and make informed decisions. When these explanations are deemed rational and comprehensible, consumers develop a sense of trust in the AI-based system (Shin, 2021). Drawing from trust theory, as suggested by Mayer *et al*. (1995), the dimensions of competence, benevolence, and integrity play pivotal roles in fostering trust in AI-based systems and ensuring consumers' acceptance of services (Benbasat and Wang, 2005). Adapting these terms to the AI context, the first dimension, perceived competence, is associated with the belief that the AI-based system delivers relevant and tailored suggestions (Whang and Im, 2018). Second, perceived human centricity (or benevolence) reflects consumers' perception that the system acts in their best interest (David *et al.*, 2024). Finally, perceived integrity involves unbiased outcomes and ethical conduct (Mehrotra *et al.*, 2024).

Distinguishing the three dimensions of trust is crucial for understanding consumers' rational assessments, emotional responses, and behavioral intentions toward the system, which collectively shape their trust (Choung *et al*., 2023). Previous research that has investigated the design attributes of explanations has overlooked this distinction, although this fine-grained analysis can potentially help clarify the ambiguities observed in prior studies (Haque *et al.*, 2023; Shin, 2021). On the basis of this rationale, the following hypothesis is posed:

H6. Perceived understanding positively influences consumer perceptions of AI-based system (H6a) competence, (H6b) human centricity, and (H6c) integrity.

Building upon perceived understanding, it is expected that consumers' perceived assurance of the AI-based system, facilitated by explanations, plays a pivotal role in shaping their trust in the system (Cho, 2006; Israelsen and Ahmed, 2019). Hence, it is hypothesized that consumers' perceived assurance serves as a precursor to trust and impacts their perceptions of the AI-based system's competence, human centricity, and integrity (McKnight *et al.*, 2002). First, consumers value the AI system's competence and seek assurance that outcomes are relevant and tailored to their individual needs (Whang and Im, 2018). Second, perceived assurance, facilitated by understandable explanations, fosters a sense of openness and consumer centricity in interactions with AI-based systems, strengthening consumer trust (Förster *et al.*, 2020). Finally, consumers' perceived assurance reinforces their belief in the system's integrity, ensuring ethical standards and protecting against manipulation or deception (Wei and Liu, 2024). Thus, perceived assurance seems to emerge as a potential factor that influences trust.

H7. Perceived assurance positively influences consumer perceptions of AI-based system (H7a) competence, (H7b) human centricity, and (H7c) integrity.

3.5. Acceptance and purchase intention of AI-based services

Finally, the literature reflects the fact that consumers' trust in AI-based systems positively influences their acceptance of the service offered by the company (Kim *et al.*, 2021). This influence stems from consumers' perceptions of the system's reliability and ability to deliver valuable outcomes (Shin, 2021). When consumers trust the system, they feel more confident in the service provided and are more willing to accept it. In line with past findings, it can be expected that the three dimensions of trust enhance consumers' acceptance of AI-based services.

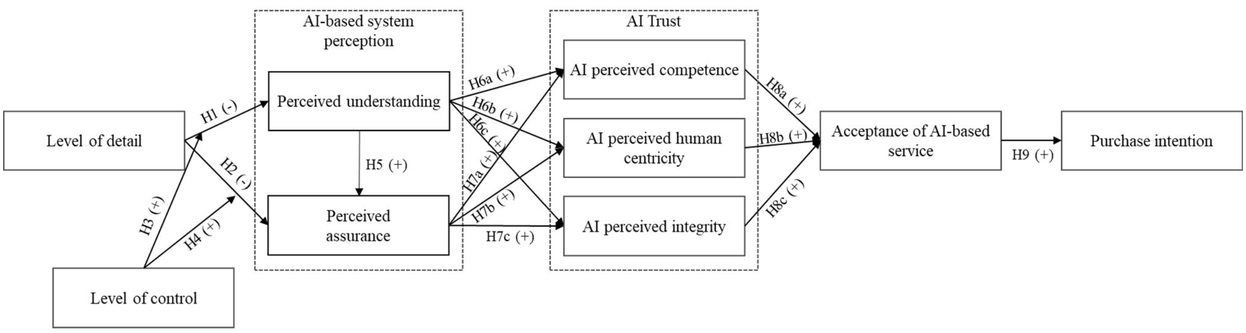
H8. Consumer perceptions of AI-based system (H8a) competence, (H8b) human centricity, and (H8c) integrity positively influence their acceptance of the service.

Furthermore, consumers' acceptance of an AI-based service is expected to positively influence their intentions to purchase that service (Yang and Hu, 2022).

H9. Consumers' acceptance of an AI-based service positively influences their purchase intentions toward the service.

This research examines how the level of detail and control in explanations influences consumers' perceptions and intentions toward AI-based services in high-credence sectors, using information overload theory as a framework. To test the hypotheses (see Figure 1), two experimental studies are conducted across different high-credence service sectors: insurance and healthcare. Study 1 focuses on the direct impact of explanation detail on trust, acceptance, and purchase intentions, whereas Study 2 further explores the moderating role of control in explanations on the relationship between the level of detail and both perceived understanding and perceived assurance.

Figure 1. Conceptual model



Source: Authors own work

4. Study 1

4.1. Research design and measurement

A between-subjects experiment was conducted to test the conceptual model (see Figure 1) by manipulating the level of detail (low vs. high). This initial study, which focused on the healthcare sector, used the case of an AI-based recommender system. Two identical fictitious websites were created for a company called "FitAI", an e-commerce platform selling personalized nutrition and wellness plans and utilizing advanced algorithms and data analysis through an AI-based recommender system to suggest the best plan on the basis of customer data. Both websites were identical in design and information, differing only in the content of the explanation across the two scenarios. The websites were designed with real interfaces and services to ensure external validity. The level of detail was manipulated by varying the amount of information about the reasoning process behind the recommendations. The low-detail explanation (55 words) listed only the key variables influencing the recommendation, whereas the high-detail explanation (120 words) included the same information but also provided additional insights into the calculation process (Web Appendix C). The content was designed on the basis of similar existing AI-based services.

The participants first received a brief survey description on Qualtrics before being randomly assigned to one of the four fictive websites. After providing details about their health, fitness goals, and physical condition, the participants had to wait a few seconds while the website fictively analyzed their data. Then, they accessed an AI-based recommended health plan, as well as an explanation providing deeper insight into the AI-based recommender system. After browsing the website, the participants were redirected to a Qualtrics questionnaire that began with an attention filter question and included validated measurement scales (see Web Appendix D). A 5-item scale was used to measure consumers' perceived understanding (Madsen and Gregor, 2000), and a 5-item scale adapted by Hicks *et al.* (2014) was used to measure perceived assurance. Items were included to measure perceived AI-based system competence, human-centeredness, and integrity (Benbasat and Wang, 2005), and a 3-item scale to measure service acceptance was adapted from Belanche *et al.* (2019). Furthermore, consumers' purchase intentions were measured via a validated 3-item scale (Dodds *et al*., 1991). The questionnaire also included a question that measured respondents' willingness to either 1) follow, 2) postpone their decision, or 3) reject the AI-based system output via a 5-point Likert scale. Finally, a 5-item scale assessing product involvement (Wang *et al*., 2012; Zaichkowsky, 1985) and a 3-item scale measuring decision involvement (Mittal, 1995) represented the control variables in the study. To gain deeper insights into consumer perceptions, two open-ended questions were included in the questionnaire following the experiment. These questions aimed to gain insight into the type of explanations and information consumers expect, as well as the underlying reasons for their preferences. A manipulation check was included to assess respondents' perceptions of the level of detail of the information, along with a reality check for study realism and a confounding variables check to ensure internal validity (see Web Appendix E). The questionnaire ended with sociodemographic questions (gender, age, professional situation, level of education, country) before the study goal was revealed and the respondents were thanked for their participation.

A total of 249 participants (57.0% female; M_{age}= 33.47 years, SD_{age}= 11.66) were recruited from the Prolific platform to participate in an online randomized experiment in return for monetary compensation of 7.36 £ per hour. Prolific was chosen because of its ability to provide a diverse, high-quality, and reliable sample while offering significant control over the sampling process and ensuring ethical compensation for participants (Palan and Schitter, 2018). Among the respondents, 59.4% were employed/workers, and 16.5% were students (see Table I). On average, the respondents rated their computer literacy as high (M=4.20, SD=0.78) on a 5-point Likert scale but perceived themselves as having lower levels of knowledge of AI (M=3.45, SD=0.89) and dietetic support (M=3.47, SD=0.95).

Table I. Sample demographics (Study 1)

Gender		Age		Professional situation		Education level		Computer literacy		AI literacy		Dietetic support literacy	
Man	42.2%	<21	4.8%	Student	16.5%	High school graduate or below	23.7%	Terrible	0.8%	Terrible	0.8%	Terrible	2.0%
Woman	57.0%	21-30	45.4%	Employed/ worker	59.4%	Bachelor's degree	45.0%	Poor	1.2%	Poor	12.9%	Poor	12.4%
Other	0.8%	31-40	28.1%	Self-employed	9.2%	Master's degree	24.1%	Average	13.7%	Average	39.0%	Average	36.5%
		41-50	9.2%	Unemployed	9.2%	Doctorate degree or above	3.6%	Good	46.2%	Good	35.7%	Good	34.9%
		51-60	8.4%	Housemaker	1.6%	Other	3.6%	Excellent	38.2%	Excellent	11.6%	Excellent	14.1%
		>61	4.0%	Retired	2.8%								
				Other	1.2%								
		$M_{age}=33.47$ $SD_{age}=11.66$						$M_{computer}=4.20$ $SD_{computer}=0.78$		$M_{AI}=3.45$ $SD_{AI}=0.89$		$M_{diet.\ support}=3.47$ $SD_{diet.\ support}=0.95$	

Source: Authors own work

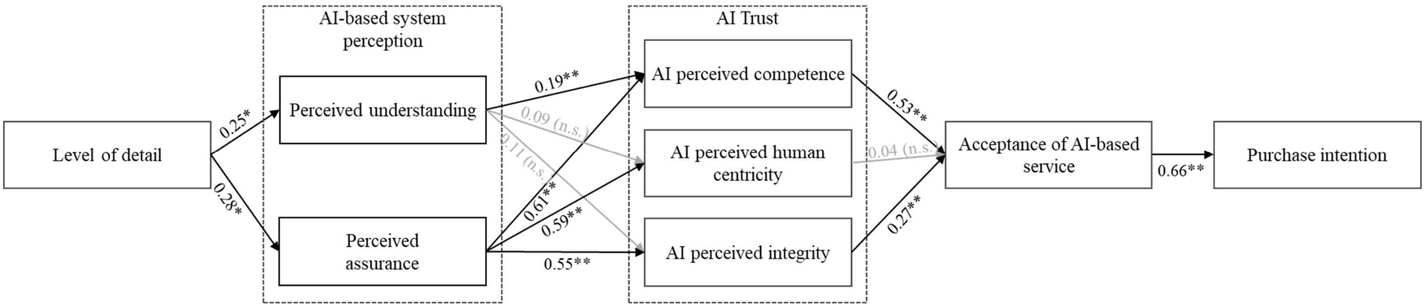
4.2. Data analysis and results

The manipulation checks reveal significant differences in participants' perceptions on the basis of the varying levels of detail provided, confirming the effectiveness of the experimental manipulation (see Web Appendix E). Specifically, participants exposed to more detailed explanations reported receiving more detailed information ($F(1,247)=30.43$; $p\leq0.001$) ($M_{high\ detailed}$=3.46; $SD_{hig\ \ detailed}$=1.02) than did the group receiving less detail ($M_{low\ detailed}$=2.75; $SD_{low\ detailed}$=1.00). The confounding variables check indicated that although the high-detail group had to read more than the low-detail group did, they did not feel more "tired" ($F(1,247)=0.20$; $p=0.658$).

To validate the measurement model, the constructs' convergent validity was confirmed (see Web Appendix F). Items loading below the recommended threshold of 0.7 were removed from the model (Henseler *et al*., 2009) (see Web Appendix G). Discriminant validity was also established, as the interconstruct correlations were lower than the square roots of the AVEs for each construct (Fornell and Larcker, 1981) (see Web Appendix H).

The conceptual model was tested via structural equation modeling (SEM) with partial least squares (PLS) regression, as recommended by Hair *et al*. (2012), and conducted via SmartPLS 4. The results obtained through the SmartPLS algorithm and bootstrapping with 5,000 subsamples are presented in Figure 2 and detailed in Web Appendix I.

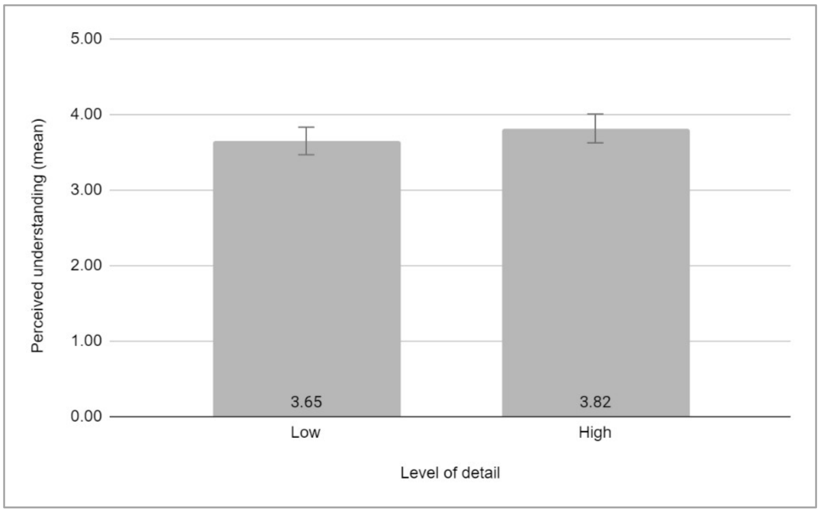
Figure 2. Structural model (**p<0.01; *p<0.05; n.s. = not significant) (Study 1)



Source: Authors own work

The analysis reveals that the level of detail significantly influences consumers' perceived understanding (β_{H1}=0.25; p_{H1}<0.05; 95% CI=[0.00; 0.50]). In contrast to expectations, a higher level of detail has a stronger effect on perceived understanding than a lower level does, although the difference is modest, as shown in Figure 3. As a result, Hypothesis 1 is not supported; rather, the opposite effect is found.

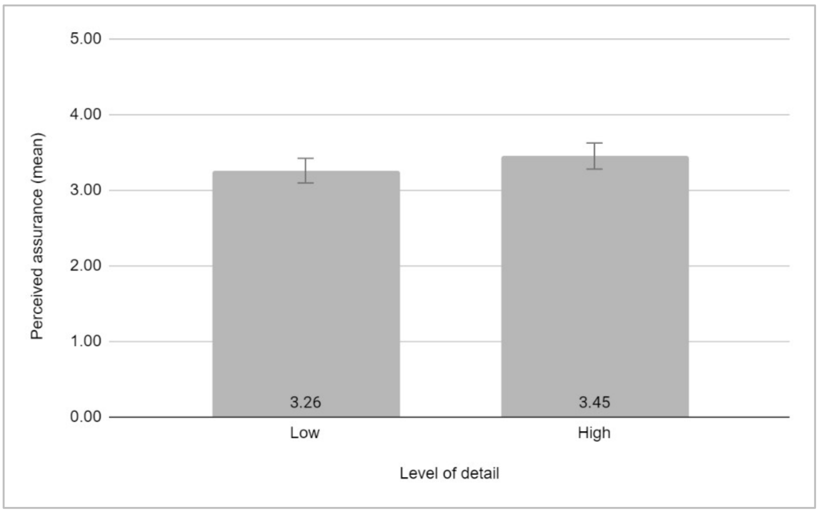
Figure 3. Perceived understanding means according to the level of detail (Study 1)



Source: Authors own work

Moreover, the level of detail in explanations significantly and positively impacted consumers' perceptions of assurance regarding the AI-based system (β_{H2}=0.28; p_{H2}<0.05; 95% CI=[0.04; 0.52]). Figure 4 shows that a higher level of detail increased perceived assurance. Because a lower level of detail is expected to enhance perceived assurance, Hypothesis 2 is not supported; rather, the opposite effect is found.

Figure 4. Perceived assurance means according to the level of detail (Study 1)



Source: Authors own work

The results also show that improving consumers' perceived understanding of the system has a positive and statistically significant effect on their perceptions of the AI-based system, particularly in terms of perceived competence (β_{H6a}=0.19; p_{H6a}<0.01). However, it does not significantly affect the perceived human-centricity (β_{H6b}=0.09; p_{H6b}>0.05) or perceived integrity (β_{H6c}=0.11; >0.05) of the system. Additionally, perceived assurance significantly enhances consumers' trust in the AI-based system across three dimensions: perceived competence (β_{H7a}=0.61; p_{H7a}<0.01), perceived human centricity (β_{H7b}=0.59; p_{H7b}<0.01), and perceived integrity (β_{H7c}=0.55; p_{H7c}<0.01). Consequently, the data support Hypotheses 6a, 7a, 7b, and 7c, whereas Hypotheses 6b and 6c are not supported. Furthermore, consumers' perceptions of both AI competence and AI integrity positively influence their acceptance of the service, validating H8a (β_{H8a}=0.53; p_{H8a}<0.01) and H8c (β_{H8c}=0.27; p_{H8c}<0.01).

However, perceived human centricity does not significantly influence acceptance (β_{H8b}=0.04; p_{H8b}>0.05), resulting in a lack of support for Hypothesis 8b. Additionally, further analysis of consumer behavior outcomes reveals a significant and positive effect on intentions to purchase the service (β_{H9}=0.66; p_{H9}<0.01), supporting H9.

Finally, when the two open questions are analyzed to understand the type of explanations and information consumers would have rather expected, it appears that while consumers are drawn to AI-based services for their speed and convenience, they also expect detailed and transparent explanations, especially in sensitive areas such as the healthcare context. As reflected by Verbatims 1 and 2, this need for detailed information arises from a desire to fully understand the reasoning process, feel safe, and ensure that the outputs of the AI-based system are trustworthy and effective.

> *I would like to have many details to know if the suggestions are reasonable because I can't trust AI without being sure that it is safe.* (Verbatim 1)

> *I would expect to receive full and in-depth explanations about an AI-based service, considering that it is information from AI. Most people still believe that AI advice or information is not as accurate as information from humans.* (Verbatim 2)

Many consumers emphasize the importance of receiving more information to make informed decisions, protect their privacy, and verify the accuracy of AI. They are interested in knowing how AI operates, where it sources information, and how personalized its outcomes are. Trust and transparency are critical, as consumers often compare AI-based recommendations to those from human experts and expect AI to match the same level of detail and reliability. Given that AI is still relatively new and less understood, comprehensive explanations are vital for building consumer trust.

> *I expect to know what the service does and how it uses one's data to create a dietary plan. This will help me understand and be more willing to follow the plan.* (Verbatim 3)

> *I would prefer to receive more details in an explanation to ensure informed decisions and trust.* (Verbatim 4)

While these findings offer preliminary evidence that detailed explanations positively impact consumer acceptance and purchase intentions toward AI-based healthcare services, further investigations are needed. Specifically, the relationships between the detail of explanations and the moderating role of consumers' control over how the explanations were displayed on acceptance are further explored, and the findings are replicated for greater generalizability. Hence, Study 2 was conducted in a different high-credence sector.

5. Study 2

5.1. Research design and measurement

To replicate the first study, while examining the moderating role of the level of control over an explanation, a second study was conducted in another high-credence service sector, i.e., AI-based insurance recommendations. A two-factor between-subjects experiment was conducted, manipulating the level of detail (low vs. high) and the level of control (automatic vs. on-demand) of explanations. Four identical fictitious websites representing an insurance company called CoverAI were created, featuring real interfaces and products to ensure external validity. The participants interacted with one of these websites and received AI-based car insurance recommendations. These websites were identical in design, differing only in the explanation content and its accessibility across the four scenarios.

The level of detail was manipulated by varying the amount of information about the reasoning process behind the recommendation. In Study 1, the difference in consumers' perceived understanding and assurance between the two scenarios was minimal, and the contrast between low- and high-detailed explanations increased. The low-detail explanation (53 words) listed key variables influencing the recommendation (traffic in the driver's living area, changes in the driver's risk levels, driving behavior and phone use while driving) along with their order of significance in the calculation. The highly detailed explanation (398 words) included the same information but offered additional insights into the calculation and risk assessment processes (Web Appendix J). The information was kept neutral to avoid biasing consumers' perceptions. Then, the level of control was manipulated by allowing participants to choose whether to view the explanation (via a "Read the explanation" button) or automatically display it.

The participants were first given instructions on Qualtrics and then randomly directed to one of the four websites. Upon accessing the website, participants could provide relevant vehicle details, namely, the driver's license year and first registration year, whether it was a used car, the car brand, and the type of fuel. They had to wait a few seconds as the website fictively analyzed their data and integrated it with additional external data extracted by AI, such as their driving behavior, vehicle details, claims history, credit scores, or environmental data. Upon completion of the loading process, the participants were then presented with an AI-based recommended car insurance contract. This contract included intermediary coverage that offered basic legal coverage, such as civil liability, damage to the vehicle, and deductible options. An explanation was provided on the basis of the experimental conditions. After browsing the website, the participants completed an online Qualtrics questionnaire, which started with a filter question to test the participants' attention to the survey and included validated measurement scales from Study 1 and additional control variables to account for individual-level factors: need for interaction (Dabholkar, 1996), perceived AI creepiness (Stevens, 2016), and propensity to trust (McKnight *et al.*, 2002) (see Web Appendix D). The realism of the scenarios was assessed with a dedicated question, and manipulation checks ensured that the participants perceived the differences in explanation detail and control. The questionnaire ended with sociodemographic questions, followed by a debriefing and a thank you message.

A total of 235 participants (44.7% female; M_{age}= 28.15 years, SD_{age}= 8.55) were randomly recruited from the Prolific platform to participate in an online experiment in return for monetary compensation of 6.39 £ per hour. Among the respondents, 49.3% were employed/workers, 30.4% were students, 8.8% were self-employed, and 8.8% were unemployed (see Table II). On average, the respondents reported high computer literacy (M=4.11, SD=0.69) and somewhat lower knowledge of AI (M=3.21, SD=0.87), although they reported low insurance literacy (M=2.73, SD=1.00).

Table II. Sample demographics (Study 2)

Gender		Age		Professional situation		Education level		Computer literacy		AI literacy		Insurance literacy	
Man	52.3%	<21	6.0%	Student	30.2%	High school graduate or below	34.5%	Terrible	0.4%	Terrible	1.7%	Terrible	12.8%
Woman	44.7%	21-30	66.0%	Employed/ worker	48.1%	Bachelor's degree	46.4%	Poor	0%	Poor	18.7%	Poor	26.4%
Other	3.0%	31-40	18.3%	Self-employed	9.4%	Master's degree	16.2%	Average	16.2%	Average	41.3%	Average	39.1%
		41-50	6.4%	Unemployed	8.9%	Doctorate degree or above	0.9%	Good	54.9%	Good	33.2%	Good	18.7%
		51-60	3.0%	Retired	0.4%	Other	2.1%	Excellent	28.5%	Excellent	5.1%	Excellent	3.0%
		>61	0.4%	Other	3.0%								
		M_{age} = 28.15 SD_{age} = 8.55						$M_{computer}$ = 4.11 $SD_{computer}$ = 0.69		M_{AI} = 3.21 SD_{AI} = 0.87		$M_{insurance}$ = 2.73 $SD_{insurance}$ = 1.01	

Source: Authors own work

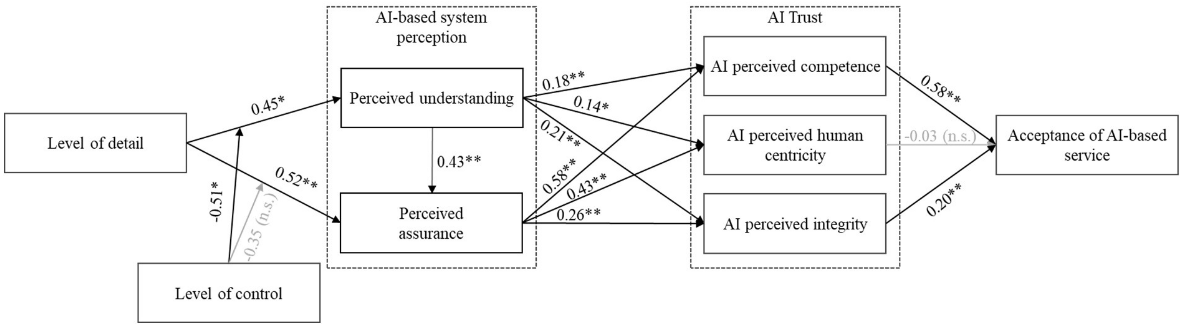
5.2. Data analysis and results

Manipulation checks reveal significant differences in participants' perceived levels of detail, demonstrating the effectiveness of the manipulation (see Web Appendix K). Specifically, groups exposed to highly detailed explanations reported a heightened sense of receiving more details (F(1,233)=57.71; p≤0.001), ($M_{high\ detailed}$=3.82; $SD_{high\ detailed}$=0.83) than did the other group ($M_{low\ detailed}$=2.92; $SD_{low\ detailed}$=0.99). Similarly, participants assigned to the "on-demand explanations" condition, which was characterized by greater levels of control, reported more perceived control over the presentation of explanations (F(1,233)=11.61; p≤0.001), ($M_{on-demand}$=3.33; $SD_{on-demand}$=1.04) than did those in the other group ($M_{automatic}$=2.84; $SD_{automatic}$=1.15).

To assess the validity of the measurement model, the constructs' convergent validity was first confirmed (see Web Appendix L). The item loadings exceeded the recommended value of 0.7 (Henseler *et al.*, 2009) (see Web Appendix M). Furthermore, discriminant validity was validated, as the interconstruct correlations were lower than the square roots of the AVEs for each construct (Fornell and Larcker, 1981) (see Web Appendix N).

For Study 1, the evaluation of the conceptual model was conducted via structural equation modeling (SEM) employing a partial least squares (PLS) regression methodology. The results of the SmartPLS algorithm, followed by bootstrapping with 5,000 subsamples, are presented in Figure 5. Notably, with respect to the hypotheses about the level of detail, the analysis revealed a significant influence of the level of detail on consumers' perceived understanding ($\beta H1$=0.45; $pH1$<0.05; 95% CI=[0.10; 0.78]). Contrary to initial expectations, a higher level of detail was found to exert a more pronounced effect on perceived understanding than a lower level of detail, although the magnitude of this difference was small. Therefore, Hypothesis 1 is not supported.

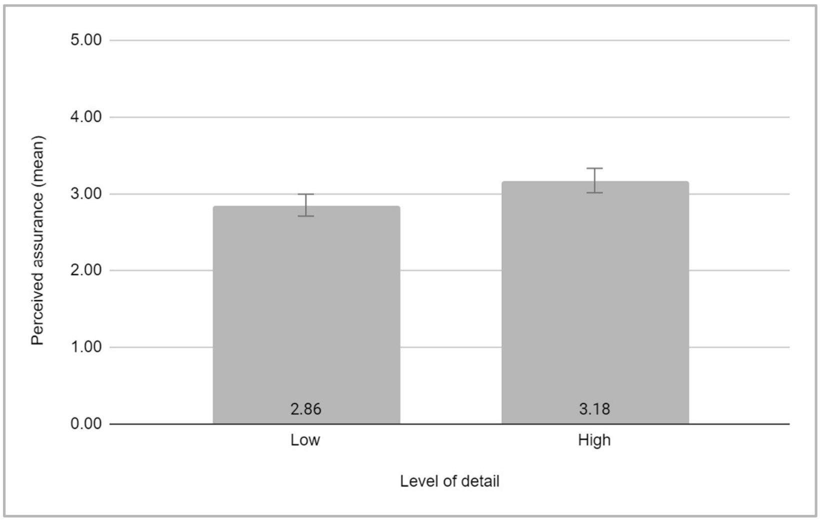
Figure 5. Structural model (**p<0.01; *p<0.05; n.s. = not significant)



Source: Authors own work

Furthermore, the results reveal a significant and positive impact of the level of detail of explanations on consumers' perceived assurance of AI-based systems (β_{H2}=0.52; p_{H2}<0.01; 95% CI=[0.18; 0.86]). As illustrated in Figure 6, a higher level of detail led to an increase in perceived assurance, albeit to a lesser extent than a lower level of detail did. Because a lower level of detail was expected to enhance perceived assurance, Hypothesis 2 is not supported.

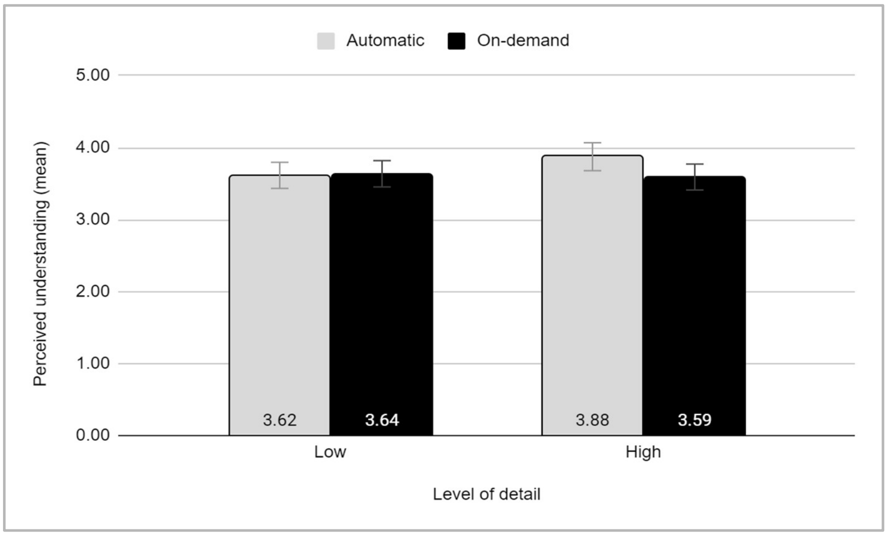
Figure 6. Perceived assurance means according to the level of detail (Study 2)



Source: Authors own work

When the moderating effect of the level of control is added, significant differences in the perception of understanding the AI-based system are observed, depending on the level of detail (see Figure 7). Hypothesis 3, which states that the level of control positively moderates the relationship between the level of detail and perceived understanding, is not supported by the data (β_{H3}=-0.51; p_{H3}<0.05). On the one hand, when consumers have less control over the display of explanations, they perceive a better understanding of the AI-based system with more detailed explanations (M=3.88; SD=0.52) than do those with fewer details (M=3.62; SD=0.66). On the other hand, when consumers had more control over the display of explanations, their perceived understanding remained relatively stable but was still significant, with a slight increase in perceived understanding when they encountered less detailed explanations (M=3.64; SD=0.63) compared with more detailed explanations (M=3.59; SD=0.60).

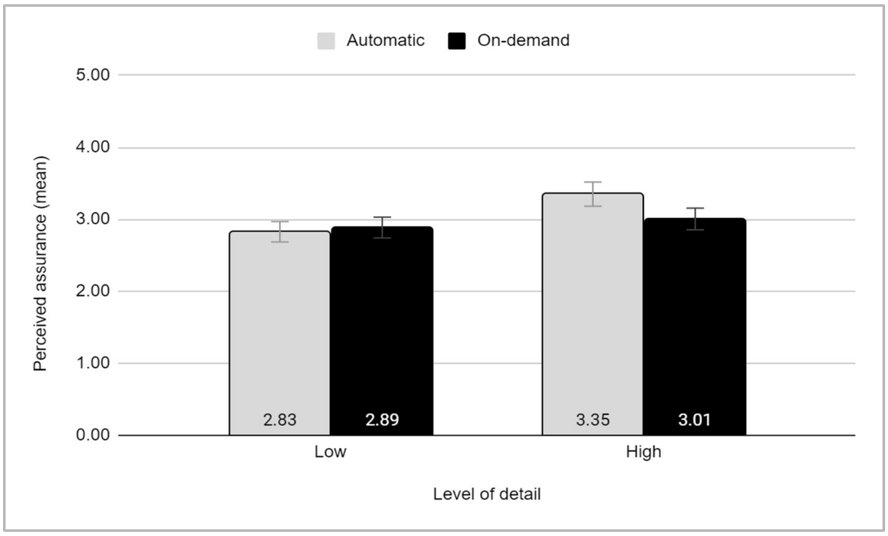
Figure 7. Interaction effects of the level of control and the level of detail on perceived understanding (Study 2)



Source: Authors own work

As reflected in Figure 5, which shows the structural model, the moderating effect of the level of control does not significantly affect the relationship between the level of detail and perceived assurance (β_{H4} =-0.35; p_{H4}>0.10) (see Figure 8). Therefore, the data do not support Hypothesis 4.

Figure 8. Interaction effects of the level of control and the level of detail on perceived assurance (Study 2)



Source: Authors own work

The results also show that consumers' perceived understanding significantly and positively affects their perceived assurance with respect to the AI-based system, supporting Hypothesis 5 (β_{H5}=0.43; p_{H5}<0.01). The results further indicated that increasing perceived understanding of the system had a positive and significant effect on consumers' perceptions of AI with respect to perceived competence (β_{H6a}=0.18; p_{H6a}<0.01), perceived human-centricity (β_{H6b}=0.14; p_{H6b}<0.05), and perceived integrity (β_{H6c}=0.21; p_{H6c}<0.01). Additionally, perceived assurance positively impacts consumers' trust in three dimensions of AI-based systems: perceived competence (β_{H7a}=0.58; p_{H7a}<0.01), perceived human centricity (β_{H7b}=0.43; p_{H7b}<0.01), and perceived integrity (β_{H7c}=0.26; p_{H7c}<0.01). Hence, hypotheses 6a, 6b, and 6c and 7a, 7b, and 7c were empirically supported. Finally, consumers' perceptions of both AI competence and AI integrity positively influence their acceptance of the service, thereby supporting H8a (β_{H8a}=0.58; p_{H8a}<0.01) and H8c (β_{H8c}=0.20; p_{H8c}<0.01). However, their perception of AI human-centeredness did not significantly affect their acceptance (β_{H8b}=-0.03; p_{H8b}>0.05). Consequently, Hypothesis 8b was not supported by the data.

6. Discussion and conclusion

6.1. Theoretical contributions

This research makes four main contributions to the literature on XAI and services.

First, this research adopts a consumer-centric perspective on XAI, emphasizing the importance of understanding consumer perceptions of explanations to reduce their resistance to AI-based services. It highlights XAI as a critical tool that enhances consumer acceptance of AI-based services, particularly in high-credence sectors, where trust and reliance in the service provider's expertise are paramount (Eisingerich and Bell, 2007). In this context, offering explanations not only deepens consumer understanding but also adds a layer of service by addressing uncertainties and fostering trust. The present research builds on Rai (2020) by exploring practical applications of XAI to improve consumer acceptance across various service sectors. While Chen *et al*. (2024) focus on the presence of explanations, this study centers on the format of these explanations and their specific role in enhancing the acceptance of AI-based services, particularly in high-credence sectors. By investigating how adapting XAI can address these needs, this study offers a different perspective on effectively integrating explainability into these services. The findings provide new insights into an explanation design to increase consumer trust and acceptance, addressing the gap in context-specific explanatory design patterns highlighted by Schoonderwoerd *et al*. (2021).

Second, in addition to developing a better understanding of the role of explanations, the present study advances research by investigating the effects of different types of XAI design on consumer behavior. More specifically, the balance between detailed information and perceived information overload is examined. Unlike prior studies that argue for simplified explanations to avoid overload (Guesmi *et al*., 2021a; Zhao *et al*., 2019), the findings reveal that consumers prefer detailed explanations, which significantly enhance the perceived understanding, trust, acceptance and purchase intention of AI-based services, aligning with the literature advocating comprehensive explanations (Chatti *et al*., 2022; Haque *et al*., 2023). When consumers have greater control over how they receive and interpret detailed information, they can navigate and process the information on their own terms (Millecamp *et al*., 2019). The findings highlight that high-detail explanations with limited control over the presentation format enhance perceived understanding more effectively than high-control scenarios do, suggesting that nonexpert consumers in high-credence contexts benefit most from comprehensive explanations when their control over the display of information is limited. Conversely, greater control over the presentation format allows consumers to better navigate and interpret information, reducing the impact of detail on understanding (Westphal *et al*., 2023). This effect may stem from the inherent complexity of AI-related information in high-credence service sectors, where consumers rely heavily on expert knowledge. In these contexts, comprehensive explanations with limited control over their presentation format improve consumers' perceived understanding. Conversely, when consumers have greater control over the information presentation format, they may experience increased perceived information load as they navigate and interpret the details themselves, thereby diminishing the beneficial impact of detailed explanations on perceived understanding and perceived assurance. These findings are consistent with signaling theory, indicating that detailed explanations can serve as effective signals to bridge the knowledge gap between consumers and AI providers, thereby reducing information asymmetry and enhancing perceived understanding, trust, and acceptance (Aguirre *et al*., 2015; Osburg *et al*., 2020). The open-ended results highlight that consumers expect detailed and transparent explanations to ensure safety and reliability, further supporting signaling theory's predictions in terms of enhancing trust and acceptance.

Our findings build on insights from Chen (2024) and complement the work of Kim *et al*. (2024) and Chen *et al*. (2024), who emphasize the importance of tailoring explanations to consumers. The results also extend prior research that focused separately on the level of detail (Chatti *et al*., 2022; Mohseni *et al*., 2021) or on the level of control (Millecamp *et al*., 2019; Haque *et al*., 2023) but did not consider their interplay. Additionally, the present findings challenge traditional views on information overload by demonstrating that, in high-credence service contexts, detailed explanations can enhance perceived understanding, perceived assurance and trust, particularly when consumers have limited control over how the information is presented. This builds on He *et al*. (2023) by providing empirical evidence that consumers prefer detailed explanations in specific contexts, contrary to concerns about information overload. Extending the work of Hu and Krishen (2019), this study explores how the level of detail in explanations interacts with consumer control over their presentation. While Hu and Krishen (2019) emphasize the role of consumer control over information quantity, the present research finds that in high-credence services, detailed explanations with limited consumer control enhance understanding and trust more effectively than high-control scenarios do, which may lead to increased perceived information load.

Third, this research identifies perceived assurance as crucial for building consumer trust. This highlights that detailed and understandable explanations are key to providing this assurance, demonstrating that perceived assurance acts as a mediating path, which significantly impacts trust in the system and acceptance of AI-based services. This research builds on past studies by integrating perceived assurance as an important antecedent of trust, addressing the gaps noted by Israelsen and Ahmed (2019), and calls for research from Bock *et al*., 2020. The present findings advance Haque *et al*.'s (2023) framework by emphasizing perceived assurance as a critical factor influencing consumer trust. Additionally, this study extends He *et al*.'s (2023) research by showing how perceived assurance, through understandable explanations, affects consumer trust beyond the medical domain.

Fourth, this research provides a more nuanced understanding of the influence of trust in the acceptance of AI-based services by examining its three dimensions and their interaction with explanation design. This finding shows that perceived assurance most strongly impacts perceived AI competence and human centricity. This is due to the psychological aspects of trust formation, where assurance from understandable explanations fosters a sense of security and reliability, leading consumers to view the system as competent and human-centric (Förster *et al*., 2020;

Whang and Im, 2018). This finding extends the work of Longoni *et al*. (2019) and Schoonderwoerd *et al.* (2021), who explored the psychological aspects of trust but did not focus on perceived assurance as a trust antecedent in the context of XAI.

In conclusion, this research advances explainable AI in high-credence services by exploring how explanation detail and control affect consumer perceptions of understanding, assurance, trust, and purchase intentions. This highlights the importance of balancing explanation detail with the level of control over explanations and underscores the role of perceived assurance in building consumer trust. By analyzing the dimensions of trust, this study offers a nuanced theoretical understanding of XAI design and new insights into XAI's impact on consumer behavior.

6.2. Managerial implications

This study explores how explanations affect consumers' acceptance and purchase intentions of AI-based services in a high-credence context and provides valuable practical insights into the strategic use of XAI to gain a competitive advantage.

Tailored explanations are crucial, with the level of detail and control significantly influencing consumers' perceptions of understanding and assurance. To effectively meet consumers' needs and enhance trust, service providers should focus on delivering highly detailed explanations that clarify the AI system's reasoning, avoiding mere result listings and instead showcasing the underlying rationale. Balancing detail to avoid overwhelming consumers while ensuring clarity is key. Service providers should carefully balance the level of control in explanations on the basis of the details provided. They should choose to either offer more information or enable more control over how explanations are displayed but not both simultaneously. For example, incorporating "read more" buttons can give consumers the option to access additional information, such as detailed algorithm descriptions or real-time examples, when needed.

Given the importance of perceived assurance, service managers should prioritize strategies that enhance the assurance role of explanations. Adapting terminology and reassuring consumers foster trust in the system and positive attitudes toward AI-based services. Furthermore, they should emphasize traceability and explain to consumers how their input influences the system’s outcome, which can improve consumers’ feelings of assurance when facing AI-based systems. Allowing consumers to see how their past actions or preferences influence specific results can further reinforce their feeling of assurance.

Demonstrating the AI system's competence and integrity is also essential for consumer acceptance. Therefore, service providers should demonstrate the system's ability to deliver accurate and relevant outputs. In the context of AI-based recommender systems, service providers can demonstrate competence via evaluation metrics such as decision support precision and recall, mean reciprocal rank (MRR), and normalized discounted cumulative gain (NDCG) (Zhang *et al.*, 2016). Providing detailed explanations that highlight the data points used for recommendations and how these factors influence outcomes allows consumers to assess the logic behind suggestions and build confidence in the system's competence. Perceived system integrity can be reinforced by providing more transparency about data collection methods, data sources, data integrity, reliability and ethical considerations. Service managers should integrate error handling, explain limitations, and acknowledge the system's continuous learning process to foster long-term trust and reduce consumers’ frustration with occasional errors.

6.3. Research limitations and suggestions for further research

While this research provides valuable insights into how the explanation format influences consumer perceptions of AI-based services, several limitations and avenues for future research should be noted.

First, conducting a field study in partnership with a company could increase the practical implications of the findings. Engaging with real-world data and consumer interactions would deepen the understanding of how the theoretical framework functions in actual business contexts and uncover practical challenges in implementing XAI in high-credence sectors. This approach would also address ethical considerations, regulatory compliance, and technical limitations, enhancing the research's external validity and fostering valuable knowledge exchange between academia and industry for actionable managerial insights. Additionally, future research could explore how different explanation designs impact the overall consumer experience (Knijnenburg *et al.*, 2012).

Second, as consumer familiarity with AI services grows, their understanding and perceptions—shaped by mechanisms such as word-of-mouth—may evolve. Since trust in AI is dynamic, future research could include longitudinal studies to investigate how changes in awareness and trust over time affect consumer behavior and responses to explanations in AI-based services.

Additionally, the present study focused on high-credence service sectors, which may limit the generalizability of the findings. High-involvement categories, such as financial investing or medical decisions, may generate more apprehension than low-involvement items, such as songs or news articles. Future studies could include low-credence services for comparison, as the results may differ.

Fourth, future research should explore whether the mere presence of explanations creates an illusion of understanding, as suggested by prior studies (Ostinelli *et al*., 2024). While explanations are vital for building trust, it remains unclear whether consumers prefer detailed explanations or if simply knowing explanations are available is sufficient. Investigating this topic could provide valuable insights into the effectiveness of XAI in improving consumer trust and acceptance of AI-based services.

Finally, future research should investigate how explanations can reveal and address AI bias (Hou *et al*., 2024). Investigating how the disclosure of AI biases within explanations affects consumer trust and acceptance can further deepen the understanding of XAI's role in promoting equitable AI technologies.

References

Aguirre, E., Mahr, D., Grewal, D., De Ruyter, K. and Wetzels, M. (2015, "Unraveling the personalization paradox: The effect of information collection and trust-building strategies on online advertisement effectiveness", *Journal of Retailing*, Vol. 91 No. 1, pp.34-49.

André, Q., Carmon, Z., Wertenbroch, K., Crum, A., Frank, D., Goldstein, W., Huber, J., van Boven, L., Weber, B. and Yang, H. (2018), "Consumer choice and autonomy in the age of artificial intelligence and big data", *Customer Needs and Solutions*, Vol. 5 No. 1-2, pp.28-37.

Arrieta, A.B., Díaz-Rodríguez, N., Ser, J.D., Bennetot, A., Tabik, S., Barbado, A., Garcia, S., Gil-Lopez, S., Molina, D., Benjamins, R., Chatila, R. and Herrera, F. (2020), "Explainable artificial intelligence (XAI): concepts, taxonomies, opportunities and challenges toward responsible AI", *Information Fusion*, Vol. 58, pp.82-115.

Belanche, D., Casaló, L.V. and Flavián, C. (2019), "Artificial intelligence in FinTech: understanding robo-advisors adoption among customers", *Industrial Management and Data Systems*, Vol. 119 No. 7, pp.1411-1430.

Benbasat, I. and Wang, W. (2005), "Trust in and adoption of online recommendation agents", *Journal of the Association for Information Systems*, Vol. 6 No. 3, pp.72-101.

Bock, D.E., Wolter, J.S. and Ferrell, O.C. (2020), "Artificial intelligence: disrupting what we know about services", *Journal of Services Marketing*, Vol. 34 No. 3, pp.317-334.

Chatti, M.A., Guesmi, M., Vorgerd, L., Ngo, T., Joarder, S., Ain, Q.U. and Muslim, A. (2022), "Is more always better? The effects of personal characteristics and level of detail on the perception of explanations in a recommender system", in *Proceedings of the 30th ACM*

Conference on User Modeling, Adaptation and Personalization, Association for Computing Machinery, New York, NY, USA, pp.254-264.

Chen, C. (2024), "How consumers respond to service failures caused by algorithmic mistakes: the role of algorithmic interpretability", *Journal of Business Research*, Vol. 176, p.114610.

Chen, C., Tian, A.D. and Jiang, R. (2024), "When post hoc explanation knocks: consumer responses to explainable AI recommendations", *Journal of Interactive Marketing*, Vol. 59 No. 3, pp.234-250.

Cho, J. (2006), "The mechanism of trust and distrust formation and their relational outcomes", *Journal of Retailing*, Vol. 82 No. 1, pp.25-35.

Choung, H., David, P. and Ross, A. (2023), "Trust in AI and its role in the acceptance of AI technologies", *International Journal of Human–Computer Interaction*, Vol. 39 No. 9, pp.1727-1739.

Chromik, M., Eiband, M., Buchner, F., Krüger, A. and Butz, A. (2021), "I think I get your point, AI! The illusion of explanatory depth in explainable AI", in *Proceedings of the 26th International Conference on Intelligent User Interfaces*, College Station, TX, USA, pp.307-317.

Coussement, K., Abedin, M. Z., Kraus, M., Maldonado, S. and Topuz, K. (2024), "Explainable AI for enhanced decision-making", *Decision Support Systems*, p.114276.

Dabholkar, P.A. (1996), "Consumer evaluations of new technology-based self-service options: an investigation of alternative models of service quality", *International Journal of Research in Marketing*, Vol. 13 No. 1, pp.29-51.

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

David, P., Choung, H. and Seberger, J.S. (2024), "Who is responsible? US public perceptions of AI governance through the lenses of trust and ethics", *Public Understanding of Science*. doi:10.1177/09636625231224592.

Day, G.S. and Boisi, G.T. (2011), "Closing the marketing capabilities gap", *Journal of Marketing*, Vol. 75 No. 4, pp.183-195.

Dazeley, R., Vamplew, P., Foale, C., Young, C., Aryal, S. and Cruz, F. (2021), "Levels of explainable artificial intelligence for human-aligned conversational explanations", *Artificial Intelligence*, Vol. 299, p.103525.

De Bruyn, A., Viswanathan, V., Beh, Y.S., Brock, J.K.-U. and von Wangenheim, F. (2020), "Artificial intelligence and marketing: pitfalls and opportunities", *Journal of Interactive Marketing*, Vol. 51 No. 1, pp.91-105.

Dodds, W.B., Monroe, K.B. and Grewal, D. (1991), "Effects of price, brand, and store information on buyers' product evaluations", *Journal of Marketing Research*, Vol. 28 No. 3, p.307-319.

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

Dwivedi, R., Dave, D., Naik, H., Singhal, S., Omer, R., Patel, P., Qian, B., Wen, Z., Shah, T., Morgan, G. and Ranjan, R. (2023), "Explainable AI (XAI): core ideas, techniques, and solutions", *ACM Computing Surveys*, Vol. 55 No. 9, pp.1-33.

Eisingerich, A.B. and Bell, S.J. (2007), "Maintaining customer relationships in high credence services", *Journal of Services Marketing*, Vol. 21 No. 4, pp. 253-262.

Esmaeilzadeh, H. and Vaezi, R. (2022), "Conscious empathic AI in service", *Journal of Service Research*, Vol. 25 No. 4, pp.549-564.

EU Artificial Intelligence Act. (2024), "Regulation (EU) 2024/1689", available at: https://eur-lex.europa.eu/legal-content/FR/TXT/PDF/?uri=OJ:L_202401689 (accessed 21 August 2024).

European Data Protection Supervisor. (2023), "TechDispatch #2/2023 - explainable artificial intelligence", available at: https://www.edps.europa.eu/data-protection/our-work/publications/techdispatch/2023-11-16-techdispatch-22023-explainable-artificial-intelligence_en (accessed 2 April 2024).

Fan, H. and Poole, M.S. (2006), "What is personalization? Perspectives on the design and implementation of personalization in information systems", *Journal of Organizational Computing and Electronic Commerce*, Vol. 16 No. 3-4, pp.179-202.

Felzmann, H., Villaronga, E.F., Lutz, C. and Tamò-Larrieux, A. (2019), "Transparency you can trust: transparency requirements for artificial intelligence between legal norms and contextual concerns", *Big Data and Society*, Vol. 6 No. 1, p.2053951719860542.

Flavián, C., Pérez-Rueda, A., Belanche, D. and Casaló, L.V. (2022), "Intention to use analytical artificial intelligence (AI) in services – the effect of technology readiness and awareness", *Journal of Service Management*, Vol. 33 No. 2, pp.293-320.

Fornell, C. and Larcker, D.F. (1981), "Evaluating structural equation models with unobservable variables and measurement error", *Journal of Marketing Research*, Vol. 18 No. 1, pp.39-50.

Förster, M., Klier, M., Kluge, K. and Sigler, I. (2020), "Fostering human agency: a process for the design of user-centric XAI systems", in George, J.F., Paul, S., De', R., Karahanna, E., Sarker, S. and Oestreicher-Singer, G. (Eds.), *Proceedings of the 41st International Conference on Information Systems, ICIS 2020, Making Digital Inclusive: Blending the Local and the Global,* Hyderabad, India, December 13-16, 2020, p.12.

Frank, D.-A., Jacobsen, L.F., Søndergaard, H.A. and Otterbring, T. (2023), "In companies we trust: consumer adoption of artificial intelligence services and the role of trust in companies and AI autonomy", *Information Technology and People*, Vol. 36 No. 8, pp.155-173.

Gaczek, P., Pozharliev, R., Leszczyński, G. and Zieliński, M. (2023), "Overcoming consumer resistance to AI in general health care", *Journal of Interactive Marketing*, Vol. 58 No. 2-3, pp.321-338.

Gefen, D. (2002), "Reflections on the dimensions of trust and trustworthiness among online consumers", *ACM SIGMIS Database: The DATABASE for Advances in Information Systems*, Vol. 33 No. 3, pp.38-53.

Girard, T. and Dion, P. (2010), "Validating the search, experience, and credence product classification framework", *Journal of Business Research*, Vol. 63 No. 9-10, pp.1079-1087.

Gregor, S. and Benbasat, I. (1999), "Explanations from intelligent systems: theoretical foundations and implications for practice", *MIS Quarterly*, Vol. 23 No. 4, p.497.

Grennan, L., Kremer, A., Singla, A. and Zipparo, P. (2022), "Why businesses need explainable AI-and how to deliver it", Quantum Black AI by McKinsey, available at: https://www.mckinsey.com/capabilities/quantumblack/our-insights/why-businesses-need-explainable-ai-and-how-to-deliver-it (accessed 30 March 2024).

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

Guesmi, M., Chatti, M.A., Sun, Y., Zumor, S., Ji, F., Muslim, A., Vorgerd, L. and Joarder, S.A. (2021a), "Open, scrutable and explainable interest models for transparent recommendation", in Glowacka, D. and Krishnamurthy, V.R. (Eds.), *Joint Proceedings of the ACM IUI 2021 Workshops*, Association for Computing Machinery, College Station, United States, pp.1-8.

Guesmi, M., Chatti, M.A., Vorgerd, L., Joarder, S., Zumor, S., Sun, Y., Ji, F. and Muslim, A. (2021b), "On-demand personalized explanation for transparent recommendation", in *Adjunct Proceedings of the 29th ACM Conference on User Modeling, Adaptation and Personalization*, Association for Computing Machinery, New York, NY, USA, pp.246-252.

Guo, Y., Li, Y., Liu, D. and Xu, S.X. (2024), "Measuring service quality based on customer emotion: an explainable AI approach", *Decision Support Systems*, Vol. 176, p.114051.

Hair, J.F., Sarstedt, M., Ringle, C.M. and Mena, J.A. (2012), "An assessment of the use of partial least squares structural equation modeling in marketing research", *Journal of the Academy of Marketing Science*, Vol. 40 No. 3, pp.414-433.

Hair Jr, J.F. and Sarstedt, M. (2021), "Data, measurement, and causal inferences in machine learning: opportunities and challenges for marketing", *Journal of Marketing Theory and Practice*, Vol. 29 No. 1, pp.65-77.

Haque, A.K.M.B., Islam, A.K.M.N. and Mikalef, P. (2023), "Explainable artificial intelligence (XAI) from a user perspective: a synthesis of prior literature and problematizing avenues for future research", *Technological Forecasting and Social Change*, Vol. 186, p.122120.

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

Henseler, J., Ringle, C.M. and Sinkovics, R.R. (2009), "The use of partial least squares path modeling in international marketing", *Advances in International Marketing*, Vol. 20 No. 1, pp.277-319.

He, X., Hong, Y., Zheng, X. and Zhang, Y. (2023), "What are the users' needs? Design of a user-centered explainable artificial intelligence diagnostic system", *International Journal of Human–Computer Interaction*, Vol. 39 No. 7, pp.1519-1542.

Hicks, K., Cocks, K., Corbacho Martin, B., Elton, P., MacNab, A., Colecliffe, W. and Furze, G. (2014), "An intervention to reassure patients about test results in rapid access chest pain clinic: a pilot randomised controlled trial", *BMC Cardiovascular Disorders*, Vol. 14, p.138.

Hou, T.Y., Tseng, Y.C. and Yuan, C.W.T. (2024), "Is this AI sexist? The effects of a biased AI's anthropomorphic appearance and explainability on users' bias perceptions and trust", *International Journal of Information Management*, Vol. 76, p.102775.

Hu, H.F. and Krishen, A.S. (2019), "When is enough, enough? Investigating product reviews and information overload from a consumer empowerment perspective", *Journal of Business Research*, Vol. 100, pp.27–37.

Huang, M.-H. and Rust, R.T. (2022), "AI as customer", *Journal of Service Management*, Vol. 33 No. 2, pp.210-220.

Husairi, M.A. and Rossi, P. (2024), "Delegation of purchasing tasks to AI: the role of perceived choice and decision autonomy", *Decision Support Systems*, Vol. 179, p.114166.

IBM Institute for Business Value. (2023), "5 trends for 2024", available at: https://www.ibm.com/downloads/cas/LMZBNZDQ (accessed 13 February 2024).

Israelsen, B.W. and Ahmed, N.R. (2019), "Dave...I can assure you ...that it's going to be all right ..." a definition, case for, and survey of algorithmic assurances in human-autonomy trust relationships", *ACM Computing Surveys*, Vol. 51 No. 6, pp.1-37.

Kalaignanam, K., Tuli, K.R., Kushwaha, T., Lee, L. and Gal, D. (2021), "Marketing agility: the concept, antecedents, and a research agenda", *Journal of Marketing*, Vol. 85 No. 1, pp.35-58.

Khan, A.W. and Mishra, A. (2024), "AI credibility and consumer-AI experiences: a conceptual framework", *Journal of Service Theory and Practice*, Vol. 34 No. 1, pp.66-97.

Kim, D., Song, Y., Kim, S., Lee, S., Wu, Y., Shin, J. and Lee, D. (2023), "How should the results of artificial intelligence be explained to users? - Research on consumer preferences in user-centered explainable artificial intelligence", *Technological Forecasting and Social Change*, Vol. 188, p.122343.

Kim, J., Giroux, M. and Lee, J.C. (2021), "When do you trust AI? The effect of number presentation detail on consumer trust and acceptance of AI recommendations", *Psychology and Marketing*, Vol. 38 No. 7, pp.1140-1155.

Kim, M., Kim, S., Kim, J., Song, T.-J. and Kim, Y. (2024), "Do stakeholder needs differ? - Designing stakeholder-tailored explainable artificial intelligence (XAI) interfaces", *International Journal of Human-Computer Studies*, Vol. 181, p.103160.

Knijnenburg, B.P., Willemsen, M.C., Gantner, Z., Soncu, H. and Newell, C. (2012), "Explaining the user experience of recommender systems", *User Modeling and User-Adapted Interaction*, Vol. 22, pp.441-504.

Lee, S.-H., Lee, B.-Y. and Kim, H.-W. (2019), "Decisional factors leading to the reuse of an on-demand ride service", *Information and Management*, Vol. 56 No. 4, pp.493-506.

Longo, L., Brcic, M., Cabitza, F., Choi, J., Confalonieri, R., Del Ser, J., ... and Stumpf, S. (2024), "Explainable Artificial Intelligence (XAI) 2.0: a manifesto of open challenges and interdisciplinary research directions", *Information Fusion*, Vol. 106, p.102301.

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

Longoni, C. and Cian, L. (2022), "Artificial intelligence in Utilitarian vs. Hedonic contexts: the "word-of-machine" effect", *Journal of Marketing*, Vol. 86 No. 1, pp.91-108.

Madsen, M. and Gregor, S. (2000), "Measuring human-computer trust", in Gable, G. and Vitale, M. (Eds.), *11th Australasian Conference on Information Systems*, Information Systems Management Research Centre, Brisbane, Australia, pp.6-8.

Masialeti, M., Talaei-Khoei, A. and Yang, A. T. (2024), "Revealing the role of explainable AI: how does updating AI applications generate agility-driven performance?", *International Journal of Information Management*, Vol. 77, p.102779.

Maslowska, E., Malthouse, E.C. and Hollebeek, L.D. (2022), "The role of recommender systems in fostering consumers' long-term platform engagement", *Journal of Service Management*, Vol. 33 No. 4/5, pp.721-732.

Mayer, R.C., Davis, J.H. and Schoorman, F.D. (1995), "An integrative model of organizational trust", *Academy of Management Review*, Vol. 20 No. 3, pp.709-734.

McKnight, D.H., Choudhury, V. and Kacmar, C. (2002), "Developing and validating trust measures for e-commerce: an integrative typology", *Information systems research*, Vol. 13 No. 3, pp.334-359.

Mehmood, K., Verleye, K., De Keyser, A. and Larivière, B. (2023), "Piloting personalization research through data-rich environments: a literature review and future research agenda", *Journal of Service Management*, Vol. 34 No. 3, pp.520-552.

Mehrotra, S., Jorge, C.C., Jonker, C.M. and Tielman, M.L. (2024), "Integrity-based explanations for fostering appropriate trust in AI agents", *ACM Transactions on Interactive Intelligent Systems*, Vol. 14 No. 1, pp.1-36.

Millecamp, M., Htun, N.N., Conati, C. and Verbert, K. (2019), "To explain or not to explain: the effects of personal characteristics when explaining music recommendations", in *Proceedings of the 24th International Conference on Intelligent User Interfaces*, Association for Computing Machinery, New York, NY, USA, pp.397-407.

Miller, T. (2019), "Explanation in artificial intelligence: insights from the social sciences", *Artificial Intelligence*, Vol. 267, pp.1-38.

Mitra, K., Reiss, M.C. and Capella, L.M. (1999), "An examination of perceived risk, information search and behavioral intentions in search, experience and credence services", *Journal of Services Marketing*, Vol. 13 No. 3, pp.208-228.

Mohseni, S., Zarei, N. and Ragan, E.D. (2021), "A multidisciplinary survey and framework for design and evaluation of explainable AI systems", *ACM Transactions on Interactive Intelligent Systems*, Vol. 11 No. 3-4, pp.1-45.

Oh, C., Song, J., Choi, J., Kim, S., Lee, S. and Suh, B. (2018), "I lead, you help but only with enough details: understanding user experience of co-creation with artificial intelligence", in *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*, Association for Computing Machinery, New York, NY, USA, pp.1-13.

Orth, U.R. and Wirtz, J. (2014), "Consumer processing of interior service environments: the interplay among visual complexity, processing fluency, and attractiveness", *Journal of Service Research*, Vol. 17 No. 3, pp.296-309.

Osburg, V.S., Yoganathan, V., Brueckner, S. and Toporowski, W. (2020), "How detailed product information strengthens eco-friendly consumption", *Management Decision*, Vol. 58 No. 6, pp.1084-1099.

Osburg, V.S., Yoganathan, V., Kunz, W.H. and Tarba, S. (2022), "Can (A) I give you a ride? Development and validation of the CRUISE framework for autonomous vehicle services", *Journal of Service Research*, Vol. 25 No. 4, pp.630-648.

Ostinelli, M., Bonezzi, A. and Lisjak, M. (2024), "Unintended effects of algorithmic transparency: the mere prospect of an explanation can foster the illusion of understanding how an algorithm works", *Journal of Consumer Psychology*. doi:10.1002/jcpy.1416.

Palan, S. and Schitter, C. (2018), "Prolific. ac—A subject pool for online experiments", *Journal of Behavioral and Experimental Finance*, Vol. 17, pp.22-27.

Park, S.S., Tung, C.D. and Lee, H. (2021), "The adoption of AI service robots: a comparison between credence and experience service settings", *Psychology and Marketing*, Vol. 38 No. 4, pp.691-703.

Phillips-Wren, G. and Adya, M. (2020), "Decision making under stress: the role of information overload, time pressure, complexity, and uncertainty", *Journal of Decision Systems*, Vol. 29 No. sup1, pp.213-225.

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

Rai, A. (2020), "Explainable AI: from black box to glass box", *Journal of the Academy of Marketing Science*, Vol. 48 No. 1, pp.137-141.

Ribeiro, M.T., Singh, S. and Guestrin, C. (2016), ""Why should I trust you?" Explaining the predictions of any classifier", in *Proceedings of the ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, Association for Computing Machinery, New York, USA, pp.1135-1144.

Roetzel, P. G. (2019), "Information overload in the information age: a review of the literature from business administration, business psychology, and related disciplines with a bibliometric approach and framework development", *Business Research*, Vol. 12 No. 2, pp.479–522.

Schmidt, P., Biessmann, F. and Teubner, T. (2020), "Transparency and trust in artificial intelligence systems", *Journal of Decision Systems*, Vol. 29 No. 4, pp.260-278.

Schoonderwoerd, T.A., Jorritsma, W., Neerincx, M.A. and Van Den Bosch, K. (2021), "Human-centered XAI: Developing design patterns for explanations of clinical decision support systems", *International Journal of Human-Computer Studies*, Vol. 154, p.102684.

Shin, D. (2020), "User perceptions of algorithmic decisions in the personalized ai system: perceptual evaluation of fairness, accountability, transparency, and explainability", *Journal of Broadcasting and Electronic Media*, Vol. 64 No. 4, pp.541-565.

Shin, D. (2021), "The effects of explainability and causability on perception, trust, and acceptance: implications for explainable AI", *International Journal of Human-Computer Studies*, Vol. 146, p.102551.

Wang, D., Yang, Q., Abdul, A. and Lim, B.Y. (2019), "Designing theory-driven user-centric explainable AI", in *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*, Association for Computing Machinery, New York, NY, USA, pp.601.

Wang, X., Yu, C. and Wei, Y. (2012), "Social media peer communication and impacts on purchase intentions: a consumer socialization framework", *Journal of Interactive Marketing*, Vol. 26 No. 4, pp.198-208.

Wei, W. and Liu, L. (2024), "Trustworthy distributed AI systems: robustness, privacy, and governance", *ACM Computing Surveys*. doi:10.1145/3645102.

Westphal, M., Vössing, M., Satzger, G., Yom-Tov, G.B. and Rafaeli, A. (2023), "Decision control and explanations in human-AI collaboration: improving user perceptions and compliance", *Computers in Human Behavior*, Vol. 144, p.107714.

Whang, C. and Im, H. (2018), "Does recommendation matter for trusting beliefs and trusting intentions? Focused on different types of recommender system and sponsored recommendation", *International Journal of Retail and Distribution Management*, Vol. 46 No. 10, pp.944-958.

Wien, A.H. and Peluso, A.M. (2021), "Influence of human versus AI recommenders: the roles of product type and cognitive processes", *Journal of Business Research*, Vol. 137, pp.13-27.

Wu, G., Hu, X. and Wu, Y. (2010), "Effects of perceived interactivity, perceived web assurance and disposition to trust on initial online trust", *Journal of Computer-Mediated Communication*, Vol. 16 No. 1, pp.1-26.

Wysocki, O., Davies, J.K., Vigo, M., Armstrong, A.C., Landers, D., Lee, R. and Freitas, A. (2023), "Assessing the communication gap between AI models and healthcare professionals: explainability, utility and trust in AI-driven clinical decision-making", *Artificial Intelligence*, Vol. 316, p. 103839.

Yang, C. and Hu, J. (2022), "When do consumers prefer AI-enabled customer service? The interaction effect of brand personality and service provision type on brand attitudes and purchase intentions", *Journal of Brand Management*, Vol. 29 No. 2, pp.167-189.

Yang, F., Huang, Z., Scholtz, J. and Arendt, D.L. (2020), "How do visual explanations foster end users' appropriate trust in machine learning?", in *Proceedings of the 25th International Conference on Intelligent User Interfaces*, Association for Computing Machinery, New York, NY, USA, pp.189-201.

Yue, B. and Li, H. (2023), "The impact of human-AI collaboration types on consumer evaluation and usage intention: a perspective of responsibility attribution", *Frontiers in Psychology*, Vol. 14, pp.1277861.

Zaichkowsky, J.L. (1985), "Measuring the involvement construct", *Journal of Consumer Research*, Vol. 12 No. 3, pp.341-352.

Zhang, R., Bao, H., Sun, H., Wang, Y. and Liu, X. (2016), "Recommender systems based on ranking performance optimization", *Frontiers of Computer Science*, Vol. 10, pp.270-280.

Zhang, Y. and Chen, X. (2020), "Explainable recommendation: A survey and new perspectives", *Foundations and Trends® in Information Retrieval*, Vol. 14 No. 1, pp.1-101.

Zhao, R., Benbasat, I. and Cavusoglu, H. (2019), "Do users always want to know more? Investigating the relationship between system transparency and users' trust in advice-giving systems", in vom Brocke, J., Gregor, S. and Müller, O. (Eds.), *Proceedings of the 27th European Conference on Information Systems (ECIS)*, Stockholm and Uppsala, Sweden, June 8-14, p.42.