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Embarrassed by Robots? How AI Types Affect Customer Experience

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   - We critically assessed the AI-generated output, ensuring its alignment with our research objectives.
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   - We acknowledge the use of DeepL, ChatGPT, and Perplexity AI transparently, emphasizing that it contributed to our work but did not replace human judgment.
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During the preparation of this master's thesis, the author utilized DeepL, ChatGPT, and Perplexity AI for the following purpose:

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2. After using DeepL, ChatGPT, and Perplexity AI, the author diligently reviewed and edited the content produced by the tool. The author take full responsibility for the final content presented in this thesis.

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04/08/2025

Amélie Lévêque

Abstract

In an era where artificial intelligence (AI) is reshaping the way services are delivered, the integration of service robots presents both opportunities and challenges for managing customer experiences. This thesis therefore studies the underexplored influence of different types of artificial intelligence (mechanical AI, thinking AI, and feeling AI) embedded in service robots on customer embarrassment during service encounters. While prior studies have established that service robots can reduce social discomfort, and consequently embarrassment, compared to human employees, they have largely treated AI as a uniform category, overlooking distinctions between different types of AI intelligence. Addressing this gap through a comprehensive literature review and experimental research, this study employed a 3 (AI type: mechanical, thinking, feeling) by 2 (context sensitivity: high vs. low) between-subjects design with 210 participants, who were randomly exposed to one of six scenarios.

Results reveal that more advanced AI (thinking and feeling) significantly increase embarrassment compared to mechanical AI, especially in high-sensitivity contexts. However, no significant difference was found between thinking and feeling AI, revealing that these two advanced AI types elicited similar levels of embarrassment. While higher AI intelligence resulted in stronger perceptions of automated social presence, this variable did not mediate the relationship between AI type and customer embarrassment. These findings offer both theoretical and managerial implications, suggesting that not all forms of AI are perceived equally and that their implementation in socially sensitive service contexts should be approached with careful consideration.

First and foremost, I would like to express my sincere gratitude to my supervisor, Professor Simon Hazée, who has accompanied me throughout this project by providing insightful comments, relevant articles, and valuable advice. His support, as well as the time he dedicated to answering my questions, was truly invaluable. Thanks to his guidance, the structure and approach of my thesis became significantly more coherent, allowing me to move in the right direction and progress each stage of the process with more confidence.

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Introduction

The introduction of artificial intelligence (AI) is revolutionizing the way businesses interact with their customers and has rapidly become an integral part of the business world (Ameen et al., 2021). The rapid development of AI is changing the service encounter and is increasingly reshaping service by performing various tasks, constituting a major source of innovation today (Huang and Rust, 2018). The infusion of service robots powered by artificial intelligence are becoming increasingly common and fundamentally changes the nature of service encounters (Pitardi et al., 2022). From household robots and automated healthcare assistants to virtual agents that transform customer service into self-service, AI is rapidly reshaping everyday interactions (Huang and Rust, 2018).

According to the International Federation of Robotics, more than 205 000 professional service robots were installed worldwide in 2023, marking a 30% increase over the previous year. Based on the data from Statista's market forecast for service robotics worldwide, the service robotics market is experiencing significant growth and is projected to reach approximately $40.58 billion in revenue by 2025. Commercial service robotics represents the largest segment, expected to generate around $23.03 billion in 2025 (Statista, 2025). This highlights the dominant and expanding role of service robots, as well as the growing demand for efficient and scalable service solutions.

Despite the rapid expansion of service robot adoption, limited research has examined customer experience, behavioral responses, and perceptions related to this emerging technology. While some studies have explored different types of AI intelligence (Huang & Rust, 2018; Huang et al., 2019) and others have investigated how customers feel, particularly in terms of perceived embarrassment when interacting with service robots compared to human employees (Pitardi et al., 2022; Holthöwer & van Doorn, 2022), there remains a gap in understanding how specific types of AI intelligence influence customer embarrassment. Building on this gap, the present thesis aims to extend the existing literature on customer–AI interaction by addressing the following research question: **"How do different types of AI intelligence (mechanical, thinking, and feeling), possessed by service robots, influence customers' embarrassment across service contexts of varying sensitivity?".**

To provide an answer, this thesis follows a structured approach, beginning with a literature review to establish a theoretical framework. Based on the insights gathered, hypotheses are developed. A 3 (mechanical vs. thinking vs. feeling AI) by 2 (high vs. low context sensitivity) between-subjects experimental design is employed to test these hypotheses. The quantitative study assesses the variables of customer embarrassment and perceived automated social presence. Data analysis then examines the significance of the relationships between AI types and both variables. Finally, the study discusses theoretical implications and offers managerial recommendations. This thesis contributes to the growing literature on service robots by exploring how different forms of AI intelligence shape customer experience and perception in socially sensitive service situations.

Part I: Literature Review

1. Service robots

1.1. Origin and definition

The term "robot", derived from the Czech word *robota* which means "forced labor", is also used to describe mechanical devices programmed to execute specific physical tasks (Belanche et al., 2019). It implies a certain degree of autonomous action without human intervention (International Federation of Robotics, 2016), although the extent of autonomy can vary widely, ranging from simple machines performing repetitive, menial tasks to highly intelligent and sophisticated systems.

The definition of service robots has evolved alongside technological advancements and the diversification of their roles. De Keyser et al. (2022) reviewed and consolidated the various definitions and descriptions found in the literature (Appendix 1). For this research, given the focus on service encounters, the definition proposed by Wirtz et al. (2018) is adopted, which consider service robots as "system-based autonomous and adaptable interfaces that interact, communicate and deliver service to an organization's customers". This comprehensive definition captures several critical dimensions.

As highlighted by De Keyser et al. (2022), service robots are not isolated entities but are typically embedded within broader systems or networks (e.g., connections to external databases, CRM systems). They are capable of autonomous decision-making based on data collected through various sensors and sources, enabling them to adapt to the situation by learning from past interactions (Pitardi et al., 2022). The integration of artificial intelligence (AI) is what enables this autonomy and adaptability. "*Adaptability*" refers to a robot's ability to adjust its behavior based on previous experiences, while "*autonomy*" indicates that it can operate independently, without human intervention, during the service delivery process (Pitardi et al., 2022).

Another main characteristic of service robots, in contrast to other forms of frontline technology, is their interaction modalities (Pitardi et al., 2022). They are able to communicate and deliver interactive services to a variety of actors through various formats (De Keyser et al., 2022). As a result, service robots can therefore be considered as service agent (McLeay et al., 2021) and differentiate themselves from traditional self-service technologies (SSTs) with their social and interactive capabilities (Belanche et al., 2020). In this context, Caic et al. (2019) define physically embodied robots as "fully or partially automated technologies that co-create value with humans through their social functionalities," highlighting their role in enhancing human-robot interaction and co-creating value in service delivery.

In terms of representation, service robots can be either physical or virtual (e.g., Pepper robots vs the voice-based assistant Alexa). Due to their system-based architecture, the difference between physical and virtual service robots is often limited to the visual appearance of the customer interaction interface (Pitardi et al., 2022). Their design may be humanoid, displaying human-like features (e.g., Sophia), or non-humanoid, with a purely functional structure (e.g., the Roomba cleaning robot) (Wirtz et al., 2018).

In customer-facing service scenarios, Larivière et al. (2017) highlight that robots can either play a role of augmentation by assisting and complementing human employees, or act as a substitution by entirely replacing them.

1.2. Roles and Underlying Types of Artificial Intelligence

The service tasks provided by service robots are defined by the type of intelligence they possess. Huang and Rust (2018) initially identified four distinct types of intelligence required for service tasks – mechanical, analytical, intuitive, and empathetic (Appendix 2). These types are categorized based on the nature of the service and on the increasing difficulty for AI to master them. As AI evolves in a predictable order, typically progressing from mechanical and analytical intelligence toward more intuitive and empathetic forms, it gradually shifts from handling routine tasks to more complex and nuanced service functions, thereby expanding its role in service delivery (Huang and Rust, 2018).

However, in subsequent research, Huang, Rust, and Maksimovic (2019) simplified these four intelligences into three: mechanical, thinking, and feeling. This multiple AIs view emphasizes that different forms of AI can be used in service to engage customers, each designed to perform distinct tasks and deliver its unique benefits to the service. The more complex, personalized, and emotionally charged the service is, the higher the level of AI required, in terms of the difficulty for AI to perform the service function (Huang and Rust, 2021).

Before precisely defining these different types of AI, it is essential to establish a foundational understanding of AI in the context of service. AI refers to technologies that replicate aspects of human intelligence (HI) and are distinct from general information technologies by their ability to learn, connect, and adapt (Huang and Rust, 2021). AI can evolve its responses and improve its performance over time through continuous learning and adaptation, leveraging data from a wide range of sources. This capability is a key feature of AI and is what makes us consider such systems as intelligent (Huang, Rust, and Maksimovic 2019). However, not all AI systems are designed to learn, as this depends on the specific needs of the application (Huang and Rust, 2021). AI systems may vary significantly in their degrees of learning ability, adaptivity, and connectivity, reflecting the diverse contexts in which they are deployed (Huang and Rust, 2021). This adaptability allows AI to convert data into meaningful outputs in three fundamentally different ways, corresponding to distinct types of AI intelligences that define their capabilities in service contexts (Huang, Rust, and Maksimovic 2019).

Mechanical intelligence refers to the ability to perform simple, routine, and repetitive tasks automatically, with minimal learning and adaptation (Huang and Rust 2018; Huang, Rust, and Maksimovic 2019). It is designed for consistency, reliability, and precision, with the goals of maximizing efficiency, making it ideal for service standardization (Huang and Rust, 2021). However, mechanical AI systems typically do not understand their environment and cannot adapt automatically (Huang and Rust, 2018). Instead, they operate based on structured inputs and outputs, delivering predictable and consistent results without requiring complex decision-making (e.g., self-service kiosks, automated checkout systems).

Thinking intelligence can be either analytical or intuitive, characterized by the ability to learn and adapt autonomously from data (Huang and Rust, 2021). Analytical AI learns and adapts systematically based on data, processing information for problem-solving based on clearly defined patterns, while intuitive AI learns and adapts based on a deeper understanding of the context, interpreting complex, unstructured data beyond just observable patterns. This deeper "understanding" may be considered as the key feature that distinguishes intuitive AI from analytical AI (Huang and Rust, 2018). Therefore, thinking AI is often used in applications requiring data-driven decision-making, such as predictive analytics and personalized recommendations.

Feeling intelligence is the most advanced and challenging form of AI, designed to learn and adapt from experience. This type of AI relies on contextual and experiential learning to simulate human-like emotional intelligence, enabling it to engage in meaningful, empathetic interactions (Huang, Rust, and Maksimovic, 2019). Feeling AI possesses all the capabilities of mechanical and thinking AI but applies these capabilities to experiential data, making it ideal for service relationalization (Huang and Rust, 2021). This form of intelligence is specifically designed to recognize, interpret, and respond to human emotions in an emotionally way, facilitating the creation of personalized relationships (Huang and Rust, 2021). While still in its early stages of development, feeling AI holds significant potential for transforming high-touch service industries by creating deeper, more personalized customer relationships, but it largely remains the domain of human service employees for now (Huang and Rust, 2021).

The development of AI is cumulative, meaning that once AI advances to a higher level, it also typically retains the capabilities of lower-level intelligence (Huang and Rust, 2021). When deciding which type of AI to use for engaging customers, service providers need to understand the strengths of each AI and choose appropriately based on the nature of the service (Huang and Rust, 2021). Based on their research, Huang and Rust (2021) highlighted four major factors that shape the role of AI in service: the nature of service task, service offering, service strategy, and service process.

As a result, some tasks may be performed by humans while others handled by AI, leading to hybrid teams where AI and HI (human service employees) collaborate. Wirtz et al. (2018) emphasized that hybrid teams are the most effective for service delivery when tasks require both complex analytical and emotional skills. However, the more service tasks can be handled by AI, the fewer human employees will be needed, and the remaining human employees will focus on roles AI cannot fulfill (Huang, Rust, and Maksimovic 2019).

The following table 1 summarizes the main contributions of the three foundational studies by Huang, Rust, and colleagues, which laid the theoretical groundwork for understanding how different types of AI are shaping the future of service delivery. Each study offers a unique lens on the evolution of AI roles, from task replacement to customer engagement strategies, and ultimately to the emergence of the Feeling Economy. By organizing their findings side by side, this comparison highlights how the conceptualization of AI intelligence has developed over time and informs the strategic use of AI in various service contexts.

Table 1: Prior Research on the Different AI Types

Study	Research Objective	Type of AI studied	Key Findings
Huang and Rust, 2018	To develop a theory of AI job replacement in service, identifying how AI reshapes service tasks and employment.	Mechanical, Analytical, Intuitive, and Empathetic	AI replaces service tasks in a predictable order, leading to augmentation and eventual replacement; softer skills will be more valued as AI advances.
Huang, Rust, and Maksimovic 2019	To analyze the evolving role of AI in work and introduce the concept of the 'Feeling Economy'.	Mechanical, Thinking, and Feeling	AI is taking over mechanical and thinking tasks; feeling tasks are growing in importance, leading to a shift in human roles toward interpersonal and empathetic tasks.
Huang and Rust, 2021	To build a strategic framework for using AI in service to enhance customer engagement based on service type and stage.	Mechanical, Thinking, and Feeling	Different AIs are best for different service strategies: mechanical for standardization, thinking for personalization, and feeling for relationalization.

2. Service robots: Experiential perspective

The dominant existing research conducted on service robots mainly focuses on human-robot interaction and the factors that influence customer acceptance. Various models have focused on technology acceptance, the most popular being the Technology Acceptance Model (TAM) introduced by Davis (1989). This model highlights perceived ease of use and perceived usefulness as the two key determinants of users' acceptance of service robots (De Keyser et al., 2022).

However, given the growing ubiquity of AI in consumers' lives, the focus should shift toward exploring the customer's experience in their interaction with AI (Puntoni et al. 2020). Although AI is often characterized by computer scientists as a neutral tool evaluated based on efficiency and accuracy, this approach tends to overlook the social and individual challenges that may arise when AI is deployed (Puntoni et al. 2020). While AI can offer practical and valuable benefits to consumers, failing to incorporate customer behavioral insights in its development may negatively impact the consumer experience (Puntoni et al., 2020).

It is therefore important to understand how AI is perceived and experienced by consumers. This experiential perspective allows, on the one hand, acknowledgement of the benefits that AI can provide to customers, and on the other hand, a better understanding, based on a customer-centric view of AI, of the costs they may experience in their interactions with it

(Puntoni et al., 2020). As De Keyser et al. (2022) emphasize, research should increasingly address societally relevant outcomes, such as perceived privacy intrusion and well-being, in order to design improved consumer AI experiences. Furthermore, as noted by McLeay et al. (2021), customer perceptions of service robots are shaped by a range of ethical and societal concerns. Adopting a customer-centric perspective is therefore essential to better understand innovative service delivery, as customer experience is a key driver of competitive advantage and business success (Lemon & Verhoef, 2016), ultimately determining the success of innovation.

The customer experience (CX) is shaped by various factors across the service journey and involves cognitive, emotional, and social dimensions (Verhoef et al., 2009). To better understand CX in AI-enabled services, Chen and Prentice (2024) propose a framework built around three elements: touchpoints, context, and qualities (De Keyser et al., 2021). Among these, context plays a particularly critical role, as it influences how customers interpret and react to service interactions. Drawing on Manthiou and Klaus (2022), context includes individual, social, market, and environmental factors. In this thesis, a sensitive service context refers to a service situation in which the customer feels exposed, vulnerable, or at risk of social judgment, and consequently could perceive embarrassment. The context is particularly important in understanding customer behavior in unpredictable or sensitive service settings. A revealing example arises when embarrassing or socially awkward situations occur during AI interactions, where service robots may be preferred over human employees (Pitardi et al., 2022). This preference is especially shaped by the individual and social contexts, as customers seek to maintain privacy, avoid judgment, or minimize discomfort in public or relational settings.

3. Embarrassment and social judgement in service encounters

Embarrassing situations experienced by service customers can occur across a variety of contexts and typically arise when individuals fear being negatively evaluated or socially judged by others during an interaction (Holthöwer & van Doorn, 2022). For instance, embarrassment may arise from socially awkward interactions, such as inappropriate behaviour, emotional expression, or verbal blunders (Grace, 2007). It can also be triggered by perceived customer incompetence, being confronted with one’s own mistakes by a frontline employee or by the purchase of sensitive or intimate products, such as condoms or medication to treat a sexually transmitted disease, that are seen as more embarrassing than others (Pitardi et al., 2022). To synthesize, Guo et al. (2024) state that consumer embarrassment comes from three main sources: criticism or invasion of privacy by the service provider, the consumer's own behavior or mistakes, and inappropriate behavior by others.

The perception of social judgement plays a central role in these emotional responses, shaping consumer behaviours and attitudes (Dahl et al., 2001). The real or imagined social presence of others can lead individuals to feel socially judged, particularly in situations perceived as embarrassing (Holthöwer & van Doorn, 2022). Since people are often concerned about how they are viewed by others, this perception can threaten their social identity and provoke defensive behaviours, such as avoiding the purchase of embarrassing products or withdrawing from uncomfortable service situations (Pitardi et al., 2022). According to the social evaluation model, embarrassment stems from the concern of being negatively or unfavourably evaluated by others (Manstead & Semin, 1981).

Consequently, customers are more likely to prefer service robots in situations where human presence causes social discomfort, as robots can help reduce reluctance to engage with the service offering in embarrassing contexts (Holthöwer & van Doorn, 2022). Consumers tend to feel less judged by robots than by humans, as automation reduces the human social presence that typically triggers perceptions of social judgement (Argo et al., 2005; Dahl et al., 2001). The concept of automated social presence is defined as "the extent to which technology makes customers feel the presence of another social entity" (van Doorn et al., 2017). As emphasized by Pitardi et al. (2022), this prediction aligns with the idea that robots are perceived as having low level of agency and lacking emotion. Entities perceived as having mind are generally believed to act with intentions, form opinions and make moral and social judgements (i.e. have agency) and experience (i.e. the ability to feel emotions) (Gray et al., 2007; Gray et al., 2012). The absence of such abilities significantly influences how individuals assess and respond to service robots, often resulting in service experiences that feel less embarrassing (Pitardi et al., 2022).

Table 2 presents an overview of prior research on customer responses to service robots in embarrassing contexts. It summarizes studies comparing robots and human employees, showing how factors like perceived agency, social judgment, social anxiety, and anthropomorphism influence outcomes such as embarrassment and satisfaction. By synthesizing these findings, the table clarifies how service robots can reduce social discomfort and enhance customer experience in sensitive encounters.

Table 2: Prior Studies on Customer Responses in Embarrassing Service Contexts

Study	Research Objective	Type of AI used	Customer outcomes	Moderator variable(s)	Mediator variable(s)	Key finding(s)
Pitardi et al., 2021	Explore customer responses to service robots vs. human employees in embarrassing service encounters	Service robots – AI type not specified	- Reduced embarrassment with service robots -Lower perceived agency attributed to service robots -Preference for robots in sensitive situations	Level of embarrassment (high vs low)	Mind perception and its two dimensions of agency and emotion	Customers felt less embarrassed interacting with service robots because robots were perceived to have lower agency (i.e., less ability to judge), making them the preferred service delivery mechanism in embarrassing encounters.
Holthöwer & van Doorn, 2023	To investigate whether service robots reduce perceived social judgment in embarrassing encounters compared to humans, and how robot anthropomorphism moderates this effect	Service robots with varying anthropomorphism (*Mechanical AI and Thinking AI/Feeling AI*)	- Lower perceived social judgment - Higher service acceptance in embarrassing contexts - Conditional discomfort with anthropomorphic robots	Robot anthropomorphism (high vs. low human-likeness)	Perceived social judgment	Service robots reduced feelings of being judged in embarrassing situations compared to humans. However, high anthropomorphism increased perceived social judgment, reducing the beneficial effect.
Guo et al., 2023	To assess whether robots, compared to humans, improve satisfaction by reducing social anxiety in embarrassing service contexts	Service robots (*Thinking AI)*	-Increased customer satisfaction - Lower social anxiety - Enhanced emotional experience in embarrassing situations	Service context (embarrassing vs. non-embarrassing)	Social anxiety	Robots reduce social anxiety in embarrassing contexts, leading to higher customer satisfaction. Social anxiety mediated the link between service agent and satisfaction.
Current research	To examine how different types of AI intelligence (mechanical, thinking, and feeling) influence customers embarrassment across service contexts of varying sensitivity	Mechanical AI, Thinking AI, and Feeling AI	-Variation in perceived embarrassment depending on AI type -Higher embarrassment with advanced AI in high-sensitivity contexts	Context sensitivity (high vs low)	Automated social presence	More advanced AI types (Thinking and Feeling AI) lead to greater embarrassment, particularly in high-sensitivity contexts. While advanced AI increase perceived automated social presence, this did not mediate embarrassment.

4. Conclusion

This literature review highlights the evolution and growing complexity of service robots, both in terms of their technological capabilities and their role in shaping customer experience. Although service robots are expected to become increasingly common in our daily service encounters (Puntoni et al., 2020), existing research offers limited guidance on how different types of AI intelligence possessed by service robots (mechanical AI, thinking AI, feeling AI) influence customer experiences.

Two main streams of research have emerged in the literature. On the one hand, studies on service robots and AI types have established the distinctions between mechanical, thinking, and feeling AI and their varying roles in customer engagement, service function, and task complexity (Huang & Rust, 2018; Huang et al., 2019). On the other hand, research examines how service robots, compared to human employees, can reduce perceived social judgment and discomfort in embarrassing service situations (Pitardi et al., 2022; Holthöwer & van Doorn, 2022). Context plays a crucial role in shaping customer preferences, particularly in situations that involve embarrassment or social sensitivity. While previous studies have demonstrated that customers prefer robots over humans in socially awkward interactions, they have largely treated AI as a singular, undifferentiated concept. This reveals a key research gap: the need to explore how different types of AI intelligence possessed by a robot specifically influence customer experiences and feelings of embarrassment, depending on the sensitivity of the service context.

Moreover, while most existing studies compare robots to human employees, no existing research has explicitly examined how the different types of AI intelligence possessed by service robots influence customer experience and perceived embarrassment. Therefore, this thesis aims to extend prior research by addressing the following question: **"How do different types of AI intelligence (mechanical, thinking, and feeling), possessed by service robots, influence customers' embarrassment across service contexts of varying sensitivity?".** This contribution is both timely and necessary for both academic research and managerial practice, as organizations increasingly deploy AI-driven service agents across diverse, and sometimes delicate, customer interactions.

Part II: Hypothesis Development

To develop our research model (Figure 1), we build on insights drawn from the literature review and prior studies examining the role of AI in service interactions. This foundation enables us to propose several hypotheses regarding how different types of AI intelligence influence customers embarrassment in sensitive service contexts. These hypotheses will be further analyzed and tested in Part III of this thesis.

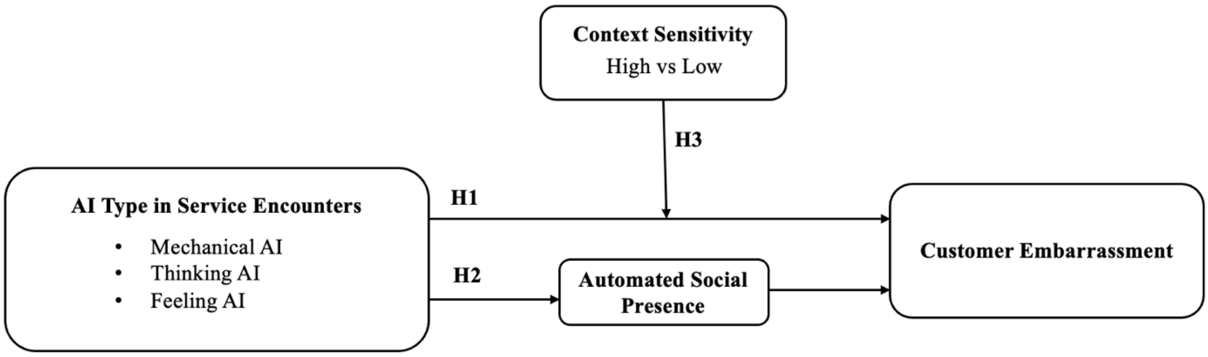

Figure 1 : Research Model

H1: Customers interacting with service robots possessing higher levels of AI intelligence (i.e., feeling AI) will experience greater embarrassment in sensitive service contexts compared to customers interacting with robots with lower levels of AI intelligence (i.e., mechanical AI).

Service robots with more advanced AI capabilities are likely to increase customers embarrassment for several reasons. First, feeling AI is specifically designed to simulate human-like emotional understanding and empathetic responses (Huang & Rust, 2018; Huang, Rust, & Maksimovic, 2019). This means such robots are perceived as more socially capable and relational. While this is usually beneficial, it may inadvertently recreate the sense of being socially evaluated, increasing discomfort in sensitive situations (Pitardi et al., 2022; van Doorn et al., 2017). According to Gray et al. (2007), entities perceived to have a mind (i.e., agency and experience) are seen as capable of forming opinions and making social judgments.

Second, research shows that the presence of a social entity increases self-consciousness and the fear of evaluation (Dahl et al., 2001; Argo et al., 2005). Therefore, when customers anticipate interacting with a socially aware and relational robot that feels “aware” and capable of forming impressions, they may expect higher levels of observation and potential judgment, leading them to feel more exposed and uncomfortable compared to interacting with a more mechanical, neutral system. In addition, unlike mechanical AI, which feels more transactional, feeling AI introduces a layer of interpersonal awareness that can make the interaction feel more like interacting with a human, thereby intensifying embarrassment.

Taken together, these arguments support the prediction that the more humanlike and emotionally intelligent the robot, the greater the perceived embarrassment when customers imagine engaging in an embarrassing service context.

H2: The effect of AI type on customer embarrassment will be moderated by the perceived sensitivity of the service context, such that in highly sensitive contexts (e.g., medical or intimate services), higher AI intelligence will lead to greater embarrassment, whereas in low-sensitivity contexts, this difference will be attenuated.

This hypothesis builds on the idea that the context in which customers interact with service robots, as emphasized by Chen and Prentice (2024), strongly shapes their perceptions and experiences by influencing how they interpret and evaluate the interaction. Prior research shows that the perceived sensitivity of a service situation amplifies concerns about privacy, personal exposure, and potential judgment (Holthöwer & van Doorn, 2022). Contextual factors strongly influence embarrassment, as customers become more aware of how they might be perceived in moments they consider personal or potentially awkward. The more personal or embarrassing the situation, the more customers value the perceived neutrality and anonymity of AI, which can make less humanlike, more mechanical robots feel safer and less threatening (Holthöwer & van Doorn, 2022).

In highly sensitive contexts, the benefits of simpler, less relational AI may therefore be amplified, while advanced, socially aware robots may increase discomfort. By comparison, in low-sensitivity contexts like routine purchases or transactional services, customers are less concerned about evaluation, and the impact of AI intelligence on embarrassment is correspondingly weaker. This suggests that perceived context sensitivity acts as a moderator that conditions the relationship between AI type and customer embarrassment, strengthening or attenuating the effect depending on how personally significant and potentially exposing the interaction is judged to be.

H3: The relationship between AI type and customer embarrassment will be mediated by the perception of automated social presence, such that higher levels of AI intelligence (e.g., feeling AI) will increase perceptions of automated social presence, which in turn will lead to higher embarrassment.

While prior work shows that automation reduces the human social presence that typically triggers feelings of judgment (Argo et al., 2005; Dahl et al., 2001), recent research highlights that important differences remain among the various types of AI implemented in service robots (Huang, Rust, and Maksimovic, 2019). The literature indicates that as AI intelligence increases from mechanical to thinking to feeling, robots acquire more advanced capacities for social interaction, emotional understanding, and adaptive communication (Huang & Rust, 2018; Huang, Rust, & Maksimovic, 2019), making them feel more “humanlike” and relational, which strengthens perceptions of automated social presence (van Doorn et al., 2017). Automated social presence determines the extent to which technology feels socially “watchful”. This perception refers to the customer’s feeling that the robot is socially aware, attentive, and capable of observing their behavior, even though it is not actually a human and is not truly able to judge in the same way a person would. Therefore, feeling AI likely creates stronger perceptions of automated social presence, which in turn drive customer embarrassment.

In contrast, mechanical AI, which is designed primarily for efficiency and routine tasks, is likely to reinforce the impersonal nature of automation and reduce feelings of social judgment compared to more advanced forms of AI (van Doorn et al., 2017). Overall, these arguments support the mediating role of automated social presence in explaining how AI intelligence shapes customers’ embarrassment during interactions with service robots.

Part III: Quantitative Research

1. Methodology

1.1. Experiment design

1.1.1. Between-subjects experimental design

The hypotheses were tested through a between-subjects experimental design using a 3x2 matrix: three types of artificial intelligence (mechanical AI, thinking AI, and feeling AI) and two levels of context sensitivity (high versus low). Six scenarios were developed to examine the impacts of these variables on customer embarrassment and perceived automated social presence (Table 3).

Table 3: 3x2 matrix comprising the 6 scenarios presented to the respondents

<table>
<tr><th></th><th>High-Sensitivity Context (HS)</th><th>Low-Sensitivity Context (LS)</th></tr>
<tr><td>Mechanical AI

(M)</td><td>
Vous souffrez actuellement d’une infection sexuellement transmissible diagnostiquée récemment par votre médecin. Après une consultation médicale, vous devez vous rendre à la pharmacie la plus proche pour récupérer le traitement prescrit.

Lorsque vous arrivez à l’accueil, vous constatez qu’un robot en libre-service, au design simple et purement fonctionnel, s’occupe de la délivrance des médicaments. Le robot affiche des instructions basiques et vous fournit votre traitement de façon neutre et sans aucune interaction sociale.

Interaction :
Robot : « Veuillez entrer le code de votre prescription. »
Vous : [Vous saisissez le code]
Robot : « Médicament identifié. Merci de le récupérer dans le compartiment prévu. »</td><td>
Vous vous apprêtez à voyager et arrivez à l’aéroport pour vous enregistrer avant votre vol.

Lorsque vous atteignez le comptoir d’enregistrement, vous constatez qu’un robot en libre-service, au design simple et purement fonctionnel, prend en charge l’enregistrement. Le robot affiche des instructions basiques et effectue le processus sans aucune interaction sociale.

Interaction :
Robot : « Veuillez scanner votre passeport. »
Vous : [Vous scannez votre passeport]
Robot : « Bagage enregistré. Impression de votre carte d’embarquement en cours. »
Robot : « Enregistrement terminé. »</td></tr>
<tr><td>Thinking AI

(T)</td><td>
Vous souffrez actuellement d’une infection sexuellement transmissible diagnostiquée récemment par votre médecin. Après une consultation médicale, vous devez vous rendre à la pharmacie la plus proche pour récupérer le traitement prescrit.

Lorsque vous arrivez à l’accueil, vous êtes accueilli(e) par un robot assistant capable de s’adapter à vos besoins et d’analyser votre dossier. Le robot utilise un ton poli et vous propose des informations complémentaires.

Interaction :
Robot : « Bonjour. Veuillez entrer le code de votre prescription, s’il vous plaît. »
Vous : [Vous saisissez le code]
Robot : « Traitement détecté : antibiotique pour infection sexuellement transmissible. Ce médicament doit être pris conformément à l’ordonnance. Souhaitez-vous plus de détails sur son utilisation ou ses effets secondaires ? »</td><td>
Vous vous apprêtez à voyager et arrivez à l’aéroport pour vous enregistrer avant votre vol.

Lorsque vous atteignez le comptoir d’enregistrement, vous êtes accueilli(e) par un robot assistant capable de s’adapter à vos besoins et d’analyser vos informations. Le robot utilise un ton poli et vous propose des suggestions utiles.

Interaction :
Robot : « Bonjour et bienvenue. Je vois que vous voyagez fréquemment avec nous. Souhaitez-vous un siège côté couloir comme lors de votre dernier vol ? »
Vous : « Oui, s’il vous plaît. »
Robot : « Siège côté couloir confirmé. Votre carte d’embarquement est en cours d’impression. Je vous souhaite un excellent voyage. »</td></tr>
</table>

<table>
<tr>
<td>Feeling AI

(F)</td>
<td>
Vous souffrez actuellement d’une infection sexuellement transmissible diagnostiquée récemment par votre médecin. Après une consultation médicale, vous devez vous rendre à la pharmacie la plus proche pour récupérer le traitement prescrit.

Lorsque vous arrivez à l’accueil, un robot interactif conçu pour être empathique et rassurant vous accueille. Le robot adopte un ton bienveillant et cherche à rendre l’expérience agréable et personnalisée.

Interaction :
Robot : « Bonjour. Je suis ici pour vous aider en toute confidentialité. Pouvez-vous me communiquer votre code de prescription? »
Vous : [Vous communiquer le code]
Robot : « Merci. Je comprends que ce sujet puisse être sensible et parfois difficile à aborder. Votre traitement antibiotique est prêt. Si vous souhaitez des conseils supplémentaires ou poser des questions, je suis à votre disposition. »</td>
<td>
Vous vous apprêtez à voyager et arrivez à l’aéroport pour vous enregistrer avant votre vol.

Lorsque vous atteignez le comptoir d’enregistrement, un robot interactif conçu pour être empathique et rassurant vous accueille. Il adopte un ton bienveillant et cherche à rendre l’expérience agréable et personnalisée.

Interaction :
Robot : « Bonjour ! Je suis heureux de vous accompagner aujourd’hui. J’espère que vous allez bien et que vous êtes prêt(e) à commencer votre voyage? »
Vous : « Oui, merci. »
Robot : « Parfait ! Pour votre confort, j’ai sélectionné un siège côté couloir, comme lors de vos précédents voyages. Si vous avez la moindre question ou besoin d’assistance, je suis ici pour vous aider à chaque étape. Je vous souhaite un merveilleux séjour ! »</td>
</tr>
</table>

In the research setting, participants were presented with a fictional interaction between a customer and a service robot in a pharmacy or airport context. Each scenario described a different type of artificial intelligence possessed by the robot (mechanical AI, thinking AI, or feeling AI) and illustrated the interaction between the robot and the customer. The scenarios were developed with the assistance of ChatGPT-4o. Participants were instructed to imagine themselves as the customer interacting directly with the robot and to fully immerse themselves in the situation.

To manipulate the variables under study, the scenarios presented to participants described the same service task, requesting assistance in a pharmacy or at an airport, but varied systematically in the type of artificial intelligence exhibited by the robot. Each scenario maintained a consistent structure, including an introduction of the situation, a description of the robot’s behavior, and an example of the interaction, while the wording and tone of the robot were adapted to reflect either a mechanical, thinking, or feeling AI type. The main manipulation was introduced through the robot’s communication style. This ensured that any differences in participants’ reactions could be attributed to the variations in AI characteristics and context.

In the mechanical AI scenarios, the robot was presented as a self-service kiosk, delivering basic, neutral messages without any personalization or emotional content, emphasizing a purely functional and transactional interaction.

In the thinking AI scenarios, the robot used polite, adaptive language to demonstrate awareness of the customer’s needs and to offer relevant suggestions or information.

In the feeling AI scenarios, the robot adopted a warm and empathetic tone, acknowledging the customer's feelings and providing reassurance throughout the exchange.

The two contexts, pharmacy (high sensitivity) and airport check-in (low sensitivity), were selected to examine whether the perceived sensitivity of the situation would amplify or attenuate customer embarrassment. The airport was selected as a low-sensitivity context, but still potentially embarrassing due to the public nature of the setting and the potential exposure of personal requests in an impersonal environment.

1.1.2. Study design

LimeSurvey was the platform used for creating and publishing the survey. The experiment was therefore conducted through an online survey, proved to be the most efficient approach for quickly distributing the questionnaire and seamlessly randomizing the six scenarios required for the between-subjects design. Moreover, conducting the survey online enabled immediate data encoding. The content of the online survey is included in Appendix 3.

To begin with, respondents were informed about the purpose of the survey. A consent form was presented to ensure data privacy and compliance with GDPR regulations. After giving their consent, respondents were presented with an introduction message outlining the context they were expected to immerse themselves in. After that, they were randomly assigned to one of six scenarios. Following this, a series of questions concerning the key variables studied in this paper were asked, including customer embarrassment and automated social presence. Additionally, respondents answered a question regarding their familiarity with this type of service, and two further questions were included to verify the realism of the scenario. The measurement scales and items for these variables are further detailed in section 1.3. below. Afterward, socio-demographic questions were asked to describe the sample population, and the survey concluded with a message confirming completion and thanking the respondents. It is also important to note some of the activated settings, including the requirement to answer all questions and the inability to navigate back to the previous page.

1.2. Sampling

The required sample size for the experiment was determined based on parallel studies. In comparison with other studies from the literature (Pitardi et al., 2022; Holthöwer & van Doorn, 2022) that employed highly similar quantitative analyses, a comparable number of participants was used. A convenience sampling approach was adopted, whereby participants were recruited from the researcher's personal and academic network. While this method facilitated efficient data collection, it may limit the generalizability of the results due to potential sample bias.

A total of 230 complete responses were collected between July 18 and July 22. The survey was shared via a URL link on Facebook, WhatsApp and Instagram to individuals or groups. Before analyzing and interpreting the collected responses, data cleaning was necessary. Next to the 230 responses, 503 were incomplete and therefore removed. Similarly, the 20 responses completed in under 120 seconds, a timeframe deemed too short to ensure respondents fully understood the scenario and responded accurately, were also removed. At the end of the cleaning process, 210 responses were retained for analysis. There were 32 participants assigned to the S1HSM scenario, 27 to S2HST, 34 to S3HSF, 43 to S4LSM, 34 to S5LST, and 40 to S6LSF. All survey responses can be accessed through the OSF link provided in Appendix 4.

When looking at the composition of the sample population (Table 4), a noticeable gender imbalance can be observed, with 66.2% of respondents being female and 33.8% male. Regarding age, respondents range from 18 to 80 years old, with a mean age of 37 and a median of 25. The majority of respondents are students (39%), followed closely by full-time employees (36.2%). Additionally, the most prevalent highest level of education among respondents is a master's degree, accounting for 49,5% of the sample population. This distribution remains relatively consistent across the six scenarios randomly presented to respondents (Appendix 5). However, there is a wider gender imbalance in the S5LST scenario, with only 23,5% of male respondents compared to 76,5% of females.

Table 4: Demographic profile of survey respondents (N = 210)

Gender	
Male	33,8%
Female	66,2%
Non-binary/Third gender	0%
Prefer not to respond	0%

Age	
Min	18
Mean	37
Median	25
Max	80

Current occupation	
Full-time Employee	36,2%
Part-time Employee	3,8%
Unemployed	4,8%
Retired	9,5%
Student	39%
Other	6,7%

Highest level of education	
No diploma	1%
Certificate of Higher Secondary Education	12,4%
Technical or Vocational Education	1,9%
Bachelor	27,6%
Master	49,5%
PhD	2,4%
Continuing Education or Other	1,9%
Other	3,3%

1.3. Measurements

To carry out the experiment based on the questionnaire detailed above, the dependent, mediating, and moderating variables from the research model along with a few additional variables, had to be measured. Each of these variables was associated with one to three items (Table 5). For most of the questions, a 7-point Likert scale was used to evaluate the respondents' level of agreement with each item statement: "Strongly disagree", "Disagree", Somewhat disagree", "Neither agree nor disagree", "Somewhat agree", "Agree", "Strongly agree". The decision to adopt a 7-point scale instead of a 5-point scale was made to improve accuracy and reliability (Russo et al., 2021). The scale used to measure familiarity with this type of service differed, ranging from 1 = "Not familiar at all" to 7 = "Very familiar". It is worth mentioning that all items and scale points were translated into French for the purpose of experiment using advanced tools, specifically ChatGPT-4o and DeepL.

To ensure the reliability of combining results from each item of a variable into an average, the internal consistency of the items must be assessed. Scale reliability refers to Cronbach's Alpha (α) for scales with three items and Pearson Correlation Coefficient (r) to scales with two items.

A principal component analysis (PCA) was conducted on the three embarrassment items (EMB1, EMB2, EMB3) to assess their dimensionality. The analysis revealed one component explaining 86.52% of the total variance, with high communalities (>0.82) for all items (Appendix 6). These results support the use of a composite embarrassment score by averaging the three items. In addition, Cronbach's alpha was calculated and showed high internal consistency ($\alpha = 0.921$), further justifying the aggregation of the items.

A Cronbach's alpha measure exceeding 0.7 indicates that internal reliability among items is achieved (Bujang et al., 2018). A Pearson correlation was conducted to assess the internal consistency of the two items measuring automated social presence and scenario realism (Appendix 7). For both constructs, results showed a moderate correlation with $r > 0.50$ and $p < 0.001$, indicating acceptable internal consistency. These results are considered acceptable for exploratory research and two-item scales (Eisinga et al., 2013).

Table 5: Summary of the relevant variables and their measurement scales

Variables	Items	Wording	Scale reliability	References
Customer embarrassment	EMB1	I feel embarrassed in this situation	α = 0.921	Adapted from the embarrassment scale (Dahl et al., 2001)
	EMB2	I feel uncomfortable in this situation		
	EMB3	I feel awkward in this situation		
Automated Social Presence	ASP1	It feels as if the robot is socially aware of me	$r = 0.551$	Adapted from van Doorn et al., 2017
	ASP2	I have the impression that the robot can observe and evaluate me		
Familiarity	FAM1	I am familiar with this type of service	/	Blair and Roese (2013)
Scenario realism	SR1	I had no difficulty picturing myself in the situation presented	$r = 0.571$	Adapted from Dabholkar (1994)
	SR2	The situation described was realistic		
Context Sensivity	SENS1	High – pharmacy	/	/
	SENS2	Low – airport		

2. Results

The analyses were conducted using SPSS statistical software. An exploratory approach was applied to test each hypothesis, with a significance level of 0.05 used for all statistical tests. The findings are detailed below.

2.1. Testing H1

To test H1, a one-way ANOVA was conducted to examine the direct effect of AI type (mechanical, thinking, and feeling) on customer embarrassment. Given the between-subjects design with three AI conditions and a single dependent variable, this analysis is appropriate for detecting potential differences in embarrassment levels across AI types.

Before performing this one-way ANOVA, three standard assumptions must be verified: independence of observations, normality of residual errors, and homogeneity of variances (Henson, 2015). Independence was ensured by the between-subjects survey design, as participants were randomly assigned to one of the six scenarios (Appendix 8). Normality was assessed using the Shapiro-Wilk test. In this case, the distribution of residual errors for embarrassment was found to be non-normal across all AI types, with p-values below 0.05 for each group (Appendix 9). Given that ANOVA is considered robust to moderate violations of normality when group sizes are reasonably large and balanced (Glass et al., 1972; Harwell et al., 1992; Lix et al., 1996), the analysis was carried out despite the non-normal distribution. Levene's test revealed a significant result ($p = 0.035$, which is below 0.05), leading to the rejection of the null hypothesis of equal error variances across groups for embarrassment (Appendix 10).

Although Levene's test indicated a violation of the homogeneity of variances assumption, ANOVA is generally recognized as robust to such violations when group sizes are approximately equal (Blanca et al., 2018). To ensure the reliability of the results, two additional robustness tests were conducted to address the issue of non-homogeneity: the Brown-Forsythe's and Welch's tests, the latter being chosen for its assumption-free approach regarding variance equality (Gastwirth et al., 2009). Additionally, a post hoc test was performed to gain a deeper understanding of group differences and identify where significant effects occurred.

As shown in Table 6 and Table 7, the effect of AI type on customer embarrassment yielded a significant F ratio of $F(2, 207) = 9.381$, $p < 0.001$, indicating that the level of embarrassment significantly varied depending on the type of AI encountered. Specifically, perceived embarrassment was lower when interacting with Mechanical AI (M = 2.39, SD = 1.41) compared to more advanced AI types means, Thinking AI (M = 3.43, SD = 1.77) and Feeling AI (M = 3.36, SD = 1.64). However, the difference between Thinking AI and Feeling AI was not in the expected direction, with Feeling AI resulting in slightly lower embarrassment than Thinking AI.

To better understand these mean differences, a post hoc test was conducted (Table 8), confirming that both Thinking AI and Feeling AI resulted in significantly higher embarrassment than Mechanical AI ($p < 0.001$). However, no significant difference was found between Thinking and Feeling AI ($p > 0.05$), indicating that these two advanced AI types elicited similar levels of embarrassment.

In addition, robustness checks using the Welch and Brown-Forsythe tests yielded consistent results with the standard ANOVA (Table 9). This reinforces confidence in the finding that interacting with more advanced AI types leads to greater embarrassment than with lower-level AI, supporting H1.

Table 6: Descriptive statistics of customer embarrassment for each AI type

AI_Type	Mean	Std. Deviation	N
Mechanical AI	2.3911	1.41036	75
Thinking AI	3.4262	1.77340	61
Feeling AI	3.3604	1.64113	74
Total	3.0333	1.66697	210

Table 7: One-way ANOVA test on embarrassment (LM)

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	48.264[a]	2	24.132	9.381	<.001
Intercept	1947.956	1	1947.956	757.230	<.001
AI_Type	48.264	2	24.132	9.381	<.001
Error	532.502	207	2.572		
Total	2513.000	210			
Corrected Total	580.767	209			

a. R Squared = .083 (Adjusted R Squared = .074)

Table 8: Post hoc test on embarrassment

Dependent Variable: Embarrassment
Games-Howell

(I) AIType	(J) AIType	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	Upper Bound
Mechanical AI	Thinking AI	-1.03512*	.27942	<.001	-1.6987	-.3715
	Feeling AI	-.96925*	.25083	<.001	-1.5633	-.3752
Thinking AI	Mechanical AI	1.03512*	.27942	<.001	.3715	1.6987
	Feeling AI	.06587	.29657	.973	-.6377	.7694
Feeling AI	Mechanical AI	.96925*	.25083	<.001	.3752	1.5633
	Thinking AI	-.06587	.29657	.973	-.7694	.6377

*. The mean difference is significant at the 0.05 level.

Table 9: Robust tests of equality of means on embarrassment

Embarrassment

	Statistic[a]	df1	df2	Sig.
Welch	10.347	2	131.407	<.001
Brown-Forsythe	9.186	2	188.121	<.001

a. Asymptotically F distributed.

2.2 Testing H2

To test Hypothesis 2, a two-way ANOVA was conducted. This analysis is appropriate as both AI Type (Mechanical, Thinking, Feeling) and Context Sensitivity (High, Low) are categorical independent variables, and the dependent variable, customer embarrassment, is continuous.

As previously mentioned, certain assumptions must be checked before proceeding with the analysis. Independence was ensured by the randomized between-subjects survey design (Appendix 11). Normality was assessed through the distribution of residuals obtained via the General Linear Model (GLM) and was rejected based on the Shapiro-Wilk tests (Appendix 12). In this case, Levene's test demonstrates that the null hypothesis of equality of error variances across groups cannot be rejected, thereby confirming homogeneity (Appendix 13).

As displayed in Table 10 and Table 11, both the main effects and the interaction effect are statistically significant. Specifically, there is a significant main effect of both AI Type and Context Sensitivity on customer embarrassment ($p < 0.001$). Most importantly, the interaction between AI type and Context Sensitivity is also significant, $F(2, 204) = 3.46$, $p = 0.033$. This indicates that the impact of AI type on customer embarrassment varies depending on the sensitivity of the service context.

Descriptive statistics further support this finding: in high-sensitivity contexts, embarrassment levels increase sharply with AI intelligence (from M = 2.70 for Mechanical AI to M = 4.28 for Thinking AI). However, in low-sensitivity contexts, the variation in embarrassment across AI types is less pronounced. To better understand these mean differences, the pairwise comparison table was examined (Table 12). It reveals that in high-sensitivity contexts, only Mechanical AI generates significantly lower embarrassment than Thinking AI ($p < 0.001$). In low-sensitivity contexts, only Mechanical AI also leads to significantly less embarrassment than Feeling AI ($p = 0.003$), although the difference is less stark. Again, there is no significant difference between Thinking AI and Feeling AI in either context ($p > 0.05$), suggesting that these two forms of AI elicit comparable levels of embarrassment from users regardless of the service setting's sensitivity.

These findings support H2, confirming that context sensitivity moderates the relationship between AI type and customer embarrassment. In highly sensitive contexts, higher AI intelligence leads to greater embarrassment, whereas in less sensitive contexts, this effect persists but is reduced.

Table 10: Descriptive statistics of customer embarrassment by AI Type and Context

AI_Type	Context_Sensivity	Mean	Std. Deviation	N
Mechanical AI	High	2.6979	1.58025	32
	Low	2.1628	1.23950	43
	Total	2.3911	1.41036	75
Thinking AI	High	4.2840	1.48123	27
	Low	2.7451	1.70572	34
	Total	3.4262	1.77340	61
Feeling AI	High	3.4412	1.72664	34
	Low	3.2917	1.58373	40
	Total	3.3604	1.64113	74
Total	High	3.4301	1.71212	93
	Low	2.7179	1.56691	117
	Total	3.0333	1.66697	210

Table 11: Two-way ANOVA test on embarrassment (LM)

Dependent Variable: Embarrassment

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	89.566[a]	5	17.913	7.440	<.001
Intercept	1977.581	1	1977.581	821.307	<.001
AI_Type	48.368	2	24.184	10.044	<.001
Context_Sensivity	28.192	1	28.192	11.708	<.001
AI_Type * Context_Sensivity	16.653	2	8.326	3.458	.033
Error	491.200	204	2.408		
Total	2513.000	210			
Corrected Total	580.767	209			

a. R Squared = .154 (Adjusted R Squared = .133)

Table 12: Pairwise comparisons of embarrassment across AI Types by Context

Pairwise Comparisons

Dependent Variable: Embarrassment

Context_Sensivity	(I) AIType	(J) AIType	Mean Difference (I–J)	Std. Error	Sig.[b]	95% Confidence Interval for Difference[b] Lower Bound	Upper Bound
High	Mechanical AI	Thinking AI	-1.586*	.405	<.001	-2.565	-.607
		Feeling AI	-.743	.382	.160	-1.666	.179
	Thinking AI	Mechanical AI	1.586*	.405	<.001	.607	2.565
		Feeling AI	.843	.400	.109	-.123	1.808
	Feeling AI	Mechanical AI	.743	.382	.160	-.179	1.666
		Thinking AI	-.843	.400	.109	-1.808	.123
Low	Mechanical AI	Thinking AI	-.582	.356	.311	-1.442	.277
		Feeling AI	-1.129*	.341	.003	-1.952	-.306
	Thinking AI	Mechanical AI	.582	.356	.311	-.277	1.442
		Feeling AI	-.547	.362	.398	-1.420	.327
	Feeling AI	Mechanical AI	1.129*	.341	.003	.306	1.952
		Thinking AI	.547	.362	.398	-.327	1.420

Based on estimated marginal means

*. The mean difference is significant at the .05 level.

b. Adjustment for multiple comparisons: Bonferroni.

The figure 2 illustrates how embarrassment levels increase with the AI's level of intelligence in both contexts. In high-sensitivity situations, the difference is more pronounced, with Thinking AI evoking the highest levels of embarrassment. In low-sensitivity contexts, the variation across AI types is less marked, though there is still an increase in customer embarrassment from Mechanical AI to Feeling AI.

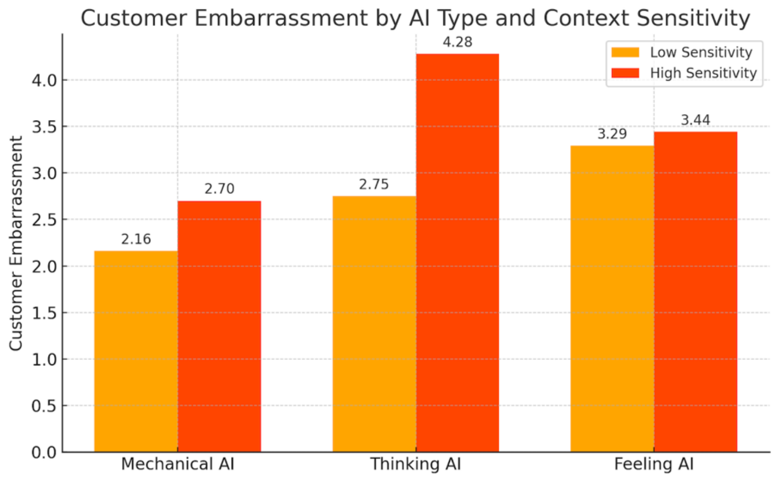

Figure 2 : Findings of H2

2.3 Testing H3

In order to test H3, a mediation analysis was conducted to examine the potential mediating role of automated social presence in the relationship between AI Type (mechanical, thinking, and feeling) and customer embarrassment. The PROCESS macro in SPSS (Hayes, 2013) was used for this analysis, employing Model 4 with the bootstrapping option set to 5000 samples to ensure robust confidence intervals for the indirect effects.

For mediation to be established, two conditions must be met: first, AI type must significantly influence the perception of automated social presence, and second, automated social presence must significantly influence embarrassment. A full mediation is indicated when the direct effect of AI type on embarrassment becomes non-significant once the mediator is included in the model, while a partial mediation occurs if the direct effect remains significant but is reduced.

In the mediation analysis using PROCESS, the independent variable AI Type was treated as a multicategorical variable with three levels: Mechanical AI, Thinking AI, and Feeling AI. To allow for proper estimation, the model generated two dummy variables to represent the comparisons. Mechanical AI was selected as the reference group as a methodological choice, based on post hoc analyses which revealed no statistically significant difference in customer embarrassment between Thinking AI and Feeling AI, as demonstrated in the results for H1 and H2. This decision enabled a clearer analytical contrast between a lower-level AI and more advanced AI types. As a result, two dummy variables were created: X1 represents the shift from Mechanical AI to Thinking AI, and X2 represents the shift from Mechanical AI to Feeling AI. The detailed output result of the simple mediation analysis is reported in Appendix 14.

2.3.1. Simple mediation analysis

As illustrated in Figure 3, the shift from Mechanical AI to Thinking AI (X1) significantly increased perceived automated social presence ($b = 0.8198$, $p < 0.001$), as did the shift to Feeling AI (X2) ($b = 1.4648$, $p < 0.001$). However, the effect of automated social presence on embarrassment was not statistically significant ($b = 0.0941$, $p = 0.3108$).

Although both AI transitions had a significant direct effect on embarrassment (X1: $b = 0.9580$, $p = 0.001$; X2: $b = 0.8314$, $p = 0.0054$), the indirect effects through automated social presence were not significant. The bootstrap confidence intervals for both X1 and X2 included zero, indicating no significant mediation. Thus, although AI type variables increase perceptions of social presence, this perception does not significantly mediate the relationship with embarrassment. As a result, H3 is not supported.

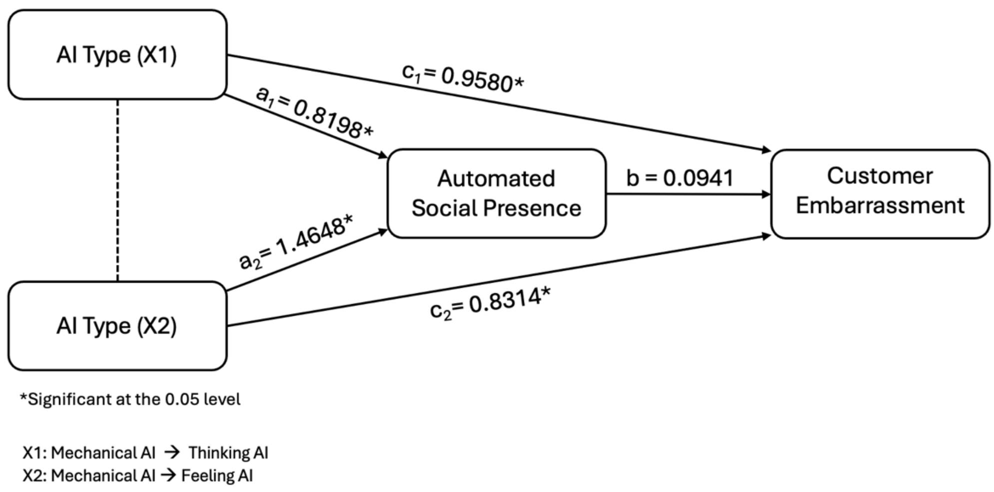

Figure 3 : Mediation Model

2.3.2. Moderated mediation analysis

Although the simple mediation analysis did not show a significant indirect effect of AI Type on embarrassment through automated social presence (ASP), a moderated mediation analysis was conducted to explore whether this indirect effect varies depending on context sensitivity. The significant direct effects of AI Type on both ASP and embarrassment suggest that mediation may still occur under specific conditions. This supports the use of a moderated mediation approach to uncover potential conditional effects that may be obscured in the overall analysis.

In this case, context sensitivity, whether the situation is high or low in sensitivity, may moderate the relationship between ASP and embarrassment. It is possible that automated social presence increases embarrassment in high-sensitivity contexts while having little to no effect in less sensitive situations.

To investigate this, a moderated mediation analysis using Model 14 of the PROCESS macro was conducted. This model tests whether the effect of the mediator (ASP) on the dependent variable (embarrassment) is moderated by context sensitivity. For this analysis, context sensitivity was coded as 0 for low-sensitivity and 1 for high-sensitivity contexts (ContS1 in the output). The full output result of the moderated mediation analysis is provided in Appendix 15.

Based on the results, there is no evidence of a significant moderated indirect effect of AI Type on customer embarrassment through ASP. While the direct effect of ASP on embarrassment is statistically significant (b = 0.2751, p = 0.0163), the interaction between ASP and context sensitivity is not (b = -0.2195, p = 0.2106), indicating that context sensitivity does not significantly moderate this relationship (Table 13). Additionally, the indices of moderated mediation are not significant for either X1 (Thinking AI) or X2 (Feeling AI), as the 95% bootstrap confidence intervals for the conditional indirect effects include zero.

Thus, although direct effects from AI Type to both ASP and embarrassment remain significant, the mediation pathway through ASP does not differ significantly between high and low sensitivity service contexts.

Table 13: Extract from the SPSS Output: Moderated Mediation Analysis

Outcome Variable: Embarrassment

```
OUTCOME VARIABLE:
 Embarss

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .3874      .1500     2.4197     7.2026     5.0000   204.0000      .0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     1.4552      .3351     4.3429      .0000      .7945     2.1158
X1            .8203      .2813     2.9159      .0039      .2657     1.3750
X2            .6272      .2917     2.1498      .0327      .0520     1.2024
ASPglob       .2751      .1136     2.4216      .0163      .0511      .4991
ContS1       1.3811      .4954     2.7877      .0058      .4043     2.3579
Int_1        -.2195      .1748    -1.2558      .2106     -.5642      .1251

Product terms key:
 Int_1    :        ASPglob  x        ContS1

Test(s) of highest order unconditional interaction(s):
       R2-chng          F        df1        df2          p
M*W      .0066     1.5771     1.0000   204.0000      .2106
```

Model includes AI Type as the independent variable (X1 = Mechanical to Thinking AI, X2 = Mechanical to Feeling AI), ASPglobal as the mediator, and Context Sensitivity (ContS1) as the moderator.

2.4 Testing scenario realism and familiarity

A one-way ANOVA was conducted to assess whether scenario realism differed significantly across the six scenarios. The analysis revealed a significant effect, $F (5, 204) = 7.789$, $p < 0.001$, indicating that perceived realism varied depending on the experimental condition. Bonferroni post hoc tests showed that, in both high and low sensitivity contexts, more advanced AIs (Thinking and Feeling AI) were associated with significantly lower perceived realism compared to Mechanical AI. Similarly, familiarity was significantly higher with Mechanical AI in low sensitivity contexts than in all other conditions, indicating that simpler AI is more commonly associated to familiar service situations, especially in less sensitive settings (Appendix 16).

Part IV: Discussion, theoretical insights, and managerial implications

1. Summary of the key findings

This research investigated how different types of AI (mechanical, thinking, and feeling) influence customer embarrassment in service interactions. It also examined the moderating effect of context sensitivity and the mediating role of perceived automated social presence on customer embarrassment. The study was based on an online experiment, which produced the following findings (Table 14).

Table 14: Overall results of the experiment

Hypotheses	Accepted/Rejected
H1	Accepted
H2	Accepted
H3	Rejected

2. Discussion and theoretical implications of this study

This study contributes to the growing literature on service robots by investigating how different forms of AI intelligence (mechanical, thinking, and feeling) shape customer experience, more specifically perceived embarrassment, in service encounters of varying sensitivity. Grounded in the multiple AIs framework (Huang & Rust, 2018; 2021), the study offers a more nuanced understanding of how distinct forms of artificial intelligence shape customer perceptions and reactions. By analyzing customer responses to varying levels of AI intelligence, this research advances a more AI-focused perspective. Accordingly, it bridges two previously separate streams of research: the typology of AI intelligence (Huang & Rust, 2018; 2021) and the customer embarrassment in sensitive service interactions (Dahl et al., 2001; Grace, 2007; Pitardi et al., 2022).

The choice of context sensitivity as a moderating variable and automated social presence as a mediating variable is grounded in their complementary roles in shaping human–AI interactions. As highlighted by Chen and Prentice (2024), context significantly influences how customers evaluate service interactions, particularly when AI is involved. Automated social presence, in turn, explains the mechanism through which AI is perceived as socially engaging (van Doorn et al., 2017). Together, these variables enable a richer and more meaningful understanding of customer–service robot interactions.

While previous studies have shown that consumers tend to prefer AI over human employees in embarrassing situations (Pitardi et al., 2022; Holthöwer & van Doorn, 2022), this research focuses specifically on the different types of AI intelligence and their distinct effects on the customer perceived embarrassment. Rather than comparing AI to human service providers, the study isolates the roles of mechanical, thinking, and feeling AI to understand how each influences consumer perceptions in socially sensitive contexts. The findings offer significant contributions to the existing literature by uncovering the nuanced impact of AI intelligence type on customer embarrassment, thereby enriching our understanding of customer–robot interaction beyond a simple human-versus-AI comparison.

The results of this study, based on the three tested hypotheses, offer valuable insights and make several key contributions to the literature on AI in service encounters. First, the confirmation of Hypothesis 1 demonstrates that the level of customer embarrassment significantly varies depending on the type of AI encountered. Specifically, the finding that more advanced AI types, such as thinking and feeling AI, trigger higher levels of embarrassment compared to mechanical AI provides a novel perspective. This result challenges the commonly held assumption that AI, by nature of being non-human, reduces discomfort in socially sensitive situations, an assumption also critically examined by Puntoni et al. (2020), who argue that the presence of AI can, in some cases, amplify psychological costs rather than alleviate them, depending on how the AI is perceived.

Interestingly, the absence of a significant difference in embarrassment between thinking and feeling AI was unexpected, suggesting that participants did not perceive a meaningful distinction between these two advanced forms of AI in terms of their perceived embarrassment. This result is discussed in the limitations section and opens avenues for future research on how users interpret and respond to different high-level AI types.

Regarding the second hypothesis, the study findings indicate that context sensitivity significantly moderates the relationship between AI type and customer embarrassment. Specifically, the interaction effect reveals that the impact of AI intelligence on embarrassment is not uniform but varies according to the sensitivity of the service context. This aligns with prior work emphasizing the importance of contextual factors in shaping customer experience (Chen & Prentice, 2024). More advanced AI tends to lead to greater embarrassment in high-sensitivity contexts, while this effect is less pronounced in low-sensitivity contexts.

Lastly, the analysis conducted to test H3 offers a deeper understanding of how AI type, perceived automated social presence, and context sensitivity work together to influence customer embarrassment. This hypothesis allowed for both a simple mediation and a moderated mediation analysis, providing deeper insight into the role of perceived automated social presence. The results show that the shift from mechanical AI to more advanced AI significantly increased perceptions of automated social presence, but this variable did not mediate the effect on embarrassment. In other words, even though participants felt that advanced AI exhibited more automated social presence, this did not explain the increase in embarrassment.

Notably, these findings contribute to and expand prior research showing that consumers tend to feel less judged by robots than by humans, as automation reduces the human social presence that typically triggers perceptions of social judgment (Argo et al., 2005; Dahl et al., 2001). In the present study, however, the focus shifts within the spectrum of AI from mechanical to more socially advanced types, revealing that as AI becomes more sophisticated, it also evokes stronger perceptions of automated social presence. This nuance offers a meaningful addition to the literature by suggesting that, while automation generally lowers feelings of judgment compared to human interaction, increasing levels of AI intelligence may reintroduce certain social cues that affect how the interaction is perceived. This resonates with the work of Holthöwer and van Doorn (2022), who examined robot anthropomorphism and found that it amplifies perceived automated social presence, making consumers feel more socially judged and highlighting how the design and human-likeness of AI can shape customer perceptions. Nevertheless, although these more advanced AIs heightened perceived automated social presence, this variable did not significantly mediate the relationship with embarrassment, pointing to the complexity of the mechanisms at play and inviting further exploration.

A final note concerns scenario realism and familiarity. Participants rated the scenarios as fairly realistic (average score = 5.16) but reported low familiarity with such services (average score = 2.73), suggesting that limited real-world exposure may have influenced their perceptions of the AI interactions.

3. Managerial implications of this study

This study offers further insights for managers considering the implementation of AI-powered service robots in customer interactions. Since customer experience is a key driver of competitive advantage and business success (Lemon & Verhoef, 2016), aligning AI integration with customer needs and expectations is critical to the success of innovation. Effective service innovations, such as the thoughtful deployment of AI, can create real value for customers (Hollebeek et al., 2021). Understanding how different forms of AI impact customer experience can help managers design interactions that are not only technologically efficient but also grounded in customer behavioral insights and perceptions.

First, the finding that more advanced AI types (thinking and feeling AI) can increase customers' embarrassment, particularly in socially sensitive contexts, suggests that managers should exercise caution when deploying such systems. It is important to consider that the type of AI intelligence embedded in a service robot can meaningfully influence how customers perceive and emotionally experience the service.

Second, organizations need to pay attention to the context sensitivity of the environments in which service robots are deployed, as this may magnify feelings of negative social judgment. Based on the findings, managers should favor the deployment of service robots with lower levels of AI intelligence (mechanical AI) in potentially embarrassing service encounters, especially in high-sensitivity contexts where customers are more vulnerable and may feel uncomfortable more easily.

Finally, while advanced AI increased perceptions of automated social presence, this alone did not explain greater embarrassment, indicating that emotional responses are driven by complex, multi-layered factors. This underscores the need for careful design and testing of AI interfaces, not only in terms of functionality but also in how they are interpreted and experienced by customers. As AI technologies continue to evolve, firms will increasingly require practical guidance on when, how, and to what extent service robots should be implemented, and how to strategically leverage AI to engage customers more effectively and meaningfully (Huang & Rust, 2020).

Part V: General conclusions

1. Overall summary

In conclusion, this thesis investigates how different types of AI intelligence (mechanical, thinking, and feeling) shape customer embarrassment in service encounters of varying sensitivity. As noted in the discussion section, the study moves beyond the traditional human-versus-AI comparison by focusing on distinctions between AI types, offering new insights into how varying levels of intelligence influence customer perception and feelings of embarrassment. To address the research question **"How do different types of AI intelligence (mechanical, thinking, and feeling), possessed by service robots, influence customers' embarrassment across service contexts of varying sensitivity?",** three hypotheses were developed. To build this work, the thesis draws upon an extensive literature review and empirical analysis.

The analysis of the online survey results shows that two hypotheses were accepted, and one was rejected at a 95% confidence level. The findings revealed that the type of AI intelligence significantly influences customer embarrassment, and that this effect is moderated by the sensitivity of the service context. However, although more advanced AI types increased perceptions of automated social presence, this variable did not significantly mediate the relationship with embarrassment. Lastly, no significant effect was found when testing for moderated mediation, indicating that context sensitivity does not significantly alter the nonexistent mediating effect of automated social presence on embarrassment.

Overall, the results of the study show that more advanced AI types (thinking and feeling) lead to greater customer embarrassment, particularly in high-sensitivity contexts. The absence of a significant difference in embarrassment between thinking and feeling AI suggests that customers perceive them as similarly sophisticated. Although automation is often associated with reduced social pressure, this study shows that certain forms of AI may reintroduce the feeling of another social entity being present. These findings highlight the complexity of customer perceptions in AI-driven service interactions and underscore the importance of deepening our understanding of how different AI forms interact with individual and contextual factors in shaping customer outcomes.

2. Limitations and Suggestions for Future Research

This study offers valuable insights into customer perceptions of service robots in service contexts, yet several limitations must be acknowledged, each of which provides promising avenues for future research.

First, the research employed a scenario-based experimental design, which, although effective for controlling variables and testing causality, may not fully capture the complexity and spontaneity of real-life interactions with service robots. The vignettes were brief and relied on static images, which might have limited participants' ability to imagine how they would perceive AI in a dynamic, real-world setting. Additionally, the coherence between each robot's appearance and the type of AI intelligence it was intended to represent (mechanical, thinking, or feeling) may not have been entirely realistic or consistent. Participants may have struggled to interpret the robot's role based on the vignette, particularly if the design appeared too unfamiliar or advanced. This may have affected the consistency of the results.

This highlights the need for future studies to refine stimulus design, ensuring that visual and behavioral cues are more clearly aligned with each AI type. More nuanced pre-testing or manipulation checks could also be introduced to confirm how participants perceive the intended distinctions between AI intelligences. For instance, the unexpected finding that Thinking AI was perceived as more embarrassing than Feeling AI may reflect a mismatch between the robot's visual design and the expected behavior associated with that AI type. However, this does not rule out the possibility that Thinking AI is genuinely perceived as more embarrassing than Feeling AI. Future research could address these issues by incorporating more immersive and interactive formats, such as video simulations or live demonstrations, to better reflect how customers perceive AI in realistic service interactions and potentially reveal more nuanced emotional responses.

Second, another limitation of the study is the absence of a manipulation check to verify whether participants perceived the experimental conditions as intended. Specifically, no questions were included in the questionnaire to assess whether respondents perceived the context as high or low in sensitivity, or whether they correctly identified the type of AI presented (mechanical, thinking, or feeling). Without these checks, it is unclear whether participants interpreted the scenarios in line with the intended manipulations. This limits the ability to confirm that the independent variables, context sensitivity and AI type, were effectively perceived and distinguished by participants. Including manipulation checks in future studies would enhance internal validity by ensuring that observed effects can be more confidently attributed to the manipulated variables.

Third, the measurement of automated social presence may represent a limitation of this study. Although the items were adapted from van Doorn et al. (2017), the scale consisted of only two items developed specifically for the present research. Relying on a limited number of self-constructed items, rather than a fully validated scale, may have reduced the reliability and depth of the measurement. The relatively low internal consistency ($r = 0.551$) also suggests that the construct may not have been fully captured. In addition, the wording of the item "It feels as if the robot is socially aware of me" (ASP1) may not be fully coherent with the intended construct of automated social presence. This question shifts the focus toward the robot's awareness of the participant's presence, rather than the participant's own perception of a social presence triggered by the robot. As automated social presence is fundamentally about the user's impression that "someone" is present due to the robot's capabilities, and not about being seen or acknowledged by the robot, this phrasing may have introduced confusion and further impacted the validity of the measurement. Future research would benefit from developing or adopting a more comprehensive and validated scale for measuring automated social presence, allowing for deeper and more reliable insight into how users experience the automated social presence of AI across different service contexts.

Fourth, while the study focused on automated social presence and context sensitivity, other mediating or moderating variables could have been considered. Future research could explore additional factors such as perceived control, trust, social judgment or privacy concerns, as well as contextual variables such as whether the service takes place in a public or private context. Individual variables specific to each person, such as age, may also provide valuable insights. Including these variables could contribute to a more comprehensive understanding of the pathways leading to customer embarrassment in service encounters involving AI.

Finally, the sample size, while adequate for hypothesis testing, was limited in its cultural scope. A convenience sampling approach was used, with all participants drawn from a French-speaking Belgian population within the researcher's personal network, which limits the generalizability of the findings across different cultures and customer profiles. Future studies could replicate this experiment using larger and more diverse samples across regions and cultural contexts, particularly as customer perceptions of AI are likely to vary based on cultural norms and familiarity with technology.

Overall, this study opens several promising directions for further research. Addressing these limitations will allow future studies to deepen theoretical insight and improve measurement precision. Given the accelerating integration of AI into service contexts, understanding customer perceptions of distinct type of AI intelligence remains a highly relevant research area. Expanding on the findings of this thesis will not only refine theoretical understanding but also inform the responsible and effective implementation of AI technologies in diverse service contexts. This line of inquiry will help practitioners anticipate challenges and design more effective AI-driven services.

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Appendices

Appendix 1: Overview of Service Robot Definitions/Descriptions Over Time

Author	Year	Service robot definition (only unique definitions are retained)
Caic *et al.*	2018	A socially assistive robot is one that provides assistance through social interaction in a human-like manner as their main value proposition
Wirtz *et al.*	2018	Service robots are system-based autonomous and adaptable interfaces that interact, communicate and deliver service to an organization's customers
Caic *et al.*	2019	Social robots are autonomous systems that can understand social cues through facial and voice recognition technology and can interact with users in humanlike manners
De Keyser *et al.*	2019	A conversational agent can be considered as a physical or virtual autonomous technological entity capable of reactive and proactive behavior in its environment, with the ability to accept natural language as input and generate natural language as output in order to engage in a social conversation with its users
Jörling *et al.*	2019	Service robots are information technology in a physical embodiment, providing customized services by performing physical as well as nonphysical tasks with a high degree of autonomy
Longoni *et al.*	2019	Medical AI refers to any machine that uses any kind of algorithm or statistical model to perform perceptual, cognitive and conversational functions typical of the human mind, such as visual and speech recognition, reasoning and problem solving
Luo *et al.*	2019	AI chatbots are computer programs that simulate human conversations through voice commands or text chats and serve as virtual assistants to users
Przegalinska *et al.*	2019	Chatbots are interactive, virtual agents that engage in verbal interactions with humans
Belanche *et al.*	2020b	Service robots refer to autonomous technology employed in frontline operations with some physical interface
Figueiredo and Pinto	2020	A robot equals software that mirrors human actions on a screen using a mouse and a keyboard
Sands *et al.*	2020	Chatbots are AI-enabled service agents that can conduct "natural" conversations with consumers and given them individual information
Schuetzler *et al.*	2020	Conversational agents (CAs) – frequently operationalized as chatbots – are computer systems that leverage natural language processing to engage in conversations with human users
Sheehan *et al.*	2020	Chatbots are computer programs with natural language capabilities, which can be configured to converse with human users

Thomaz *et al.*	2020	Conversational agents (also called chatbots, conversational AI-bots, virtual assistants and dialog systems) are natural language computer programs designed to approximate human speech (written or oral) and interact with people via a digital interface
Van Pinxteren *et al.*	2020	Conversational agents are "systems that mimic human conversation" using communication channels such as speech, text, but also facial expressions and gestures
Balakrishnan and Dwivedi	2021	A chatbot is a computer program that conducts a conversation in natural language and sends a response based on business rules and data tuned by the organization
Blut *et al.*	2021	Service robots are defined as autonomous agents whose core purpose is to provide services to customers by performing physical and nonphysical tasks. They can be physically embodied or virtual
Brengman *et al.*	2021	Service robots are defined as robots which operate semi- or fully autonomously to perform services useful to the well-being of humans and equipment, excluding manufacturing operations
Butt *et al.*	2021	An AI-powered avatar is defined as a human-like avatar that thinks, acts and interacts with the gamer during the gameplay to augment the game performance

Hernandez-Ortega and Ferreira	2021	Smart voice assistants are software agents that employ natural language processing and machine learning to assimilate, understand and respond to the consumer's demands
Huang and Kao	2021	Virtual service agents refer to service agents who fulfill customers' needs via digital platforms
Lin *et al.*	2021	A virtual salesperson is a web-based software that offers personalized suggestions and recommendations to online customers
Murtarelli *et al.*	2021	Chatbots are machine conversation systems that interact with human users via natural conversational language
Park *et al.*	2021	Service robots are programmed entities with a degree of autonomy to perform intended tasks in a service industry
Pitardi and Marriott	2021	Virtual assistants are Internet-enabled devices that provide daily technical, administrative and social assistance to their users, including activities from setting alarms and playing music to communicating with other users
Pizzi *et al.*	2021	Conversational agents are computer-generated graphically displayed entities that represent either imaginary characters or real humans controlled by artificial intelligence
Rajaobelina *et al.*	2021	Chatbots are systems aimed at communicating with users using natural language based on AI; they are designed to imitate human speech in approximating written text or vocal speech as best as possible to interact with people via a digital interface
Schanke *et al.*	2021	Chatbots are autonomous software agents that support text-based exchanges with human users, drawing on tools and techniques from the domain of natural language processing. Chatbots have the potential to automate basic, repeatable, standardized customer service interactions, relieving the need for those interactions to be handled by human employees
Sowa *et al.*	2021	Cobots (also known as collaborative robots) are robots intended to interact with humans in a shared space
Tsai *et al.*	2021	A chatbot is an AI-powered, automated, yet personalized, virtual assistant
Whang and Im	2021	Voice assistants (also referred to as smart speaker or AI speakers) are voice-controlled smart devices designed to provide personal assistance for users' daily activities
Wien and Peluso	2021	An AI recommender refers to any type of autonomous system that uses algorithms to produce recommendations for consumers
Xiao and Kumar	2021	Robots are mechanical machines or intangible computer programs that perform rule-based work, and tend to be configurable with basic features like authentication, security, auditing, logging and exception handling
Amelia *et al.*	Amelia *et al.*	Frontline service robots refer to social humanoid robots that perform frontline service tasks and interact and co-create value with customers through their cognitive and social capabilities
Flavian *et al.*	2021	Robo-advisors are digital platforms comprising interactive and intelligent user assistance components that use information technology to guide customers through an automated investment advisory process
Mele *et al.*	this issue	Cognitive assistants are computers that help actors understand what is going on around them
Mozafari *et al.*	this issue	Chatbots are text-based virtual robots that emulate human-to-human conversation through natural language processing
Paluch *et al.*	this issue	Collaborative service robots embodied machines equipped with some degree of AI and functional autonomy that are designed to work alongside frontline service employees (FSEs) and perform similar service roles as their counterparts
This paper	this issue	Service robots are *system-based autonomous and adaptable interfaces that interact, communicate and deliver service to customers, employees and/or other (service) robots*

Source: Adopted from De Keyser, A., & Kunz, W. H. (2022). Living and working with service robots: A TCCM analysis and considerations for future research. *Journal of Service Management*, 33(2), 165-196. doi: https://doi.org/10.1108/JOSM-12-2021-0488

Appendix 2: Four Intelligence Types – Description and AI Applications

Table 1. Intelligences, Nature of Tasks, Job Replacement, and Service Implications.

Intelligences			Job Replacement	
AI	Skill/Labor	Nature of Tasks	AI Applications	Literature
Mechanical				
• Minimal degree of learning or adaption • Precise, consistent, and efficient • For example, self-service technologies and service robots • Rely on observations to act and react repetitively	• Skills that require limited training or education • Call center agents, retail salespersons, waiters/ waitress, and taxi drivers	• Simple, standardized, repetitive, routine, and transactional tasks • Tasks require consistency • Commodity service	• McDonald's "Create Your Taste" touch screen kiosks • Robot Pepper takes on frontline greeting tasks • Virtual bots turn customer service into self-service	• Service robots get jobs done autonomously (Colby, Mithas, and Parasuraman 2016) • Low-skill manufacturing labor reallocates to service occupations (Autor and Dorn 2013; Buera and Kaboski 2012) • Productization replaces repetitive manual tasks (Sawhney 2016)
Analytical				
• Learns and adapts systematically based on data • Logical, analytical, and rule-based learning • For example, IBM's chess player Deep Blue • Rational decision-making	• Technical skills requiring training and expertise on data and analysis • Technology-related workers, data scientists, accountants, financial analyst, auto service technicians, and engineers	• Analytical, rule-based, systematic complex tasks • Tasks require logical thinking in decision-making • Data, information, and knowledge-based service	• Toyota's in-car intelligent systems replace problem diagnose tasks for technicians • IBM's Watson helps H&R Block for tax preparation • Penske's onboard technology takes over navigation tasks	• Marketing analytics take on the data and analysis tasks (Wedel and Kannan 2016) • Machines replace and augment knowledge workers (Davenport and Kirby 2015) • Smart services leverage customer information (Wünderlich, Wangenheim, and Bitner)
Intuitive				
• Learns and adapts intuitively based on understanding • Artificial neural networks-based or statistical-based deep learning • For example, Watson's Jeopardy, Google's DeepMind AlphaGo, and AI poker player Libratus • Boundedly rational decision-making	• Hard thinking professionals that require creative thinking for problem-solving skills • Marketing managers, management consultants, lawyers, doctors, sales managers, and senior travel agents	• Complex, chaotic and idiosyncratic tasks • Tasks require intuitive, holistic, experiential and contextual interaction, and thinking • Personalized, idiosyncratic, experience- and context-based service	• Associated Press's robot reporters take on the reporting task for Minor League Baseball games • Artificial intuition takes on the data interpretation task in Gestalt psychology • Narrative Science's AI Quill writes as if human authors	• Robot managers take on managerial tasks (Young and Cormier 2014) • High-paying jobs, such as portfolio managers, physicians, and senior managers, can be automated using current technology (Chui, Manyika, and Miremadi 2015) • Image-recognition AI outperforms dermatologists for skin cancer diagnosis (Esteva et al. 2017)
Empathetic				
• Learn and adapt empathetically based on experience • Emotion recognition, affective computing, and communication style learning • For example, Hanson's humanoid robot Sophia and chatbot Replika • Decision-making incorporates emotions	• Soft empathetic professionals that require social, communication, and relationship building skills • Thinking jobs requiring people skill, for example, politicians and negotiators or feeling jobs, for example, psychiatrists	• Social, emotional, communicative, and highly interactive service • Tasks that require empathy, emotional labor, or emotional analytics • High-touch service	• Chatbots communicate with customers and learn from it • Replika replaces psychiatrists for psychological comfort • Sophia robots interact with customers as if employees	• Artificial empathy to infer a consumer's internal states (Xiao and Ding 2014) • Incorporating emotions into marketing modeling (Roberts et al. 2015) • Frontline emotional labor performed by AI (Rafaeli et al. 2017)

Source: Adopted from Huang, M.-H., & Rust, R. T. (2018). Artificial Intelligence in Service. *Journal of Service Research*, 21(2), 155-172. https://doi.org/10.1177/1094670517752459

Appendix 3: Content of the online survey

Start of Block: Intro & Consent

Q1: Bienvenue!

Dans le cadre de mon mémoire en ingénieur de gestion à la Louvain School of Management, je réalise une étude visant à examiner comment différents types d'intelligence artificielle (IA) intégrés aux robots de service influencent les réactions des clients, notamment leur niveau d'embarras perçu dans des contextes plus ou moins sensibles.

La participation à cette étude est entièrement volontaire et garantit un anonymat complet. Toutes les données seront collectées, traitées de manière collective, et publiées uniquement sous une forme agrégée. Les informations recueillies seront exclusivement utilisées à des fins de recherche.

Votre contribution ne vous prendra que 5 minutes. Si vous avez des questions concernant cette étude veuillez me contacter : amelie.leveque@student.uclouvain.be

Si vous avez 18 ans ou plus, comprenez les déclarations ci-dessus et consentez librement à participer à l'étude, répondez 'oui' ci-dessous.

○ Oui
○ Non

End of Block: Intro & Consent

Start of Block: High-Sensitivity – Mechanical AI

Q2: Dans cette étude, vous serez exposé.e à une interaction fictive entre vous, en tant que client.e, et un robot de service. Cette interaction décrira une situation de service avec une illustration de l'échange entre vous et le robot.

Nous vous demandons de vous immerger pleinement dans cette situation et de considérer votre expérience et vos sentiments comme si vous étiez réellement le/la client.e concerné.e.

Q3: **Instructions**

Veuillez lire attentivement l'interaction entre le/la client.e et le robot de service, puis répondre aux questions qui suivent pour nous aider à comprendre votre perception et votre réaction face à cette situation.

Vous souffrez actuellement d'une infection sexuellement transmissible diagnostiquée récemment par votre médecin. Après une consultation médicale, vous devez vous rendre à la pharmacie la plus proche pour récupérer le traitement prescrit.

Lorsque vous arrivez à l'accueil, vous constatez qu'un robot en libre-service, au design simple et purement fonctionnel, s'occupe de la délivrance des médicaments. Le robot affiche des instructions basiques et vous fournit votre traitement de façon neutre et sans aucune interaction sociale.

Interaction :
Robot : « Veuillez entrer le code de votre prescription. »
Vous : [Vous saisissez le code]
Robot : « Médicament identifié. Merci de le récupérer dans le compartiment prévu. »

End of Block: High-Sensitivity – Mechanical AI

Start of Block: High-Sensitivity – Thinking AI

Q4: Dans cette étude, vous serez exposé.e à une interaction fictive entre vous, en tant que client.e, et un robot de service. Cette interaction décrira une situation de service avec une illustration de l'échange entre vous et le robot.

Nous vous demandons de vous immerger pleinement dans cette situation et de considérer votre expérience et vos sentiments comme si vous étiez réellement le/la client.e concerné.e.

Q5: **Instructions**

Veuillez lire attentivement l'interaction entre le/la client.e et le robot de service, puis répondre aux questions qui suivent pour nous aider à comprendre votre perception et votre réaction face à cette situation.

Vous souffrez actuellement d'une infection sexuellement transmissible diagnostiquée récemment par votre médecin. Après une consultation médicale, vous devez vous rendre à la pharmacie la plus proche pour récupérer le traitement prescrit.

Lorsque vous arrivez à l'accueil, vous êtes accueilli(e) par un robot assistant capable de s'adapter à vos besoins et d'analyser votre dossier. Le robot utilise un ton poli et vous propose des informations complémentaires.

Interaction :
Robot : « Bonjour. Veuillez entrer le code de votre prescription, s'il vous plaît. »
Vous : [Vous saisissez le code]
Robot : « Traitement détecté : antibiotique pour infection sexuellement transmissible. Ce médicament doit être pris conformément à l'ordonnance. Souhaitez-vous plus de détails sur son utilisation ou ses effets secondaires ? »

End of Block: High-Sensitivity – Thinking AI

Start of Block: High-Sensitivity – Feeling AI

Q6: Dans cette étude, vous serez exposé.e à une interaction fictive entre vous, en tant que client.e, et un robot de service. Cette interaction décrira une situation de service avec une illustration de l'échange entre vous et le robot.

Nous vous demandons de vous immerger pleinement dans cette situation et de considérer votre expérience et vos sentiments comme si vous étiez réellement le/la client.e concerné.e.

Q7: **Instructions**

Veuillez lire attentivement l'interaction entre le/la client.e et le robot de service, puis répondre aux questions qui suivent pour nous aider à comprendre votre perception et votre réaction face à cette situation.

Vous souffrez actuellement d'une infection sexuellement transmissible diagnostiquée récemment par votre médecin. Après une consultation médicale, vous devez vous rendre à la pharmacie la plus proche pour récupérer le traitement prescrit.

Lorsque vous arrivez à l'accueil, un robot interactif conçu pour être empathique et rassurant vous accueille. Le robot adopte un ton bienveillant et cherche à rendre l'expérience agréable et personnalisée.

Interaction :
Robot : « Bonjour. Je suis ici pour vous aider en toute confidentialité. Pouvez-vous me communiquer votre code de prescription? »
Vous : [Vous communiquez le code]
Robot : « Merci. Je comprends que ce sujet puisse être sensible et parfois difficile à aborder. Votre traitement antibiotique est prêt. Si vous souhaitez des conseils supplémentaires ou poser des questions, je suis à votre disposition. »

End of Block: High-Sensitivity – Feeling AI

Start of Block: Low-Sensitivity – Mechanical AI

Q8: Dans cette étude, vous serez exposé.e à une interaction fictive entre vous, en tant que client.e, et un robot de service. Cette interaction décrira une situation de service avec une illustration de l'échange entre vous et le robot.

Nous vous demandons de vous immerger pleinement dans cette situation et de considérer votre expérience et vos sentiments comme si vous étiez réellement le/la client.e concerné.e.

Q9: **Instructions**

Veuillez lire attentivement l'interaction entre le/la client.e et le robot de service, puis répondre aux questions qui suivent pour nous aider à comprendre votre perception et votre réaction face à cette situation.

Vous vous apprêtez à voyager et arrivez à l'aéroport pour vous enregistrer avant votre vol.

Lorsque vous atteignez le comptoir d'enregistrement, vous constatez qu'un robot en libre-service, au design simple et purement fonctionnel, prend en charge l'enregistrement. Le robot affiche des instructions basiques et effectue le processus sans aucune interaction sociale.

Interaction :
Robot : « Veuillez scanner votre passeport. »
Vous : [Vous scannez votre passeport]
Robot : « Bagage enregistré. Impression de votre carte d'embarquement en cours. »
Robot : « Enregistrement terminé. »

End of Block: Low-Sensitivity – Mechanical AI

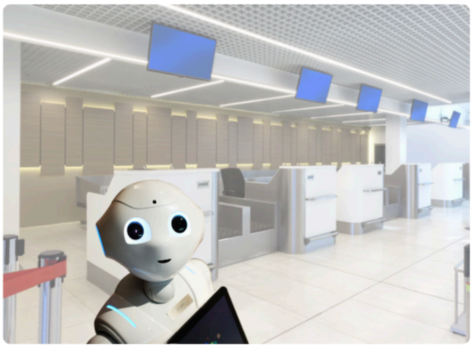
Start of Block: Low-Sensitivity – Thinking AI

Q10: Dans cette étude, vous serez exposé.e à une interaction fictive entre vous, en tant que client.e, et un robot de service. Cette interaction décrira une situation de service avec une illustration de l'échange entre vous et le robot.

Nous vous demandons de vous immerger pleinement dans cette situation et de considérer votre expérience et vos sentiments comme si vous étiez réellement le/la client.e concerné.e.

Q11: **Instructions**

Veuillez lire attentivement l'interaction entre le/la client.e et le robot de service, puis répondre aux questions qui suivent pour nous aider à comprendre votre perception et votre réaction face à cette situation.



Vous vous apprêtez à voyager et arrivez à l'aéroport pour vous enregistrer avant votre vol.

Lorsque vous atteignez le comptoir d'enregistrement, vous êtes accueilli(e) par un robot assistant capable de s'adapter à vos besoins et d'analyser vos informations. Le robot utilise un ton poli et vous propose des suggestions utiles.

Interaction :
Robot : « Bonjour et bienvenue. Je vois que vous voyagez fréquemment avec nous. Souhaitez-vous un siège côté couloir comme lors de votre dernier vol ? »
Vous : « Oui, s'il vous plaît. »
Robot : « Siège côté couloir confirmé. Votre carte d'embarquement est en cours d'impression. Je vous souhaite un excellent voyage. »

End of Block: Low-Sensitivity – Thinking AI

Start of Block: Low-Sensitivity – Feeling AI

Q12: Dans cette étude, vous serez exposé.e à une interaction fictive entre vous, en tant que client.e, et un robot de service. Cette interaction décrira une situation de service avec une illustration de l'échange entre vous et le robot.

Nous vous demandons de vous immerger pleinement dans cette situation et de considérer votre expérience et vos sentiments comme si vous étiez réellement le/la client.e concerné.e.

Q13: **Instructions**

Veuillez lire attentivement l'interaction entre le/la client.e et le robot de service, puis répondre aux questions qui suivent pour nous aider à comprendre votre perception et votre réaction face à cette situation.

Vous vous apprêtez à voyager et arrivez à l'aéroport pour vous enregistrer avant votre vol.

Lorsque vous atteignez le comptoir d'enregistrement, un robot interactif conçu pour être empathique et rassurant vous accueille. Il adopte un ton bienveillant et cherche à rendre l'expérience agréable et personnalisée.

Interaction :
Robot : « Bonjour ! Je suis heureux de vous accompagner aujourd'hui. J'espère que vous allez bien et que vous êtes prêt(e) à commencer votre voyage ? »
Vous : « Oui, merci. »
Robot : « Parfait ! Pour votre confort, j'ai sélectionné un siège côté couloir, comme lors de vos précédents voyages. Si vous avez la moindre question ou besoin d'assistance, je suis ici pour vous aider à chaque étape. Je vous souhaite un merveilleux séjour ! »

End of Block: Low-Sensitivity – Thinking AI

Start of Block: Questions

Q14: Veuillez répondre aux questions suivantes en vous imaginant dans la situation présentée précédemment.

Dans quelle mesure êtes-vous d'accord avec les propositions suivantes ?

Q15: Je me sens embarrassé(e) dans cette situation

- ○ Pas du tout d'accord (1)
- ○ Pas d'accord (2)
- ○ Plutôt pas d'accord (3)
- ○ Indifférent (4)
- ○ Plutôt d'accord (5)
- ○ D'accord (6)
- ○ Tout à fait d'accord (7)

Q16 : Je me sens mal à l'aise dans cette situation

- ○ Pas du tout d'accord (1)
- ○ Pas d'accord (2)
- ○ Plutôt pas d'accord (3)
- ○ Indifférent (4)
- ○ Plutôt d'accord (5)
- ○ D'accord (6)
- ○ Tout à fait d'accord (7)

Q17: Je me sens gêné(e) dans cette situation

- ○ Pas du tout d'accord (1)
- ○ Pas d'accord (2)
- ○ Plutôt pas d'accord (3)
- ○ Indifférent (4)
- ○ Plutôt d'accord (5)
- ○ D'accord (6)
- ○ Tout à fait d'accord (7)

Q18: Dans quelle mesure êtes-vous d'accord avec les propositions suivantes, basées sur la situation présentée précédemment ?

Q19: J’ai le sentiment que le robot perçoit ma présence sociale

- ○ Pas du tout d'accord (1)
- ○ Pas d'accord (2)
- ○ Plutôt pas d'accord (3)
- ○ Indifférent (4)
- ○ Plutôt d'accord (5)
- ○ D'accord (6)
- ○ Tout à fait d'accord (7)

Q20: J’ai l’impression que le robot peut m’observer et me juger

- ○ Pas du tout d'accord (1)
- ○ Pas d'accord (2)
- ○ Plutôt pas d'accord (3)
- ○ Indifférent (4)
- ○ Plutôt d'accord (5)
- ○ D'accord (6)
- ○ Tout à fait d'accord (7)

Q21: À quel point êtes-vous familier(ère) avec ce type de service?

- ○ Pas du tout familier(ère) (1)
- ○ Peu familier(ère) (2)
- ○ Plutôt peu familier(ère) (3)
- ○ Moyennement familier(ère) (4)
- ○ Plutôt familier(ère) (5)
- ○ Familier(ère) (6)
- ○ Très familier(ère) (7)

Q22: Toujours concernant la situation décrite précédemment, dans quelle mesure êtes-vous d'accord avec les propositions suivantes ?

Q23: Je n'ai eu aucune difficulté à me projeter dans la situation présentée

- ○ Pas du tout d'accord (1)
- ○ Pas d'accord (2)
- ○ Plutôt pas d'accord (3)
- ○ Indifférent (4)
- ○ Plutôt d'accord (5)
- ○ D'accord (6)
- ○ Tout à fait d'accord (7)

Q24: La situation décrite était réaliste

- ○ Pas du tout d'accord (1)
- ○ Pas d'accord (2)
- ○ Plutôt pas d'accord (3)
- ○ Indifférent (4)
- ○ Plutôt d'accord (5)
- ○ D'accord (6)
- ○ Tout à fait d'accord (7)

Q25: Nous y sommes presque. Veuillez nous en dire plus à propos de vous.

Q26: Quel est votre genre?

- ○ Homme (1)
- ○ Femme (2)
- ○ Non-binaire/transgenre (3)
- ○ Ne souhaite pas répondre (4)

Q27: Indiquez votre âge

____

Q28 Vous êtes actuellement

- ○ Employé.e à temps plein (1)
- ○ Employé.e à mi-temps (2)
- ○ Sans emploi (3)
- ○ Retraité.e (4)
- ○ Étudiant.e (5)
- ○ Autres : (6) ________

Q29: Quel est le plus haut niveau d'éducation que vous avez complété ?

- ○ Aucun diplôme (1)
- ○ Certificat de l'enseignement secondaire supérieur (CESS) (2)
- ○ Enseignement technique ou professionnel (3)
- ○ Baccalauréat (bachelor) (4)
- ○ Master (5)
- ○ Doctorat (6)
- ○ Formation continue ou autre formation spécialisée (7)
- ○ Autres: (8) ________

End of Block: Questions

Fin du questionnaire.

Merci d'avoir pris le temps de participer à cette enquête.

Merci de cliquer sur "Suivant" afin de clôturer l'enquête!

Appendix 4: Link to all the survey responses

https://osf.io/g9ern/?view_only=f6fb01fae9b24d3eabef3b0789af4a8d

Appendix 5: Demographic distribution of survey participants across the six scenarios

Gender	S1HSM	S2HST	S3HSF	S4LSM	S5LST	S6LSF
Male	46,90%	29,60%	29,40%	34,90%	23,50%	27,50%
Female	53,10%	70,40%	70,60%	65,10%	76,50%	62,50%
Age	S1HSM	S2HST	S3HSF	S4LSM	S5LST	S6LSF
Average	37	38	41	36	34	35
Current occupation	S1HSM	S2HST	S3HSF	S4LSM	S5LST	S6LSF
Full-time Employee	34%	37%	35%	33%	44%	35%
Part-time Employee	0%	4%	6%	5%	6%	3%
Unemployed	6%	7%	3%	7%	0%	5%
Retired	9%	4%	15%	7%	9%	13%
Student	41%	41%	26%	40%	41%	45%
Other	9%	7%	15%	9%	0%	0%
Highest level of education	S1HSM	S2HST	S3HSF	S4LSM	S5LST	S6LSF
No diploma	0%	0%	6%	0%	0%	0%
Certificate of Higher Secondary Education	13%	15%	18%	14%	3%	13%
Technical or Vocational Education	0%	0%	3%	5%	0%	3%
Bachelor	41%	37%	21%	28%	18%	25%
Master	38%	37%	44%	49%	74%	53%
PhD	0%	7%	3%	2%	0%	3%
Continuing Education or Other	3%	0%	0%	0%	6%	3%
Other	6%	4%	6%	2%	0%	3%

Appendix 6: Principal component analysis (PCA) for EMB1, EMB2, EMB3

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.752
Bartlett's Test of Sphericity	Approx. Chi-Square	477.376
	df	3
	Sig.	<.001

Communalities

	Initial	Extraction
EMB1_Total	1.000	.829
EMB2_Total	1.000	.887
EMB3_Total	1.000	.880

Extraction Method: Principal Component Analysis.

Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2.596	86.524	86.524	2.596	86.524	86.524
2	.251	8.372	94.896			
3	.153	5.104	100.000			

Extraction Method: Principal Component Analysis.

Appendix 7: Pearson correlation test for ASP and SR

		ASP1_Tot	ASP2_Total
ASP1_Tot	Pearson Correlation	1	.551**
	Sig. (2-tailed)		<.001
	N	210	210
ASP2_Total	Pearson Correlation	.551**	1
	Sig. (2-tailed)	<.001	
	N	210	210

**. Correlation is significant at the 0.01 level (2-tailed).

		SR1_Tot	SR2_Tot
SR1_Tot	Pearson Correlation	1	.571**
	Sig. (2-tailed)		<.001
	N	210	210
SR2_Tot	Pearson Correlation	.571**	1
	Sig. (2-tailed)	<.001	
	N	210	210

**. Correlation is significant at the 0.01 level (2-tailed).

Appendix 8 : Between-subjects factors for the one-way ANOVA (H1)

		Value Label	N
AI_Type	1.00	Mechanical AI	75
	2.00	Thinking AI	61
	3.00	Feeling AI	74

Appendix 9: Residual error normality test for customer embarrassment (H1)

Tests of Normality

		Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	AI_Type	Statistic	df	Sig.	Statistic	df	Sig.
Embarrassment	Mechanical AI	.198	75	<.001	.854	75	<.001
	Thinking AI	.117	61	.036	.932	61	.002
	Feeling AI	.094	74	.175	.952	74	.007

a. Lilliefors Significance Correction

Appendix 10: Homogeneity test for customer embarrassment (H1)

		Levene Statistic	df1	df2	Sig.
Embarrassment	Based on Mean	3.402	2	207	.035
	Based on Median	3.602	2	207	.029
	Based on Median and with adjusted df	3.602	2	206.509	.029
	Based on trimmed mean	3.596	2	207	.029

Tests the null hypothesis that the error variance of the dependent variable is equal across groups.

a. Dependent variable: Embarrassment

b. Design: Intercept + AI_Type

Appendix 11: Between-subject factors for the two-way ANOVA (H2)

		Value Label	N
AI_Type	1.00	Mechanical AI	75
	2.00	Thinking AI	61
	3.00	Feeling AI	74
Context_Sensivity	1.00	High	93
	2.00	Low	117

Appendix 12: Residual error normality test for customer embarrassment (H2)

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Residual for Embarrassment	.100	210	<.001	.966	210	<.001

a. Lilliefors Significance Correction

Appendix 13: Homogeneity test for customer embarrassment (H2)

		Levene Statistic	df1	df2	Sig.
Embarrassment	Based on Mean	1.222	5	204	.300
	Based on Median	.798	5	204	.552
	Based on Median and with adjusted df	.798	5	180.056	.552
	Based on trimmed mean	1.192	5	204	.314

Tests the null hypothesis that the error variance of the dependent variable is equal across groups.

a. Dependent variable: Embarrassment

b. Design: Intercept + AI_Type + Context_Sensivity + AI_Type * Context_Sensivity

Appendix 14: Output simple mediation analysis (H3)

```
**************************************************************************
  Model: 4
      Y: Embarss
      X: AIType
      M: ASPglob

Sample
Size:  210

Coding of categorical X variable for analysis:
 AIType     X1     X2
  1.000   .000   .000
  2.000  1.000   .000
  3.000   .000  1.000

**************************************************************************

OUTCOME VARIABLE:
 ASPglob

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .4597      .2113     1.4475    27.7328     2.0000   207.0000      .0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     1.8933      .1389    13.6284      .0000     1.6194     2.1672
X1            .8198      .2074     3.9520      .0001      .4108     1.2287
X2           1.4648      .1971     7.4304      .0000     1.0761     1.8534

**************************************************************************

  OUTCOME VARIABLE:
   Embarss

  Model Summary
            R       R-sq        MSE          F        df1        df2          p
        .2961      .0877     2.5721     6.5990     3.0000   206.0000      .0003

  Model
                coeff         se          t          p       LLCI       ULCI
  constant     2.2129      .2551     8.6753      .0000     1.7100     2.7158
  X1            .9580      .2868     3.3407      .0010      .3926     1.5233
  X2            .8314      .2958     2.8110      .0054      .2483     1.4145
  ASPglob       .0941      .0926     1.0160      .3108     -.0885      .2768


  ****************** DIRECT AND INDIRECT EFFECTS OF X ON Y ******************

  Relative direct effects of X on Y
         Effect         se          t          p       LLCI       ULCI
  X1      .9580      .2868     3.3407      .0010      .3926     1.5233
  X2      .8314      .2958     2.8110      .0054      .2483     1.4145

  Omnibus test of direct effect of X on Y:
      R2-chng          F        df1        df2          p
        .0562     6.3480     2.0000   206.0000      .0021
  ----------

  Relative indirect effects of X on Y

   AIType      ->    ASPglob     ->    Embarss

         Effect     BootSE   BootLLCI   BootULCI
  X1      .0772      .0900     -.0961      .2654
  X2      .1379      .1561     -.1603      .4525

  ********************** ANALYSIS NOTES AND ERRORS ************************

  Level of confidence for all confidence intervals in output:
    95.0000

  Number of bootstrap samples for percentile bootstrap confidence intervals:
    5000

  ------ END MATRIX -----
```

Appendix 15: Output moderated mediation analysis (H3)

```
**************************************************************************
  Model: 14
      Y: Embarss
      X: AIType
      M: ASPglob
      W: ContS1

Sample
Size:  210

Coding of categorical X variable for analysis:
 AIType     X1     X2
  1.000   .000   .000
  2.000  1.000   .000
  3.000   .000  1.000

**************************************************************************
OUTCOME VARIABLE:
 ASPglob

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .4597      .2113     1.4475    27.7328     2.0000   207.0000      .0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     1.8933      .1389    13.6284      .0000     1.6194     2.1672
X1            .8198      .2074     3.9520      .0001      .4108     1.2287
X2           1.4648      .1971     7.4304      .0000     1.0761     1.8534

**************************************************************************
OUTCOME VARIABLE:
 Embarss

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .3874      .1500     2.4197     7.2026     5.0000   204.0000      .0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     1.4552      .3351     4.3429      .0000      .7945     2.1158
X1            .8203      .2813     2.9159      .0039      .2657     1.3750
X2            .6272      .2917     2.1498      .0327      .0520     1.2024
ASPglob       .2751      .1136     2.4216      .0163      .0511      .4991
ContS1       1.3811      .4954     2.7877      .0058      .4043     2.3579
Int_1        -.2195      .1748    -1.2558      .2106     -.5642      .1251

Product terms key:
 Int_1    :        ASPglob  x        ContS1

Test(s) of highest order unconditional interaction(s):
       R2-chng          F        df1        df2          p
M*W      .0066     1.5771     1.0000   204.0000      .2106

****************** DIRECT AND INDIRECT EFFECTS OF X ON Y *****************

Relative direct effects of X on Y
       Effect         se          t          p       LLCI       ULCI
X1      .8203      .2813     2.9159      .0039      .2657     1.3750
X2      .6272      .2917     2.1498      .0327      .0520     1.2024

Omnibus test of direct effect of X on Y:
    R2-chng          F        df1        df2          p
      .0374     4.4931     2.0000   204.0000      .0123
----------

Relative conditional indirect effects of X on Y:

INDIRECT EFFECT:
 AIType      ->    ASPglob     ->    Embarss

       ContS1     Effect     BootSE   BootLLCI   BootULCI
X1      .0000      .2255      .1113      .0167      .4535
X1     1.0000      .0456      .1309     -.2060      .3121

Index of moderated mediation (difference between conditional indirect effects):
           Index     BootSE   BootLLCI   BootULCI
ContS1     -.1800      .1569     -.5028      .1148

       ContS1     Effect     BootSE   BootLLCI   BootULCI
X2      .0000      .4029      .1910      .0305      .7789
X2     1.0000      .0814      .2284     -.3848      .5147

Index of moderated mediation (difference between conditional indirect effects):
           Index     BootSE   BootLLCI   BootULCI
ContS1     -.3215      .2804     -.9181      .1994

*********************** ANALYSIS NOTES AND ERRORS ************************

Level of confidence for all confidence intervals in output:
  95.0000

Number of bootstrap samples for percentile bootstrap confidence intervals:
  5000

------ END MATRIX -----
```

Appendix 16: Tests Results for Scenario Realism and Familiarity :

Descriptives

SR_global

	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean Lower Bound	95% Confidence Interval for Mean Upper Bound	Minimum	Maximum
Mechanical AI x High Sensitive Context	32	5.3750	1.28264	.22674	4.9126	5.8374	3.00	7.00
Thinking AI x High Sensitive Context	27	4.2778	1.31802	.25365	3.7564	4.7992	1.50	7.00
Feeling AI x High Sensitive Context	34	4.8235	1.64170	.28155	4.2507	5.3963	1.00	7.00
Mechanical AI x Low Sensitive Context	43	6.1163	.94389	.14394	5.8258	6.4068	3.50	7.00
Thinking AI x Low Sensitive Context	34	5.1029	1.40227	.24049	4.6137	5.5922	1.50	7.00
Feeling AI x Low Sensitive Context	40	4.9125	1.33919	.21174	4.4842	5.3408	1.00	7.00
Total	210	5.1643	1.42698	.09847	4.9702	5.3584	1.00	7.00

ANOVA

SR_global

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	68.222	5	13.644	7.789	<.001
Within Groups	357.360	204	1.752		
Total	425.582	209			

Descriptives

FAM_global

	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean Lower Bound	95% Confidence Interval for Mean Upper Bound	Minimum	Maximum
Mechanical AI x High Sensitive Context	32	2.7813	1.82694	.32296	2.1226	3.4399	1.00	7.00
Thinking AI x High Sensitive Context	27	2.2593	1.40309	.27002	1.7042	2.8143	1.00	5.00
Feeling AI x High Sensitive Context	34	2.0882	1.28788	.22087	1.6389	2.5376	1.00	5.00
Mechanical AI x Low Sensitive Context	43	4.3488	1.63130	.24877	3.8468	4.8509	1.00	7.00
Thinking AI x Low Sensitive Context	34	2.2941	1.44661	.24809	1.7894	2.7989	1.00	6.00
Feeling AI x Low Sensitive Context	40	2.2000	1.32433	.20939	1.7765	2.6235	1.00	5.00
Total	210	2.7333	1.70710	.11780	2.5011	2.9656	1.00	7.00

ANOVA

FAM_global

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	150.451	5	30.090	13.385	<.001
Within Groups	458.615	204	2.248		
Total	609.067	209			

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