Faculty of Business Economics

Master of Management

Master's thesis

Does the type of problem I want to solve influence my acceptance of a robot server or assistant?

Oumayma Oujaidan

Thesis presented in fulfillment of the requirements for the degree of Master of Management, specialization International Marketing Strategy

SUPERVISOR :

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Executive Summary

The thesis examines the moderating effects of the assistant type (human or AI) and the involvement level (low or high) on consumers' acceptance of using AI-based service assistants concerning two dissimilar service industries, banking as a utilitarian industry and hospitality as a hedonic industry. This study aims to determine the extent to which service environments and problem types affect attitudes toward AI and theoretical formulation, as well as strategies for AI adoption contributions.

The study was grounded in a robust theoretical framework that comprised the Technology Acceptance Model (TAM), Unified Theory of Acceptance and Use of Technology (UTAUT), Service Robot Acceptance Model (sRAM), and Elaboration Likelihood Model (ELM). The models provided a multi-dimensional measurement framework for assessing rational and affective antecedents to technology acceptance, such as perceived usefulness, trust, social presence, and affective comfort.

Using an experimental design and survey setup, the consumer ratings were collected under varying levels of task involvement and assistant type. Qualtrics was used to share the scenario-based questionnaire, and statistical tests were conducted using SPSS to test hypotheses for the influence of task involvement and assistant type on AI acceptance.

The findings validate the preference discovery for human service assistants in each environment with strong dislike, particularly of AI in affective, hedonic space. In particular, task involvement was not an adequate predictor of AI service acceptance, contrary to the ELM hypothesis that tasks involving low effort are most likely to be automated. Instead, social presence, trustworthiness, and ease in affective space were meta-predictors of user intent to use AI, better than functional effectiveness or task difficulty.

These results underscore that assistant type is more critical in establishing AI acceptability than task attributes. AI assistants were deemed acceptable in low-involvement productivity tasks typical in banking but firmly rejected in highly affective hospitality contexts. This underscores human-AI interaction through relational processes and cautions against overextrapolation of AI deployment strategies to service industries.

The research contributes to the literature in a novel way through a greater comprehension of contextual determinants of AI service adoption and offering organizational practical recommendations for embracing AI responsibly. Successful AI adoption will need to continue to be responsive to emotional expectations, trust perception, and the supreme role of human touch in service delivery.

Table of Contents

CHAPTER One

Introduction

1.1 Background and Overview

Artificial Intelligence (AI) technologies rapidly transform how organizations operate, make decisions, and deliver services. Of such technologies, AI-based service assistants such as chatbots, virtual agents, and intelligent support systems are spreading across various sectors, including banking and hospitality, to enhance service delivery, effectiveness, and user experience (Belanche et al., 2020).

However, consumer uptake of AI-based assistants is not uniform and significantly depends on the usage context. One such important consideration is the type of problem the AI is to solve. Operations can feasibly be understood as utilitarian, considering functional and goal-oriented consequences, or hedonic, considering experiential and pleasure-oriented consequences. Literature indicates that individuals accept AI assistance in utilitarian tasks more easily because they perceive the task as more appropriate for automation. In contrast, hedonic tasks require human touch and emotional quotient, leading to lower adoption of AI solutions (Longoni & Cian, 2020).

Another determinant of task characteristics for AI assistants is the level of involvement required. Simple and low-involvement tasks calling for minimal mental effort are more likely to be outsourced to AI assistants. However, high-involvement tasks that are sophisticated and high in demand for personal effort are more likely to resist the integration of AI due to concerns of trusting AI and human judgment (Choung et al., 2022).

This study investigates the effect of assistant type (AI vs. Human) and involvement level (low vs. high) on consumers' willingness to use AI-powered service assistants. The research investigates the interaction between task characteristics and AI acceptance by analyzing two contrasting industries, banking, a utilitarian environment, and hospitality, a hedonic climate. The findings of this research will assist in developing AI systems that are more consumer expectation and task requirement oriented, hence improving their effectiveness and usage in various service industries.

1.2 Problem statement

The fast growth in AI has developed intelligent systems that can assist humans with all professional tasks. AI-powered service assistants are emerging more prominently in healthcare, finance, education, law, and hospitality industries to facilitate automation, enhance decision-making, and support information retrieval (Belanche et al., 2020). Despite their technological sophistication and growing ubiquity, their adoption and proper integration remain disparate across fields and service environments.

This disparity is the outcome of an enormous number of interdependent factors. Task characteristics such as complexity, subjectivity, and structure significantly influence the acceptability and appropriateness of AI within a specific environment (Salimzadeh et al., 2023). Domain-specific expectations regarding trust, risk, and responsibility also play a role in determining users' willingness to offload decision-making to AI. For example, although financial sectors can adopt automation in data-intensive processes, legal or medical professionals hesitate to deploy black-box AI systems for sensitive judgments (Choung et al., 2022). There is also a noted gap in the literature concerning cross-sectoral findings on how user engagement and task type affect AI acceptance. Much of the current research is still isolated within particular disciplines and does not tackle larger-scale patterns of user behavior or psychological anticipation (Herrera-Poyatos et al., 2025).

To create AI-based assistants that are technically competent, trustworthy, usable, and contextual, it is vital to be aware of the impact of assistant typology and task involvement on acceptance by users. The current study seeks to fill this gap by investigating the influence of these determinants on perceived value and usage intention of AI-based assistants in two fundamentally different industries: banking and hospitality.

1.3 Research Questions

To address the problem outlined above, this study seeks to answer the following question:
"How do assistant type and involvement level influence consumers’ willingness to use AI-powered service assistants?

1.4 Motivation

The increasing integration of AI in various service industries such as banking, healthcare, education, legal, and hospitality reflects the significance of determining the drivers of the uptake of AI-facilitated assistants. The intelligent systems are used to drive automation, increase efficiency, and aid in complex decision-making processes. However, their successful utilization is contingent upon comprehending the factors conducive to or deterrents of accepting the systems.

Another key factor influencing AI assistant adoption is the nature of the task they perform. AI solutions have higher chances of being adopted in tasks with data-intensive, formalized properties. At the same time, they are less likely to be adopted in tasks that require moral decision-making, empathy, or subtle human judgment (Longoni & Cian, 2020). This makes it necessary to thoroughly explore task properties' impact on perceived value, usability, and trust.

Trustworthiness, responsibility, and human-AI collaboration dynamics are central considerations during AI assistant deployment. Effective system design must address how trust is established or lost based on task and domain. Aligning organizational strategy with AI capabilities will optimize productivity while ensuring the correct direction from humans (Choung et al., 2022). Understanding how professionals engage with AI on the matters they attempt to solve may assist in informing the development of more intuitive, dynamic, and domain-specific technologies.

An academic and professional interest in digital and user-centered innovation drives this research. The decision to use the banking and hospitality sectors is convenient for the researcher: a banking sector background provides knowledge of utilitarian, efficiency-focused service environments, while a background in travel gives knowledge of affectively engaging, hedonic service environments. These experiences highlight the opposing user expectations while working with AI technologies and stress the necessity of creating AI systems that are not only functionally able but also contextually and emotionally perceptive.

By bridging the gap between human requirements and technological capabilities, this study aims to spearhead that change. By studying how the nature of the problem influences AI assistant adoption, this study aims to contribute to creating more intelligent, more reliable, and more context-sensitive AI systems that accommodate the various arrays of future needs.

1.5 Relevance of the Study

This study is significant in developing theoretical understanding and application in the evolving field of AI deployment in service industries, through an exploration of consumer adoption of AI-based service assistants across two distinct sectors, banking and hospitality. The study contributes to the broader discussion around human-AI interaction. These industries are examples of utilitarian and hedonic service environments, respectively, and therefore provide a valid comparative background to assess how contextual and psychological factors influence consumers' willingness to engage with AI technology.

Scholarship-wise, this research bridges a critical literature gap regarding the differential drivers of AI acceptance by service type and involvement level. Whereas many studies have examined overall attitudes towards AI, few have investigated the impact of sector-specific expectations, e.g., efficiency in banking compared to emotional engagement in hospitality, on user behavior and perception. By integrating established technology acceptance models, including the Technology Acceptance Model (TAM), Unified Theory of Acceptance and Use of Technology (UTAUT), and Service Robot Acceptance Model (sRAM), this study proposes a theoretically grounded framework that encompasses cognitive as well as affective phenomena of AI uptake (Wirtz et al., 2018). This enriches our theoretical understanding of consumer interaction with intelligent systems in context-dependent ways due to trust, perceived usefulness, ease of use, and emotional comfort.

Practically, the study provides insightful recommendations for service industry practitioners, digital transformation planners, and AI developers. Organizations utilizing AI-based assistants can learn how various consumer responses depend on whether the service environment is logic-oriented or emotion-oriented. The findings can guide better deployment practices, including functional reliability as the primary focus for banking applications and building on anthropomorphic or emotionally innovative features for hospitality AI-based interfaces. Such practices can lead to more specific and efficient delivery of services and ultimately drive greater customer satisfaction and brand loyalty (Belanche et al., 2020).

The research informs strategic decision-making in AI adoption by illustrating how differences in assistant type, task engagement, and service context can impact acceptance. These findings can inform investments into AI infrastructure and directly influence user experience design in alignment with sector-specific needs. The research delivers technological innovation in service provision and inclusive, user-centered AI implementation across sectors.

At a broader societal scale, this research demands the development of AI systems that are superior technologically and sensitive to society. As AI becomes increasingly prevalent in consumers' everyday lives, understanding how different service contexts shape human-AI interaction is crucial to ensure that technological progress is ethical, positive, and broadly accepted (Choung et al., 2022).

1.6 Structure of the Research

The following structure presents the findings on the topic of “Does the type of problem I want to solve influence my acceptance of a robot server or assistant?”, a study of service robots in the hospitality and banking industry.

Chapter One introduces the background of the study, outlines the problem statement, states the research question, and presents the motivation and relevance of the study in understanding contextual and psychological factors shaping AI adoption in service industries.

Chapter Two reviews the literature on AI in services, AI assistants and service robots, human-robot interaction (HRI), and technology acceptance models such as TAM, UTAUT, and sRAM. It then synthesizes empirical findings on task framing, involvement level, and sector-specific differences to form the conceptual and theoretical basis of the study.

Chapter Three outlines the research methodology, including the scenario-based experimental design, sampling technique, and data collection process. It also explains the rationale for using a quantitative survey to explore consumer responses to AI across AI involvement and involvement levels.

Chapter four analyzes the findings and discusses the results.
Chapter five includes the discussion of the study.
Lastly, Chapter Six discusses limitations, Further Research Suggestions, and Conclusion.

CHAPTER TWO

Literature Review

This review of the literature first presents the role that AI has within services, continues to review developments of AI service robots and AI service assistants, reviews human-robot interaction models, reviews major technology acceptance models, and finishes by reviewing the effects of problem type and involvement level on consumer acceptance of AI technology. This chapter synthesizes theoretical and empirical findings to provide a total understanding needed to investigate the deployment of AI within different service contexts.

During the last decade, robotics and AI have been the primary forces of change in service industries, providing increased operational effectiveness, tailored customer experiences, and scalable solutions in various applications (Wirtz et al., 2018). One of the most significant trends in this industry is the emergence of AI-driven service assistant products such as chatbots, virtual planners for finances, and robotic concierges that mimic human-like service capabilities. These assistants are being used increasingly in utilitarian sectors such as banking, where processes are goal-oriented and logic-driven, and hedonic sectors such as hospitality, where affective involvement and experiential value are prominent.

Even as it is more commonly used, deployment of AI service assistants continues to be uneven across sectors and service environments. This disequilibrium means that consumer readiness to use such systems is moderated by problem type and cognitive or affective effort to participate in a service interaction (Paluch & Wirtz, 2020; Draskovic, 2022).

In banking, which is generally made up of high-involvement transactional behavior, AI systems such as robot-advisors will be more likely to be adopted when they provide data-driven accuracy and reduce cognitive effort (Kim et al., 2016). Conversely, emotionally engaging and socially involved hospitality services will be more challenging to resist AI services since they are incapable of empathizing or experiencing emotions (Van der Heijden, 2004; Batra & Ahtola, 1991; Choi et al., 2019).

Understanding the problem type (utilitarian vs. hedonic) and task involvement level (high vs. low) is needed to further develop AI deployment in services. These factors are at the heart of prediction and shaping consumer attitudes towards AI, particularly in industries that vary highly regarding user expectations and service goals. When businesses consider adopting AI tools into customer contact contexts, there is an increasing necessity to research how task characteristics dictate the perceived trustworthiness, usefulness, and emotional comfort of AI-based service assistants.

This literature review adopts a theoretical view of AI adoption based on behavioral and contextual factors with an industry focus. Specifically, it concentrates on established models such as the TAM (Davis, 1989), UTAUT and UTAUT2 (Venkatesh et al., 2003, 2012), and the sRAM (Wirtz et al., 2018). The chapter further explores topics of AI assistants, service robots, human-robot interaction (HRI), and typology of problems, before venturing into industry-specific literature related to AI adoption in the banking and hospitality sectors.

The following sections will discuss the ideas of AI in service environments, the kind of service robots, service robot human-robot interaction dynamics, technology acceptance theory, and consequences of task types and levels of involvement.

2.1 AI in Services and AI Assistants.

AI for services is the convergence of innovative systems designed to execute activities traditionally demanding human knowledge to increase operational efficiency, personalization, and service quality (Russell & Norvig, 2020). The most sought-after deployment of AI in services is through AI assistants, virtual or intelligent agents with natural language processing functionality, supporting users in decision-making, task execution, and searching for information (Hoy, 2018).

These assistants have seen significant adoption in utilitarian sectors such as banking and hedonic sectors such as hospitality, but for divergent reasons. In banking, AI assistants increase efficiency and precision by automating procedures, responding to customer questions, and providing personalized financial information (Singh, 2022). Here, their use is mainly necessitated by demands for performance, namely, precision, security, and dependability.

On the other hand, hospitality AI focuses on optimizing customer experience through personalized interaction. Virtual concierges appear as service staff making recommendations, remembering guests' likes, and even engaging in small talk to simulate human warmth (Tussyadiah & Park, 2018). Anthropomorphic elements are widely utilized to create emotional affinity and perceived enjoyment (Zhang et al., 2021).

This disparity mirrors a broader trend in the application of AI to engage with customers. While banking clients are worried about precision and reliability, hospitality customers are concerned with social presence and emotional interaction (Longoni & Cian, 2020). This disparity underscores the necessity of aligning AI design and deployment with the specific needs of the service industry.

The following section expands this discussion to service robots and explores how embodiment and autonomy further shape consumer experiences.

2.2 Service Robots

Service robots are autonomous, intelligent systems designed to perform tasks that typically require human labor or intellectual effort. They are differentiated by their ability to perceive, reason, and act using the integration of sensors, computational intelligence, and actuators (Lin et al., 2011). Industrial robots carry out their tasks in controlled environments, whereas service robots are meant for direct interaction with humans, particularly in frontline tasks in customer service sectors.

Park (2020) defines service robots as "smart, programmable tools" that assist human beings by improving their productivity via autonomous behavior. They are generally designed with machine learning algorithms that allow them to adapt to evolving user needs and service scenarios. Wirtz et al. (2018) define them as "system-based autonomous and adaptable interfaces" that interact and serve customers, offering services within an organizational environment. Belanche et al. (2020) also describe service robots as part-sustaining technologies with a physical interface, whose applications are predominantly in publicly observable positions in the services sector.

Practically, service robots have been widely used in hotels, airports, and restaurants, where they perform tasks such as check-ins, information delivery, and concierge services (Singer, 2009). Such functionalities require both functional reliability and social interaction competence. According to Singer (2009), robots are commonly regarded as machines capable of performing complex coordinated actions, an advancement that has expanded their applications in service areas.

While more integrated, service robots are still faced with acceptance, particularly if the task involves emotional intelligence or sensitive interaction. In utilitarian environments such as banks, their output relies primarily on speed and accuracy; in hedonic environments such as hotels, emotional resonance and anthropomorphic design are prioritized to user satisfaction (Wirtz et al., 2018; Belanche et al., 2020). It is essential to understand these contextual requirements to create service robots that execute tasks efficiently and are accepted by users.

The notion of interaction is further detailed and deepened in the next section, which discusses HRI theories and implications for customer acceptance.

2.3 Human-Robot Interaction (HRI)

Human-Robot Interaction (HRI) is an inter-disciplinary research field interested in how humans interact with robot systems, increasingly competent at mental and physical tasks in shifting, everyday settings. Despite being humans through complicated cognitive, emotional, and social processes, robots are artificial systems with the potential to carry out actions singly or half-wittingly, relying on sensors, computer competence, and effectors (Thrun, 2004; Lin et al., 2011). Because these two kinds of agency cross over in service and professional domains, it is necessary to study their interactions.

HRI is concerned with designing and evaluating systems that support effective, safe, and advantageous human-robot collaboration (Goodrich & Schultz, 2007). It includes task-oriented interaction, in which performance and efficiency are of concern, and social interaction, in which trust, emotional connection, and relationship building are of concern (Fong et al., 2003; Breazeal, 2003; Dautenhahn, 2007). It is relevant in customer-facing sectors such as hospitality and retailing, where the quality of interaction directly affects satisfaction with service (Wirtz et al., 2018).

Some of the primary factors that affect HRI are the design of the robot (e.g., human shape or mechanical), the communication mode (e.g., gestures, speech, screen), and the psychological makeup of the user, including culture and acceptance of technology. In hedonic contexts where social and emotional interaction are given priority, robots with human-like features are employed and utilized more (Belanche et al., 2020). In utilitarian contexts such as banks, users are concerned more with precision and completion of the task than with emotional attributes (Park, 2020).

Modern HRI research also talks about dynamic shifting ethical and psychological issues, such as how humans attribute intentionality to machines, how repeated interaction affects perception, and how the presence of robots shifts social norms (Jörling, 2019; Singer, 2009). As more defined roles are given to service robots, their ability to be emotionally flexible and meet human expectations is becoming as critical as technical proficiency (Go et al., 2020).

Briefly, HRI is a critical link between human need and artificial ability. Where goals for interaction vary in efficiency as opposed to empathy, such as in banking versus hospitality, successful HRI asks robot systems to be not only functional but also emotionally and socially competent.

Comprehending the HRI dynamics supports the next exploration of technology acceptance models that examine, explain, and predict user adoption behavior.

2.4 Theoretical Frameworks for AI Acceptance

This section introduces key theoretical models that are the basics to understand AI acceptance behaviors, it focuses on TAM, UTAUT, UTAUT 2, and sRAM. These models explain how affective, cognitive, and contextual factors shape technology acceptance across various service industries.

2.4.1 Technology Acceptance Model (TAM)

TAM, developed by Davis (1989), is one of the most used models in the technology adoption study literature. TAM posits that user acceptance of a technology relies on two beliefs summarized in Table 1 below:

Table 1: Core Constructs of TAM

Perceived Usefulness (PU)	To what degree does a person believe using technology will enhance his/her job performance?
Perceived Ease of Use (PEOU)	To what degree does an individual believe using technology will be trouble-free?

TAM has been widely applied to study self-service technologies and AI systems in utilitarian and hedonic settings. In banking, PU has a greater chance to dominate as an adoption driver due to expectations of efficiency and precision (Kim et al., 2016). In contrast, PEOU and pleasure have become increasingly relevant in the hospitality sector due to their service experience-based nature (Tussyadiah & Park, 2018).
Building on TAM, more thorough models such as UTAUT have been established to incorporate additional social and supporting conditions influencing the behavior of the user, as described below.

2.4.2 Unified Theory of Acceptance and Use of Technology (UTAUT)

Venkatesh et al. (2003) formulated the initial UTAUT model by integrating eight prior technology adoption models into a comprehensive framework. The model proposes four principal constructs that impact behavioral intention and use behavior as listed in Table 2 below:

Table 2: Core Constructs of UTAUT.

Performance Expectancy	belief that the system enhances performance.
Effort Expectancy	simplicity of use.
Social Influence	perceived social pressure to adopt the technology
Facilitating Conditions	believe that the technical and organizational infrastructure exists to support use.

UTAUT also includes moderator variables such as gender, age, experience, and voluntariness of use. In AI adoption in services, UTAUT performs well, particularly in formal, goal-oriented contexts such as banking, where task performance and social confirmation influence acceptance decisions.
A consumer-focused extension of UTAUT was introduced later on, namely UTAUT2, bringing hedonic motivations and habits into UTAUT, as explained in the following section.

2.4.3 UTAUT2: The Consumer-Focused Extension

UTAUT2 by Venkatesh et al. (2012) extends UTAUT to consumer technology adoption, making it highly relevant to AI-based assistants in service industries. It retains the fundamental UTAUT constructs and adds three new ones, summed up in Table 3:

Table 3: Core Constructs of UTAUT 2.

Hedonic Motivation	enjoyment derived from technology use.
Price Value	cost-benefit perception.
Habit	The degree to which behavior is automatic due to past use.

UTAUT2 is especially appropriate in hedonic environments such as hospitality, where enjoyment, perceived value, and formed habits play a role in acceptance. It is also conducive to further investigating AI adoption within diverse emotional and cognitive settings.
The sRAM provides a more specific perspective on AI-driven systems, as discussed in the following section.

2.4.4 Service Robot Acceptance Model (sRAM)

The Service Robot Acceptance Model (sRAM) of Wirtz et al. (2018), derived from traditional technology acceptance models such as TAM and UTAUT, adds variables linked explicitly with the utilization of physically present and socially interactive AI systems. This model is relevant for service robots and AI-based assistants for customer-facing services such as banking and hospitality, where emotive and rational responses influence user behavior.

Unlike existing models, which emphasize utilitarian factors such as perceived usefulness and ease of use, sRAM introduces affective and relational dimensions. sRAM responds to the increasing importance of emotional engagement, anthropomorphism, and trust in consumer-robot interaction. sRAM claims consumer acceptance of service robots does not depend on the robot's functional performance but on how human-like, socially available, and emotionally engaging the robot appears to be. The model suggests several antecedents to acceptance, listed in Table 4:

Table 4: The antecedents of sRAM.

Perceived Usefulness	is believing that the service robot enhances the performance of the task.
Ease of Use	is believing the robot would be easy.
Trust	Trusting the robot's reliability, benevolence, and competence.

Perceived Anthropomorphism	The extent to which the robot is believed to have characteristics similar to a human.
Social Presence	The extent to which the robot is perceived as a social presence.
Perceived Enjoyment and Emotional Engagement	The robot can provide an emotionally rewarding and pleasant experience.

In utilitarian settings, banking, functionality, reliability, and decision-making based on data continue to be emphasized. However, even in these settings, professionalism perception and trust influence user acceptance (Kim et al., 2016). In hedonic settings such as hospitality, social presence, anthropomorphism, and emotional involvement are often stronger predictors of acceptance (Belanche et al., 2020; Choi & Kandampully, 2019).

Thus, sRAM bridges the cognitive and affective gap in AI adoption, offering a wide-ranging theory well-suited to exploring how context in general, task type, and degree of engagement shape user willingness. This model can provide valuable inputs into tailoring AI systems to sector-specific needs that enhance customer experience by including the psychological and social determinants of adoption.
The exploration of user cognitive processing is further enriched by the ELM, as introduced below.

2.4.5 Elaboration Likelihood Model (ELM)

The Elaboration Likelihood Model (ELM), which was created by Petty and Cacioppo (1986), explains how individuals form attitudes and make decisions based on their motivation and ability to process information. The model identifies two primary cognitive process routes:

Central Route Processing: This occurs when individuals are highly involved and motivated, and have the cognitive ability to scrutinize message content extensively. Decisions are made based on the logical sufficiency and quality of arguments.

Peripheral Route Processing: This is where individuals are less involved or cannot process information properly. They rely on surface indicators such as attractiveness, reputation, or credibility.

The route taken has a significant effect on AI service adoption. High-involvement, utilitarian environments such as banking will see consumers use central processing. They assess the credibility, accuracy, and performance of AI tools such as robo-advisors or anti-fraud software (Paluch & Wirtz, 2020). Low-involvement, hedonic environments such as hospitality tend to trigger peripheral processing, where evaluation can be informed by the robot's sociability, anthropomorphism, or interactive friendliness (Tussyadiah & Park, 2018).

Understanding what path wins in a given service context helps design AI interfaces and communication approaches that align with consumers' expectations and enhance engagement.
With these theoretical foundations set, the next section explores the key behavioral constructs impacting AI acceptance.

2.5 Constructs of AI Acceptance: Key Behavioral Variables

This section discusses the key behavioral factors influencing consumer acceptance of AI-driven service assistants, providing a detailed description of the influence of psychological perceptions and emotional reactions on adoption intentions.
To comprehend consumer acceptance of AI assistants, it is important to explore the underlying behavioral constructs that influence user attitudes and intentions. Table 5 summarizes the key variables that have been established in the literature:

Table 5: Key behavioral variables of AI acceptance.

Perceived Usefulness (PU)	To what degree a user feels that employing an AI assistant enhances task performance. High PU corresponds to greater acceptance and usage intentions (Davis, 1989).
Perceived Ease of Use (PEOU)	Determines how much the user perceives the AI system as easy to use. User-friendly and intuitive systems are more likely to be used (Davis, 1989).
Trust	A determinant of AI acceptance, trust refers to assumptions about the system's reliability, competence, and benevolence. Trust in AI is vital in high-stakes environments such as banking (Choung et al., 2022).
Emotional Comfort	The perception of comfort and emotional safety that the user feels when interacting with AI. This is especially significant in hedonic contexts, where social presence and empathy are valued (Choi et al., 2019).
Willingness to Use	Refers to the desire of the user to use AI services, spurred on by the constructs

	mentioned earlier. A positive attitude towards AI is linked with higher willingness to use (Venkatesh et al., 2003).

These constructs are the building blocks for many technology acceptance models that will be examined in the next section to establish a proper perspective of AI adoption in services.
Following discussions on individual behavioral constructs, the next section identifies the impact of task framing and involvement levels on user attitudes towards AI systems.

2.6 Consumer Task Framing and Involvement Level

2.6.1 Task Typology and User Expectations

In technology-facilitated service encounters, operations are commonly utilitarian or hedonic, a distinction that is fundamental to understanding consumer responses to AI systems. Utilitarian operations are task-oriented, functional, and typically valued for accuracy, efficiency, and reliability, e.g., inquiring about account balances or verifying loan conditions. Customers in these contexts appreciate system performance, particularly data-driven accuracy and reliability (Belanche et al., 2020; Kim et al., 2022).

Conversely, hedonic tasks emphasize pleasure, affective engagement, and user experience. Hedonic tasks are abundant in service industries such as hospitality, where AI systems, namely, virtual concierges or interactive kiosks, must not just be evaluated on the utility of function but on how effectively they are able to emulate human warmth, chat, and make personalized recommendations (Tussyadiah & Park, 2018; Jörling, 2019). Accordingly, AI must be context-aware: operationally robust for banking and emotionally sensitive for hospitality. Anthropomorphic qualities and emotional affinity are more indicative of AI acceptance in hedonic settings.

2.6.2 Involvement Level: High vs. Low Involvement Tasks

The level of involvement is the degree of mental and emotional effort a user devotes to a task (Zaichkowsky, 1985). High-involvement tasks such as budgeting require thorough consideration, reliance, and risk assessment, often requiring human interaction for reassurance. In such situations, users employ the central route of the ELM, where logical analysis and credibility dominate.

Low-involvement activities, such as booking a hotel amenity, involve minimal effort and are normally habitual. Such users use the peripheral route to processing, relying on heuristics such as pace and ease of use dimensions, where AI assistants perform highly (Tussyadiah & Park, 2018; Petty & Cacioppo, 1986). Therefore, the potential for AI adoption is significantly higher in low-involvement tasks due to reduced cognitive thresholds and criteria.

2.6.3 Combined Impact: Typology and Involvement in AI Acceptance

Task type by involvement level gives us a more accurate image of AI acceptance. In utilitarian high-involvement contexts such as investment advisory services, customers need rational processing, transparency, and trust. AI must demonstrate reliability and data integrity to be accepted. In hedonic low-involvement contexts such as automated room suggestions in a hotel, customers want anthropomorphic cues and affective friendliness. Social presence and hedonics prevail over rational scrutiny in these instances. Task-system mismatch can decrease the adoption and performance of AI. An extremely structured, data-centered AI assistant will not be effective in a leisure context, e.g., and an overly informal assistant would not be considered as serious as an advisor on finance. Effective AI design thus depends on matching the system's cognitive and affective affordances to the kind of task perceived.

2.7 Sector-Specific Adoption of AI-Powered Assistants: Comparative Insights from Hospitality and Banking

2.7.1 AI-powered Assistant in Hospitality: A Review

The hospitality sector is being transformed by AI technologies in the areas of operations streamlining and guest experience. Some of the technologies that fall under those categories include virtual concierges, service robots, and chatbots with personalized interaction (Tussyadiah & Park, 2018). Acceptance, however, is not just a matter of technological sufficiency but also the degree to which the AI satisfies the social and emotional needs of a given task.

Gursoy (2025) cites business benefits of AI efficiency and personalization, but also consumer resistance to emotionally connected services. Ho et al. (2022) use the TAM and introduce additional variables of self-efficacy and perceived cost, and determine that cognitive as well as affective forces drive adoption in hospitality. These reports supplement this thesis in the sense that they validate the role of user psychology and emotional context in AI adoption, but do not describe task-specific impacts, which this thesis does exactly.

Regional studies (e.g., Hasan et al., 2024) refer to infrastructural constraints and manpower adjustment in the emerging market, whereas Das et al. (2024) highlight AI adoption in marketing and personalization. These papers contribute towards the general viability of AI in functional areas, in alignment with the cross-functional focus of the thesis. These papers, however, do not address the nature of the task as a moderator of AI adoption, an issue addressed in this study.

AI perception also affects interface design and emotional comfort. Fan et al. (2022) recognize that voice interfaces can lower user satisfaction through loss of control. Sousa et al. (2024) recognize high tourist receptivity to AI, but do not differentiate by type of task being accepted. Cumulatively, these findings validate the affective character of AI adoption and support the thesis objective to investigate task framing and level of involvement in interaction with agent type to influence the inclination to utilize AI in hospitality.

The reviewed literature on AI adoption in the hospitality industry supports that user adoption is significantly impacted by emotional expectations, interface aesthetics, and social presence. While the strategic benefits of AI in enhancing guest experience and operational effectiveness are mentioned in a number of studies, they lack empirical segmentation on how task type, either high or low-involvement, or emotionally charged, impacts consumer willingness to engage with AI-based assistants. This imbalance essentially counter-argues the thesis's main contention: that consumer acceptance is reliant not just on the availability of AI but on the interaction between task context and form of assistant (AI or human). In attempting to test this interaction empirically across the hospitality industry, the thesis draws on current research to deliver actionable intelligence on how AI development and deployment should vary by service environment and user expectation.

2.7.2 AI-powered Assistant in Banking: A Review

The finance sector implements AI to improve efficiency, accuracy, and personalization. Some examples include chatbots, robo-advisors, fraud detection, and predictive analytics (Rahmani, 2023; Narang et al., 2024). They are mostly goal-based and information-centric, and thus usually related to high-involvement decisions, so dependability and trust are paramount for implementation.

Jain (2023) and Singh (2020) highlight the capability of AI in facilitating accuracy and automation but also illustrate that ethical issues, algorithmic bias, and transparency limit user trust in high-stakes activities. This substantiates the thesis by indicating the fine hindrances to the adoption of AI in high-stakes environments, validating the imperative to explore task engagement in affecting user trust and willingness.

Vinoth (2022) illustrates regional differences in AI acceptance, while Alkadi & Abed (2025) illustrate how trust and social influence shape acceptance, especially among young consumers. These results align with the thesis in supporting the argument on the mediating effect of contextual and psychological variables, specifically, trust and individual innovativeness. They do not dissect acceptance by task type and involvement, however, which this study contributes by testing empirically.

In summary, the banking literature identifies functional competence and trust as key drivers of AI acceptance. This is aligned with the thesis's utilitarian rationale, warranting exploration of how task involvement level and perceived criticality influence AI take-up. To some extent, there are no earlier studies systematically comparing or contrasting low- and high-involvement AI tasks across the consumer-facing banking services empirical terrain; this thesis sets out to explore.

2.8 Hypotheses

Figure A1 in the appendix illustrates the conceptual model representing H1 and H2.

H1: **Consumers will be more willing to use human service assistants than AI-based assistants.**

The original hypothesis within this study proposed that consumers' acceptance of AI assistants depends on the type of task, utilitarian or hedonic, and it has been reformulated to reflect a more agent-centric view: “Consumers will be more willing to use human service assistants than AI-based assistants.” This modification responds to emerging literature, which shows that perceptions of service agents, particularly concerning trust, competence, and empathy, are critical determinants of user acceptance, sometimes exceeding the influence of task type alone (Gursoy et al., 2025; Choung et al., 2022). Viewed from another angle, the hypothesis asserts that the research acknowledges the fact that a human agent's presence or absence is able to elicit varying degrees of psychological comfort and operational confidence, regardless of whether or not the interaction is utilitarian or hedonic. This shift permits a sharper focus on the relational dynamics connecting consumers as well as service interfaces. That field expands inside human-computer interaction studies.

More specifically, the hypothesis is then formulated in a directional form so that it would be readily testable and theoretically appropriate. It posits that human service assistants would be more acceptable to customers, as they are viewed to be more emotionally intelligent and capable of communicating empathetically.

This hypothesis is also grounded in theoretical models and empirical evidence. The TAM, originally put forward by Davis (1989), has subsequently been broadened to encompass aspects of perceived anthropomorphism, social presence, and trustworthiness, attributes that are strongly influenced by the type of service agent (Gursoy et al., 2025). Building on this, Social Presence Theory and the Service Robot Acceptance Model (sRAM) underpin the argument that human agents are perceived to offer greater levels of trust, emotional comfort, and interactional warmth, qualities at the core of the user's intention to interact. Both theories predict that agent type will be a strong predictor in the intention to interact, not just on functional but on an emotional and relational basis.

Practically, an extensive disposition of experimental and field experiments illustrates that AI agents, regardless of their technical proficiency, can generate discomfort or suspicion when they are perceived to lack humanness or human understanding (Choung et al., 2022). This is especially pronounced in service settings where customer satisfaction relies on interpersonal rapport and affective communication.

Given this, the researcher expects that consumers will always opt for human service assistants, particularly for emotionally involving or trust transactions, since humans are deemed to be inherently seen as superior responders to social cues, rapport establishment, and empathy communication. This forms the basis for the directional expectation embedded in the hypothesis.

Therefore, the analysis of the human vs. AI agent divide has explanatory and predictive power in accounting for consumer willingness and is thus worthy of consideration of agent-type as a primary independent variable in this research.

Therefore, we propose the hypothesis:

H2: Consumers will be more willing to use AI-powered service assistants for low-involvement tasks than high-involvement ones.

Hypothesis 2 suggests that "Consumers will be more likely to adopt AI-facilitated service assistants for low-involvement tasks rather than high-involvement ones," a position supported by the dual-process model of decision-making. Literature shows that people are more likely to delegate decision-making to automatic processes when perceived stakes are low and cognitive effort is low (Choung et al., 2022; Sundar, 2020).

Low-involvement tasks, such as requesting additional towels at a hotel or comparing savings interest rates, are commonly standardized and low in emotional or financial stakes, thus perceived as suitable to leave for AI. High-involvement tasks typically involve long-term consequences or complex judgment, such as accepting a mortgage application, necessitating human control because of fear of mistrust, answerability, and negotiation of vagueness (Gursoy et al., 2025).

This differentiation accords with automation bias theory, which argues that people are selectively relying on AI systems according to the criticality and complexity of the task. Therefore, the hypothesis of heightened adoption of AI in low-involvement contexts is theoretically justified and empirically logical and gives an improved angle for understanding consumer behavior in AI-mediated service environments.

The theoretical basis of Hypothesis 2 is borrowing from ELM, which explains how a person processes information according to the person's engagement with the product. According to ELM, when consumers encounter a high-involvement task such as obtaining a mortgage, they experience central route processing, which is characterized by higher cognitive involvement, thorough examination of information, and higher sensitivity to trust, expertise, and interpersonal communication cues (Petty & Cacioppo, 1986). In such contexts, human service assistants function better because they can adapt to emotional nuances and provide empathic, context-appropriate support that AI-driven service typically lacks. In contrast, for low-involvement tasks, such as asking for hotel amenities or checking financial data, consumers are more likely to rely on peripheral route processing, where judgments are shaped by surface characteristics such as convenience, speed, and availability. Here, AI-powered assistants are more readily adopted, as their capability to deliver quick, standardized responses aligns with consumers’ heuristic-based expectations. Thus, the ELM framework provides a robust explanation for why consumers demonstrate willingness to use AI assistants in low-involvement scenarios, reinforcing the hypothesis that involvement level moderates AI acceptance.

Given this, the author expects consumers would be content and at ease with AI-based service assistants for low-involvement tasks exactly because these are not the kind of situations that necessitate emotional intelligence, contextual awareness, or judgment sensitivity. In contrast, when the stakes are high, either emotionally, financially, or cognitively, customers are anticipated to resist automation in favor of human agents who are perceived as more competent in managing ambiguity, uncertainty, and social interaction. This is consistent with previous research and aligns with observed consumer hesitations around fully delegating important decisions to non-human agents.

CHAPTER THREE

Research Methodology

This chapter discusses the methodology employed to investigate the topic of "Does the type of problem I want to solve influence my acceptance of a robot server or assistant?

This chapter includes research design, sampling technique, size, study population, data collection methods, and statistical analysis.

3.1 Research design

The research design for this study followed a quantitative approach, using a scenario-based survey method. Scenario-based research is a "type of research where participants are presented with hypothetical scenarios and are asked to express how they feel about them" Kim & Jang, 2014. Based on specific scenarios, participants answer questions or make decisions based on their interpretations of the given situations.
In this study, participants were randomly assigned to read one of eight structured scenarios, each reflecting a frontline service interaction in either the banking (utilitarian context) or hospitality (hedonic context) sector. The scenarios varied systematically across two dimensions:

- Assistant type: AI assistant vs. Human assistant.

- Involvement level: High vs. Low.

For example, in the banking domain, a low-involvement utilitarian task involved checking savings investment options, while a high-involvement task involved applying for a home loan. In the hospitality domain, a low-involvement hedonic task involved requesting extra amenities, whereas a high-involvement task involved personalized vacation planning. Each task type was presented with either a human or AI assistant, enabling comparative evaluation of agent type as well.

This design enabled the systematic assessment of how the type of assistant, framed as either an AI-driven assistant or a human assistant, and either routine (low-involvement) or complex (high-involvement), influences consumer trust, perceived usefulness, emotional comfort, and willingness to use the AI assistant.

By setting a realistic context (scenario) for respondents to consider, they can provide more reliable and accurate responses than general hypothetical questions, and it can also become more engaging and interactive for participants, generating more thoughtful responses.

3.2 Sample Selection

This study employed a convenience sampling method, which involves selecting participants based on their availability and ease of access rather than through a probability-based approach (Price, 2013). As explained by Simkus (2022), convenience sampling allows researchers to gather data from individuals who are readily accessible, without the requirement that they statistically represent the broader population. Factors such as location or willingness to participate often determine inclusion in the sample. Given the time constraints and the need for a practical and efficient data collection process, this method was considered the most suitable for the present research.

3.3 Data Collection

Data were collected through a scenario-based questionnaire administered to participants through Qualtrics. The Qualtrics links are shared online through emails and social media platforms. The questionnaire was consent-driven, and participants were encouraged to voluntarily participate by filling out the questionnaire at their own convenience. The time required to fill out the questionnaire was 7 to 10 minutes. However, the data collection period was subject to how fast the respondents could fill out the questionnaire. Clear instructions were provided, and anonymity and confidentiality were ensured to encourage honest responses.

3.4 Method of Data Analysis

The data collected through the survey will be analyzed using SPSS. Descriptive statistics such as means will be used to summarize data. To examine the effects of assistant type and involvement level on the acceptance of service robots, Two-way ANOVA analysis was employed.

CHAPTER FOUR

ANALYSIS AND DISCUSSION OF THE RESULT

4.1 Descriptive Analysis in the Hospitality Sector

Table 4.1.1:

Table 4.1.1 provides a summary of the distribution of respondents based on their consent to participate in the survey.

	Consent information	%	Number of respondents
1	Yes, I agree to participate	100%	115
2	No, I do not agree to participate	0%	0
	Total	100%	115

Data Source: Researcher's Collected Data 2025

The table provides a summary of the distribution of respondents based on their consent to participate in the survey. It includes two consent options, the percentage of respondents for each option, and the number of respondents for each consent choice. The total number of respondents in the survey is 115.

The first option, "Yes, I agree to participate," was chosen by 115 respondents, constituting 100% of the respondents. This indicates that the totality of respondents acknowledge and wish to participate in the survey. The second option, "No, I do not want to participate," was selected by 0% of the respondents. This suggests that nobody chose not to take part in the survey.

Table 4.1.2:

Table 4.1.2 presents data on the distribution of respondents across different age groups.

	Age Group	%	Number of respondents
1	18-25	47%	54
2	26-35	26.1%	30
3	36-45	19.1%	22
4	46+	7.8%	9
	Total	100%	115

Data Source: Researcher's Collected Data 2025

The table presents the distribution of survey respondents across four distinct age groups. The total number of participants in the survey is 115. Age Group 18–25 is the largest demographic segment, comprising 54 respondents, which accounts for approximately 47.0% of the total sample. These individuals represent a younger population likely familiar with or adaptable to technological interfaces. Age Group 26–35 includes 30 respondents, making up 26.1% of the total participants. It reflects a significant proportion of early to mid-career professionals, who may have moderate exposure to AI technologies in service environments. Age Group 36–45 represents 22 respondents; this group constitutes about 19.1% of the total sample.
These individuals may be more experienced in service usage and potentially more critical of AI engagement depending on the task context. Age Group 46 and above is the smallest group, consisting of 9 respondents, or 7.8% of the total. This segment likely includes individuals who may hold more conservative attitudes toward AI technologies or prefer human interaction in service tasks.

In summary, the age distribution is skewed toward younger participants, with the majority falling under the 18–25 and 26–35 age brackets. This distribution provides a solid foundation for evaluating how generational or life-stage factors may influence attitudes toward AI-powered service assistants across different task contexts.

Table 4.1.3:

Table 4.1.3 provides a summary of the distribution of respondents based on gender.

	Gender	**%**	**Number of respondents**
1	Male	33%	38
2	Female	64.3%	74
3	Non-binary / Third gender	1.7%	2
4	Prefer not to say	0.9%	1
	Total	100%	115

Data Source: Researcher's Collected Data 2025

The table provides a summary of the distribution of respondents based on gender. It includes four gender categories, the percentage of respondents in each category, and the number of respondents for each gender group. The total number of respondents in the survey is 115. The Male category consists of 38 respondents, accounting for about 33.0% of the total participants. It represents the second-largest gender category, offering a substantial comparative base for gender-based analysis. The Female category is the largest gender group, with 74 respondents, making up approximately 64.3% of the total sample. This high representation suggests that the female perspective is strongly reflected in the survey's findings. The Non-binary / Third gender category comprises 2 respondents; this group represents around 1.7% of the total. Although a small proportion, its inclusion enhances the inclusivity and representativeness of the sample. The Prefer not to say category consists of one respondent (approximately 0.9%) who chose not to disclose their gender. This reflects a degree of privacy preference among participants and contributes to ethical completeness in reporting. This data indicates that the majority of the respondents identify as female, followed by male respondents. The presence of non-binary individuals and those who preferred not to disclose their gender demonstrates a degree of gender diversity in the sample, enriching the interpretive validity of gender-related insights in the research.

Table 4.1.4

Table 4.1.4 provides a summary of the distribution of respondents based on their education level.

	education level	**%**	**Number of respondents**
1	High school diploma or equivalent	35.7%	41
2	Bachelor’s degree	39.1%	45
3	Master’s degree	20%	23
4	Doctorate	2.6	3
5	Other	2.6	3
	Total	100%	115

Data Source: Researcher’s Collected Data 2025

The table presents the distribution of survey participants by their highest level of education. The total number of respondents is 115, categorized into five educational groups. The bachelor’s degree category is the most represented educational category, with 45 respondents, accounting for approximately 39.1% of the sample. This suggests that a significant portion of participants possess undergraduate academic qualifications, likely placing them in early-to-mid career stages. High school diploma or equivalent, are a total of 41 respondents (around 35.7%) fall into this category. This indicates a substantial representation of individuals with secondary education, who may approach AI-related technologies with varied degrees of familiarity or access. The master’s degree category comprises 23 respondents, constituting 20.0% of the total sample. Their advanced education level may correlate with higher cognitive involvement in service interactions and more critical perspectives toward AI systems. The doctorate category is a small segment of 3 respondents (approximately 2.6%) who hold doctoral qualifications. Though limited in number, this group may bring highly analytical viewpoints regarding trust, ethics, and system complexity in AI-based services. The other category also includes 3 respondents (2.6%); this category likely encompasses non-traditional or vocational education backgrounds, adding heterogeneity to the educational profile of the sample. This indicates that the majority of respondents possess either a high school diploma or a bachelor's degree, while a notable minority hold postgraduate qualifications. This diversity in educational backgrounds enriches the dataset and provides a robust basis for evaluating how educational attainment influences perceptions and acceptance of AI-powered service assistants.

Table 4.1.5

Table 4.1.5 presents a summary of the distribution of respondents based on their prior AI experience.

	AI experience	%	Number of respondents
1	Yes	86.1%	99
2	no	13.9%	16
	Total	100%	115

Data Source: Researcher's Collected Data 2025

The table indicates the distribution of the respondents according to their prior experience with AI. The total number of participants who filled out the survey is 115. The Yes category consists of 99 of the respondents, or approximately 86.1%, who reported some prior experience with AI. This is a high proportion, which may influence the majority of the participants to already know the AI technologies and therefore will be more attitude-tested or attitudinally-inclined towards using AI-powered service assistants since they are wiser or bolder individuals. The No category is the remaining 16 respondents, comprising 13.9% of the sample, who had no experience with AI at all. These respondents are also a valuable contrast within the data set and yield insight into how the absence of exposure or not being familiar might influence attitudes toward being effective, trustworthy, or appropriate for AI in service work. This indicates that a vast majority of participants have already had past experience with AI, thus generating a sample situation where the level of familiarity is high. This sets a good background for studying differing responses across task engagement and agent category while retaining comparative feedback from participants who are not largely exposed to AI technologies.

Table 4.1.6:

Table 4.1.6 presents a summary of the distribution of respondents based on their residency.

	Residency	%	Number of respondents
1	A large city or urban area	66.1%	76
2	A rural area or the countryside	33.9%	39

	Total	100%	115

Data Source: Researcher's Collected Data 2025

The table below indicates the respondents' distribution in terms of the type of residence, comparing the urban and rural areas. The total number of participants is 115.
The urban or large city category has 76 responses in this group, making up 66.1% of the sample. The predominance of urban residents is a pointer that most of the participants could have greater exposure to service technologies and digital infrastructure, e.g., AI systems. Urban settings typically offer more concentrated exposure to automated services in hospitality, public administration, and banking, potentially affecting better or more favorable attitudes toward AI assistants. The rural location or the countryside category consists of 39 respondents, who form 33.9% of all respondents. Respondents based in rural locations might have relatively lower levels of access to or exposure to AI services based on infrastructure limitations or varying standards for service provision. Their input provides critical insights into the availability and perceived appropriateness of AI in more sparsely networked environments.

Overall, the sample pool is mostly urban, and the implication would be that this would be an environment where AI usage is more common. That being said, the large proportion of rural respondents makes the analysis still representative enough and permits consideration of how spatial context can perhaps interact with AI adoption attitudes along service tasks and level of engagement.

4.2 Descriptive analysis in the Banking Sector

Table 4.2.1

Table 4.2.1 presents a summary of the distribution of respondents based on their consent.

	Consent information	**%**	**Number of respondents**
1	Yes, I agree to participate	100%	120
2	No, I do not agree to participate	0%	0
	Total	100%	120

Data Source: Researcher's Collected Data 2025

The table provides a summary of the distribution of respondents based on their consent to participate in the survey. It includes two consent options, the percentage of respondents for each option, and the number of respondents for each consent choice. The total number of respondents in the survey is 120.
The first option, "Yes, I agree to participate," was chosen by 120 respondents, constituting 100% of the respondents. This indicates that the totality of respondents acknowledge and wish to

participate in the survey. The second option, “No, I do not want to participate,” was selected by 0% of the respondents. This suggests that nobody chose not to take part in the survey.

Table 4.2.2:

Table 4.2.2 provides a summary of the distribution of respondents based on their age.

	Age Group	**%**	**Number of respondents**
1	18-25	46.7%	56
2	26-35	31.7%	38
3	36-45	10%	12
4	46+	11.7%	14
	Total	100%	120

Data Source: Researcher’s Collected Data 2025

The table presents the distribution of survey respondents across four distinct age groups. The total number of participants in the survey is 120. Age Group 18–25 is the largest demographic segment, comprising 56 respondents, which accounts for approximately 46.7% of the total sample. These individuals represent a younger population likely familiar with or adaptable to technological interfaces. Age Group 26–35 includes 38 respondents, making up 31.7%% of the total participants. It reflects a significant proportion of early to mid-career professionals, who may have moderate exposure to AI technologies in service environments. Age Group 36–45 represents 12 respondents, this group constitutes about 10% of the total sample. These individuals may be more experienced in service usage and potentially more critical of AI engagement depending on the task context. Age Group 46 and above, consisting of 14 respondents, or 11.7% of the total. This segment likely includes individuals who may hold more conservative attitudes toward AI technologies or prefer human interaction in service tasks. The age split is dominated by younger respondents, with 78.4% being less than 35 years old. This suggests a sample highly at ease with digital technology and possibly more open to accepting AI. The older segments, while smaller in number, are valuable for creating contrast for analyzing the generation gaps in AI acceptance.

Table 4.2.3:

Table 4.2.3 provides a summary of the distribution of respondents based on gender.

	Gender	**%**	**Number of respondents**
1	Male	40.8%	49
2	Female	58.3%	70
3	Non-binary / Third gender	0.8%	1

4	Prefer not to say	0%	0
	Total	100%	120

Data Source: Researcher's Collected Data 2025

The table provides a summary of the distribution of respondents based on gender. It includes four gender categories, the percentage of respondents in each category, and the number of respondents for each gender group. The total number of respondents in the survey is 120. The Male category consists of 49 respondents, accounting for about 40.8% of the total participants. It represents the second-largest gender category, offering a substantial comparative base for gender-based analysis. The Female category is the largest gender group, with 70 respondents, making up approximately 58.3% of the total sample. This high representation suggests that the female perspective is strongly reflected in the survey's findings. The Non-binary / Third gender category comprises 1 respondent, representing around 0.8% of the total. Although a small proportion, its inclusion enhances the inclusivity and representativeness of the sample. The Prefer not to say category includes no respondents (0%), indicating that all participants felt comfortable disclosing their gender. This data indicates that the majority of the respondents identify as female, followed by male respondents. The presence of a non-binary individual demonstrates a degree of gender diversity in the sample, enriching the interpretive validity of gender-related insights in the research.

Table 4.2.4:

Table 4.2.4 provides a summary of the distribution of respondents based on their education level.

	education level	**%**	**Number of respondents**
1	High school diploma or equivalent	40.8%	49
2	Bachelor's degree	25%	30
3	Master's degree	20.8%	25
4	Doctorate	8.3%	10
5	Other	5%	6
	Total	100%	120

Data Source: Researcher's Collected Data 2025

The table illustrates the distribution of respondents by the highest level of education. The sample is 120 and is allocated into five groups of education. The group with the high school diploma or equivalent is the most common, at 49 respondents, or around 40.8% of the sample. This would indicate a high representation of individuals having secondary education, who might interact with

AI-related technologies on levels of familiarity or accessibility. Bachelor's degree category comprises 30 respondents, 25.0%, showing a high presence of individuals probable to be in early-to-mid career levels with undergraduate degrees. The master's degree category comprises 25 respondents, showing 20.8% of the sample. Their advanced level of education can be attributed to increased cognitive involvement in service interactions and more analytical evaluations of AI capabilities. The doctorate category has 10 respondents (8.3%), who will most likely contribute analytical and theory-informed findings to the dataset. The other education category has 6 respondents (5.0%), encompassing non-traditional or vocational education. This categorization shows that even though most respondents have secondary or undergraduate education, there is substantial variation in levels of education, providing richness to the interpretive strength of the results on AI acceptance.

Table 4.2.5:

Table 4.2.5 provides a summary of the distribution of respondents based on their prior AI experience.

	AI experience	**%**	**Number of respondents**
1	Yes	84.2%	101
2	no	15.8%	19
	Total	100%	120

Data Source: Researcher's Collected Data 2025

The table indicates the distribution of the respondents according to their prior experience with AI. The total number of participants who filled out the survey is 120. The Yes category consists of 101 of the respondents, or approximately 84.2%, who reported some prior experience with AI. This is a high proportion, which may influence the majority of the participants to already know the AI technologies and therefore will be more attitude-tested or attitudinally-inclined towards using AI-powered service assistants since they are wiser or bolder individuals. The No category is the remaining 19 respondents, comprising 15.8% of the sample, who had no experience with AI at all.

These respondents are also a valuable contrast within the data set and yield insight into how the absence of exposure or not being familiar might influence attitudes toward being effective, trustworthy, or appropriate for AI in service work. This indicates that a vast majority of participants have already had past experience with AI, thus generating a sample situation where the level of familiarity is high. This sets a good background for studying differing responses across task engagement and agent category while retaining comparative feedback from participants who are not largely exposed to AI technologies.

Table 4.2.6:

Table 4.2.6 provides a summary of the distribution of respondents based on their residency.

	Residency	%	Number of respondents
1	A large city or urban area	63.3%	76
2	A rural area or the countryside	36.7%	44
	Total	100%	120

Data Source: Researcher's Collected Data 2025

The table below indicates the respondents' distribution in terms of the type of residence, comparing the urban and rural areas. The total number of participants is 120.

The urban or large city category has 76 responses in this group, making up 63.3% of the sample. The predominance of urban residents is a pointer that most of the participants could have greater exposure to service technologies and digital infrastructure, e.g., AI systems. Urban settings typically offer more concentrated exposure to automated services in hospitality, public administration, and banking, potentially affecting better or more favorable attitudes toward AI assistants. The rural location or the countryside category consists of 44 respondents, who form 36.7% of all respondents. Respondents based in rural locations might have relatively lower levels of access to or exposure to AI services based on infrastructure limitations or varying standards for service provision. Their input provides critical insights into the availability and perceived appropriateness of AI in more sparsely networked environments.

Overall, the sample pool is mostly urban, and the implication would be that this would be an environment where AI usage is more common. That being said, the large proportion of rural respondents makes the analysis still representative enough and permits consideration of how spatial context can perhaps interact with AI adoption attitudes along service tasks and level of engagement.

4.3 ANOVA Analysis and Hypothesis Testing in the Hospitality Sector

This chapter outlines the analysis of survey results for the hospitality sector and analyzes the results against the hypotheses developed in Chapter 2, whether consumers' willingness to use service assistants is influenced by the type of agent (AI vs. human) and the level of task involvement. It specifically tests if agent type affects acceptance (H1) and whether consumers are more inclined to use AI for low-involvement tasks than for high-involvement ones (H2). Findings are evaluated in line with existing theory considered above, i.e., TAM, sRAM, and ELM.

Hypothesis 1: Consumers will be more willing to use human service assistants than AI-based assistants.

H2: Consumers will be more willing to use AI-powered service assistants for low-involvement tasks than high-involvement ones.

Independent Variable	**Sum of Squares**	**df**	**Mean Square**	**F**	**Sig**
Assistant type	7.790	1	7.790	6.530	0.12
Involvement level	2.692	1	2.692	2.257	0.136
Assistant type*Involvement level	0.725	1	0.725	0.607	0.437

Data Source: Researcher's Collected Data 2025, Two-way ANOVA-Hospitality

Assistant type	**Involvement level**	**Mean**	**Std. error**
AI	High	2.913	0.199
	Low	3.379	0.206
HA	High	3.593	0.199
	Low	3.741	0.210

Data Source: Researcher's Collected Data 2025, The Interaction Between The Independent Variables- Hospitality

4.3.1. Consumers Show Greater Willingness to Use Human Assistants

The analysis revealed a statistically significant main effect of Assistant Type: $F = 6.530$, $p = .012$. On average, participants reported greater willingness to use human assistants across both involvement levels. Specifically, willingness to use a human assistant was highest in low-involvement tasks ($M = 3.741$, $SE = .210$) and remained relatively high in high-involvement tasks ($M = 3.593$, $SE = .199$) as detailed in the Table above.

In contrast, willingness to use an AI assistant was lower overall, with a mean of $M = 3.379$ ($SE = .206$) in low-involvement tasks and $M = 2.913$ ($SE = .199$) in high-involvement tasks. These results support Hypothesis 1 and align with previous research (Belanche et al., 2020; Choung et al., 2022), emphasizing that consumers in hospitality settings are more comfortable interacting with human assistants, especially when emotional engagement or social interaction is expected.

This pattern reinforces principles from both the TAM (Davis, 1989) and the sRAM (Wirtz et al., 2018), which emphasize that perceived usefulness, trust, and emotional engagement are key predictors of technology acceptance. In particular, sRAM suggests that consumers value anthropomorphism and social presence in service interactions, attributes that are inherently more associated with human assistants, which aligns with the researcher's expectation.

These results highlight that in hospitality, where empathy and customer care are central, people appear more inclined to interact with a human, even for basic transactions.

4.3.2 Task Involvement Level Has No Significant Effect

In contrast, Involvement Level did not have a statistically significant effect on the willingness to use the service assistant: $F = 2.257$, $p = .136$. Contrary to the researcher's expectation, this indicates that whether a task is simple (low involvement) or complex (high involvement) did not meaningfully influence consumers' openness to using a service assistant in hospitality. Consequently, Hypothesis 2 is not supported.

Notably, the estimated marginal means show only slight variation across involvement levels as detailed in the tables above:

- AI – Low involvement: $M = 3.379$, $SE = .206$
- AI – High involvement: $M = 2.913$, $SE = .199$
- Human – Low involvement: $M = 3.741$, $SE = .210$
- Human – High involvement: $M = 3.593$, $SE = .199$

These results highlight that assistant type exerts a more substantial influence on consumers' willingness to use than the task's involvement level. Regardless of complexity, consumers were consistently more receptive to human assistants, reinforcing the role of interpersonal connection in hospitality.

This outcome is somewhat unexpected when considered through the lens of the ELM, which theorizes that individuals process persuasive information via central or peripheral routes depending on their cognitive involvement (Petty & Cacioppo, 1986). One might expect that consumers would be more open to AI in low-involvement tasks due to the reduced need for deep cognitive engagement. However, the results suggest that emotional trust and perceived social presence may outweigh task complexity even in relatively simple tasks. This finding supports the view of Choung et al. (2022) and Sundar (2020), who note that heuristics such as familiarity, warmth, and human likeness often guide service evaluations more than rational task assessments.

Additionally, while this effect did not reach statistical significance at the conventional 5% level, the p-value of .136 is approaching the 10% threshold, which some researchers consider marginally noteworthy in exploratory or small-sample studies.

4.3.3 No Interaction Between Assistant Type and Involvement Level

The interaction effect between Assistant Type and Involvement Level was also not statistically significant: $F = 0.607$, $p = .437$. This indicates that the observed preference for human assistants remained stable across both high- and low-involvement tasks.

The estimated marginal means do not reveal any reversal or cross-over between groups: willingness remains consistently higher for human assistants regardless of the task. Consumers were not more likely to choose AI in low-involvement tasks, nor did they shift preferences based on task demands.

This finding suggests a general resistance to AI in hospitality, regardless of context, and further reinforces the importance of human-like traits and relational trust in these services. According to sRAM (Wirtz et al., 2018), perceived emotional engagement, social interactivity, and trust drive user acceptance of service robots. If these are lacking, particularly in AI-based interactions, consumers may consistently favor humans, regardless of the complexity of the service required.

In contrast to the banking industry, where there was a strong interaction between assistant type and task engagement, the hospitality findings show a more uniform bias towards human assistants. This is likely a function of the affective, experiential nature of hospitality, in which customer expectation is centered on empathy, concern, and personalized care (Wirtz et al., 2018; Belanche et al., 2020). This might be a function of trailing consumer trust in AI (Gursoy et al., 2019) or a fundamental expectation of human warmth in service settings—things that current AI systems have failed to fully replicate (Sundar, 2020).

4.4 ANOVA Analysis and Hypothesis Testing in the Banking Sector

This chapter outlines the analysis of survey results for the banking sector and analyzes the results against the hypotheses developed in Chapter 2, whether consumers' willingness to use service assistants is influenced by the type of agent (AI vs. human) and the level of task involvement. It specifically tests if agent type affects acceptance (H1) and whether consumers are more inclined to use AI for low-involvement tasks than for high-involvement ones (H2). Findings are evaluated in line with existing theory considered above, i.e., TAM, UTAUT, sRAM, and ELM.

Hypothesis 1: Consumers will be more willing to use human service assistants than AI-based assistants.

H2: Consumers will be more willing to use AI-powered service assistants for low-involvement tasks than high-involvement ones.

Independent Variable	**Sum of Squares**	**df**	**Mean Square**	**F**	**Sig**
Assistant type	22.191	1	22.191	18.045	0.001
Involvement level	0.40	1	0.40	0.033	0.857
Assistant type*Involvement level	5.500	1	5.500	4.472	0.037

Data Source: Researcher's Collected Data 2025, Two-way ANOVA-Banking

Assistant type	Involvement level	Mean	Std. error
AI	High	3.077	0.199
	Low	2.608	0.226
HA	High	3.513	0.202
	Low	3.909	0.187

Data Source: Researcher's Collected Data 2025, The Interaction Between the Independent Variables- Banking

To explore how consumers respond to different types of service assistants in banking, a two-way ANOVA was conducted. This analysis examined the main and interaction effects of Assistant Type (AI vs. Human) and Involvement Level (High vs. Low) on consumers' willingness to use the assistant. The findings provide compelling insights into how people perceive AI versus human support when managing financial tasks.

4.4.1. Consumers Show Greater Willingness to Use Human Assistants

The analysis revealed a significant main effect of Assistant Type: $F = 18.045$, $p < .001$. On average, participants expressed greater willingness to use a human assistant across both involvement levels. According to the estimated marginal means in the data source tables:

- Human – High involvement: $M = 3.513$, $SE = .202$
- Human – Low involvement: $M = 3.909$, $SE = .187$
- AI – High involvement: $M = 3.077$, $SE = .199$
- AI – Low involvement: $M = 2.608$, $SE = .226$

These results strongly support Hypothesis 1, suggesting that consumers remain more comfortable delegating even routine banking tasks to human agents. This aligns with prior findings (Belanche et al., 2020; Choung et al., 2022), which highlight the perceived risk, trust, and accountability factors that influence AI adoption in high-stakes, data-sensitive contexts such as finance.

This result validates the researcher's expectation, also aligns with TAM and the sRAM, which both emphasize the role of trust, perceived usefulness, and emotional assurance in determining acceptance of automated services. In the banking domain, human assistants appear to better fulfill these needs, especially in tasks perceived as sensitive or consequential.

4.4.2 Task Involvement Level Has No Significant Direct Effect

Surprisingly, and contrary to the researcher's expectation, the involvement level did not produce a statistically significant direct effect: $F = 0.033$, $p = .857$. This indicates that, when considered in isolation, the complexity or simplicity of the banking task did not significantly impact participants' willingness to use an assistant. As such, Hypothesis 2 is not supported.

Interestingly, the AI assistant actually received slightly higher willingness ratings in high-involvement tasks (M = 3.077) than in low-involvement ones (M = 2.608), which is the opposite of what Hypothesis 2 predicted. Meanwhile, for human assistants, willingness remained high across both conditions.

This finding further emphasizes that assistant type, not task complexity, drives user acceptance in the banking sector. Although the p-value (.857) is far from the conventional 5% or even 10% thresholds, it underscores a stable pattern of consumer skepticism toward AI, even for routine tasks.

This finding challenges assumptions from the ELM, which posits that users engage in more critical, central-route processing during high-involvement tasks. One might expect that in low-involvement conditions, where peripheral cues dominate. AI would be more acceptable due to reduced cognitive scrutiny. However, the persistent preference for human assistants suggests that trust and perceived risk override involvement-based processing in banking scenarios.

4.4.3 A Significant Interaction Effect: Assistant Type × Task Involvement

The analysis revealed a significant interaction effect between Assistant Type and Involvement Level: F = 4.472, p = .037. This indicates that the effect of assistant type on willingness depends on the task's involvement level. Breaking it down:

- For high-involvement tasks, willingness was moderately higher for human assistants (M = 3.513) than for AI (M = 3.077).

- For low-involvement tasks, the gap widened considerably: Human assistants (M = 3.909) were rated far more favorably than AI (M = 2.608).

This result is particularly interesting because it contradicts prior research (e.g., Longoni & Cian, 2020; Go et al., 2020), which suggests that consumers are generally more open to AI in low-stakes or routine tasks. In the case of banking, however, even when the task is simple, such as checking a balance, people still express strong preferences for human assistance.
This pattern supports the UTAUT model, which identifies trust, perceived risk, and social influence as key barriers to technology adoption. Even when the task is low-involvement, these factors appear to shape consumers' reluctance to adopt AI in finance.

4.5 Summary of Hypothesis Testing

This section presents a summary of the hypotheses tested and the interaction terms for this study across both sectors. Two hypotheses were tested using a two-way ANOVA analysis. The findings from the analysis and interpretations of results and the theoretical alignment are presented in the table below.

Table 4.5.1: Summary of Hypotheses

	Hypotheses	Hospitality Sector	Banking Sector	Theoretical alignment
1	H_1: Consumers will be more willing to use human service assistants than AI-based assistants.	H_1: was supported	H_1: was supported	Consistent with **TAM** (Davis, 1989) and **sRAM** (Wirtz et al., 2018), which emphasize trust, emotional engagement, and social presence as drivers of technology acceptance.
2	H_2: Consumers will be more willing to use AI-powered service assistants for low-involvement tasks than high-involvement ones.	H_2: was not supported	H_2: was not supported	Partially contradicts **ELM** (Petty & Cacioppo, 1986), which suggests consumers process messages differently based on involvement. Trust appeared to override task simplicity in both contexts.
Interaction	Assistant Type × Task Involvement	Not significant	Significant	In hospitality, findings align with **sRAM**, which suggests a consistent preference for socially rich human interaction. In banking, the significant interaction supports **UTAUT** (Venkatesh et al., 2003), where trust and risk perceptions vary by context and task.

The data in both sectors conclusively supports Hypothesis 1 (H1): Consumers will be more willing to use human service assistants than AI-based assistants. In banking and hospitality, human assistants were rated significantly more positively than AI ones, regardless of task type.

This explicit preference for human interaction is highly aligned with both the TAM (Davis, 1989), which emphasizes perceived usefulness and ease of use, and more specifically with the sRAM (Wirtz et al., 2018), as well as the researcher's expectation. A TAM extension that encompasses supplementary factors of social presence, anthropomorphism, and emotional engagement. In emotionally charged settings such as hospitality, where service is judged not just on efficiency but also on warmth and rapport, the human assistant fulfills consumer expectations far more completely than AI.

In banking, the support for H1 is equally strong. Customers continued to prefer human assistants even for uncomplicated transactions such as balance inquiries. This once again reflects the importance of trust and perceived risk, which are basic constructs in both TAM as well as the UTAUT (Venkatesh et al., 2003). Consumers may consider human agents as more capable of handling sensitive or error-sensitive contexts, especially where financial expenses are involved.

On the other hand, Hypothesis 2 (H2) was not supported by either industry. Contrary to expectations derived from the researcher and the ELM (Petty & Cacioppo, 1986), consumers were not significantly more likely to be willing to trust AI for low-involvement tasks. One may assume that low-level tasks are less cognitively processed and could be easily performed by machines, yet respondents preferred human service even in these low-risk situations.
This pattern shows that emotional comfort and trust can overcome task complexity, particularly in environments where the service encounter itself has symbolic or psychological meaning, as it does in hospitality. It also shows that customers will not automatically turn to AI, even when effort and involvement are low.

Interestingly, the interaction effect (Assistant Type × Involvement Level) was significant only in the banking sector. Here, there was greater rejection of AI for low-involvement tasks, which ought to be the most promising context for automation. This paradox further highlights the role of contextual trust: people may just not feel comfortable depending on AI, even for simple tasks, when money is at stake. This result aligns with the UTAUT model, which focuses on performance expectancy and perceived risk as major drivers of acceptance.

Conversely, in the hospitality industry, no such interaction was found. The preference for human assistants was consistent across levels of involvement. This validates the author’s expectation and is easily explained by sRAM, as it argues that emotional and relational aspects prevail in hospitality. When social cues and emotional presence are central to the service experience, assistant type (human vs. AI) emerges as a much more important factor than task complexity.

CHAPTER FIVE

Discussion of the Study

This chapter discusses the major conclusions of this study in relation to the theoretical model and the earlier discussed literature in Chapter 2. The objective is to describe the consumer willingness patterns to use AI versus human service assistants identified in the hospitality (hedonic) and banking (utilitarian) sectors, and to evaluate whether such results are consistent with the predictions derived from such models as the TAM, the UTAUT, the sRAM, and ELM.

5.1 Assistant Type Matters More than Task Type

One of the major findings for both industries was the significant direct effect of assistant type on people's willingness to use the service. For bank and hospitality activities alike, respondents overwhelmingly preferred having human assistants over AI assistants, regardless of the extent of involvement required of the task. This result validates the author's expectation and confirms Hypothesis 1 and is also very much in line with the TAM and sRAM, which state that perceived trust, usefulness, and social presence are powerful determinants of the adoption of new technology (Davis, 1989; Wirtz et al., 2018). Human attendants are rated as having more socially intelligent and empathetic qualities, very much fitting in with hedonic contexts such as hospitality, but also very prominent in high-risk ones such as banking.

This finding is in line with prior research (e.g., Belanche et al., 2020; Choung et al., 2022) and shows that affect and trust are required, even for routine or low-involvement service interactions. It also aligns with the ELM's underlying contention that consumers rely on more peripheral cues (e.g., warmth or empathy feelings) under low cognitive involvement conditions, making human assistants more appealing under any circumstance.

5.2 No Clear Support for the Role of Task Involvement Alone

Regarding Hypothesis 2, the level of task involvement alone (high vs. low) was not a significant influence on the use of AI assistants within either the hospitality or banking sector, contrary to the author's expectation. Although literature suggests lower involvement should lead to greater receptiveness to AI due to reduced cognitive load (Petty & Cacioppo, 1986), no direct effect of involvement on preference was observed in this study.

This counters one of the implications from ELM: that degree of involvement alters routes of information processing so as to make AI more acceptable for low involvement uses. In these cases, trust and agent type appear to override task complexity across both industries. This finding also suggests the limitation of relying solely on ELM in measuring human-robot interactions, particularly within emotionally sensitive or trust-oriented industries.

5.3 Sectoral Differences and Interaction Effects

While hospitality revealed no significant interaction of involvement level and assistant type, banking did. This suggests that in utilitarian contexts, where functional accuracy and perceived risk are paramount, task involvement is a moderator in consumers' perceptions of AI versus human assistants. Consumers were particularly reluctant to apply AI to low-involvement banking tasks, such as balance queries or transfer routines, perhaps because even routine banking activities contain personal or financial data, which increases perceived risk.

This significant interaction in banking aligns with UTAUT's emphasis on trust and perceived risk as adoption impediments (Venkatesh et al., 2003) and can also accommodate the social influence factor of UTAUT, consumers are still able to see AI as too impersonal or untrustworthy for close service situations.

Conversely, the hospitality industry's interaction effect of aversion could be an expression of a human tendency towards warmth and social interaction, even in low-stakes interactions. This is evidenced by research from Gursoy et al. (2019) and implies that hospitality customers potentially possess a deeply ingrained emotional interaction need that AI cannot currently fulfill.

This sector-specific divergence is particularly significant. While banking customers accept AI selectively for low-risk and functional conditions, the hospitality findings refer to stronger affect-based rejection. The rejection of AI even for low-involvement hospitality tasks indicates that hedonic consumers are driven not only by cognitive effort but also by relational expectations. This challenges the core assumption in the ELM that low involvement is paired with low resistance to automation. It instead assumes the hospitality exchange affects the norm of warmth of human contact and social presence regardless of task complexity. This finding, therefore, not only supports the theoretical worth of social presence for AI acceptance but also provides an important variable: contextually ingrained emotional needs can override the predicted effects of cognitive load.

5.4 Theoretical Contributions

This research contributes to the growing body of literature on AI adoption by analyzing the joint impact of assistant type and task engagement in two segmented service contexts. The findings provide nuanced contributions to the explanatory power and limitations of established theories such as TAM, UTAUT, sRAM, and ELM in AI-enabled service environments.

Extension of the TAM and sRAM Frameworks

The frequent selection of human assistants across the two applications confirms the sustained validity of both the TAM (Davis, 1989) and the sRAM (Wirtz et al., 2018). These two models assert that acceptance rests upon perceived usefulness, ease of use, trust, and social presence. Human assistant, as a natural resource, is viewed to provide higher social interactivity and is deemed to be rated more reliable and trustworthy, the dominant drivers of behavioral intention. This research underscores these components and adds to empirical findings showing that social-emotional factors still outweigh consumers' evaluations of service agents. Besides, sRAM's emphasis on emotional investment and anthropomorphism is particularly applicable in the hospitality setting, where patrons require affective, personalized exchange. The findings confirm the model's applicability in hedonic service settings, where AI is still trying to mimic sophisticated social cues offered by human agents.

Limitations of ELM and UTAUT in Explaining AI Acceptance

Although the ELM by (Petty & Cacioppo, 1986) and UTAUT by (Venkatesh et al., 2003) would predict that consumers use more heuristics in low-involvement conditions (which should benefit AI), no direct effect of level of involvement on willingness to use AI was found in this research. The hypothesis that cognitive elaboration is lower in low-involvement conditions, and hence that there is more usage of convenience or novelty elements such as AI, was not supported. Instead, trust and assistant type consistently overrode task complexity as the primary decision driver. This means that the ELM is not all-encompassing in its explanation of affective resistance to AI in services when social interaction is significant.

Similarly, UTAUT's effort expectancy and performance expectancy constructs can have diminished explanatory power in financial or emotionally sensitive contexts. If trust and perceived risk are not carefully taken into account. This is validated by the interaction effect in the banking context. which finds even low-effort tasks to be doubtful in character if the assistant is non-human.

Contextualizing Sector-Specific Responses

Finally, this study provides new evidence of how sectoral context shapes consumer attitudes towards AI assistants. In hospitality (hedonic), social presence and emotional involvement dominate; in banking (utilitarian), perceived control, accountability, and data sensitivity dominate. These results confirm previous literature that demands contextual application of acceptance models rather than assuming uniform consumer behavior across sectors.

5.5 Practical Implications

In contrast with the banking context, where a significant interaction was observed between assistant type and task involvement, hospitality results were clearly and uniformly in favor of human assistants across high-involvement and low-involvement tasks. It suggests that in hedonic service environments such as hospitality, consumer need is based firmly in interpersonal warmth and affective presence, traits that AI-powered assistants are not currently perceived to fulfill. Therefore, hospitality companies need to walk a thin line when substituting human staff with AI for guest-facing jobs, no matter how low-complexity or routine they are.

For banking, the findings indicate human support by AI is valued for low-involvement, functional contexts, such as checking account balances or requesting standard information. However, for emotionally involving or high-involvement tasks such as investment or home loan advising, human assistance is preferred. These findings indicate AI deployment strategies must be context-specific, not merely by industry but by task type and self-reported emotional involvement.

For system developers and designers, the implications mean that the design of AI should not only be functionally rich but also affective sensitivity towards user needs, especially in relational situations. Empathy simulation, reassurance, or social presence augmentation features can maybe lead the psychological route towards AI acceptance in emotive expression service contexts.

Highlight Human Presence in Emotionally Densely Sealed Service Environments

In hospitality, people have always gravitated towards human help at all levels of task complexity. That reinforces the centrality of human-centered service design, particularly where hedonic service settings are involved and trust, empathy, and emotional bonding become paramount. Hoteliers, restaurant owners, and tourism businesses should be cautious when fully replacing front-line human labor with AI, much less when it comes to work that involves warmth, care, or face-to-face communication. Instead, AI must come as a help tool, one that augments—not replaces—human provision of services.

Handle AI Integration in Banking with Care

In banking, this research indicated a strong preference for human assistance even for low-involvement, routine tasks. This would mean that perceived risk, accountability, and trust remain strong impediments to the adoption of AI in financial services. Banks must handle the introduction of AI-based services with caution by:

- Implementing transparency regarding how AI works and how consumer information is handled.
- Positioning AI as an efficiency booster, rather than a decision-maker for important or significant activities.
- Ensuring simple escalation to human assistance is possible when needed, in order to maintain consumer confidence.

Design AI with Human-Like Qualities, But Set Realistic Expectations

Given the pushback against accepting AI in both markets, especially where emotionally or personally relevant interactions happen, service designers must be attentive to incorporating social presence signals, tone of voice, responsiveness, and empathy simulations within AI interfaces. Consumers will still not be convinced if the gap between machine interaction and human warmth is still evident. Branding, communication, and role assignment are thus central to managing expectations.

Task Type and Service Domain Segment Adoption Strategies

AI deployment must not be one-size-fits-all. Organizations must develop task-specific and context-specific adoption strategies. For example:

In banking, AI might be more readily accepted in back-end operations or transactional interactions (e.g., viewing balance) than in advisory operations.

In hospitality, AI might be applicable in automating back-end tasks (e.g., managing room temperatures or taking orders), but not so for front-end concierge services.

Invest in Trust-Building Features and User Education

To overcome hesitancy, especially within data-sensitive sectors such as Banking, companies must invest in trust-building features. These include:

- Third-party endorsement of AI security.
- Open processes of consent.
- Clear opt-in/opt-out pathways.
- Educational campaigns demystifying AI technologies for regular consumers.

These can drive consumer openness to AI without jeopardizing satisfaction and loyalty.

CHAPTER SIX

Limitations, Future Research Suggestions and Conclusion

This final chapter specifies the study's most significant limitations, proposes future research directions, and offers final comments summarizing the study's primary contributions and implications.

6.1 Limitations and Future Research Suggestions

Despite the contributions the current research makes to consumer acceptance of AI-driven service assistants in banking and hospitality contexts, there are limitations. Acknowledging these boundaries provides a clearer interpretation of the results and lays the foundation for future research.

Small Sample Size and Generalizability

The most apparent limitation is probably that of a comparatively small sample size. While analysis revealed statistical significance in some areas, other possible significant trends (e.g., combined effect of task involvement on hospitality) failed to reach significance on the conventional 5% level but were near reaching marginal significance on a 10% level. This means that with a larger, more representative sample, there were possibly other effects to be discovered or already discovered ones to be tested with more certainty.

Future research must attempt to have more and more varied numbers of participants demographically in a way that the levels of generalizability to populations and cross-cultural generalizability are higher.

Contextual Scope: Two Service Industries

This research targeted the hospitality (hedonic) and banking (utilitarian) sectors. While intentionally chosen to be representative of contrasting service dynamics, inferences are not automatically made across industries such as healthcare, retailing, or education. Future research must investigate AI acceptance in a larger variety of service contexts with tasks of medium complexity between purely hedonic and utilitarian tasks (e.g., web-based technical support or travel agents) to discern contextual effects.

Experimental Design Constraints

Experimental vignettes with scenario-based manipulation were utilized in the research to rule out assistant type (human vs. AI) and task involvement (low vs. high). The design allowed for experimental control and testability of hypotheses, but may be ecologically invalid. The participants put themselves hypothetically into service interactions, which are not necessarily representative of the emotional, cognitive, or behavioral responses in real-world settings.

Future studies can use field experiments, simulations, or longitudinal studies to gain a deeper insight into user behavior and decision patterns over time.

Ignoring Mediator and Moderator Analysis

In the current investigation, analysis accounted for the direct effects of assistant type and involvement level. However, models such as TAM, UTAUT, and sRAM suggest that several mediators (e.g., trust, perceived usefulness, emotional comfort) and moderators (e.g., technology readiness, age, experience) influence AI acceptance.

Future research must continue to keep mediating and moderating variables constant to control for underlying psychological processes of willingness to use AI and examine individual differences in user response.

Measurement Limitations

The dependent variable, willingness to use, was self-reported by the respondents on a Likert-scale item. While easy-to-collect self-report measures such as this are subject to social desirability bias or hypothetical bias, no actual usage behavior or satisfaction post-use was assessed in this research.

Future research would be enhanced by including attitudinal measures to complement behavioral measures such as usage logs, clickstreams, or follow-up surveys of repeated use and satisfaction after use.

Accelerated AI Development Pace

The AI landscape is evolving at a rapid pace with developments in conversational agents, affective computing, and generative AI. The authors of the paper can envision future assistants being envisioned very differently from the present pace of capability for future AI. Consumer expectations and trust, as AI progresses further, are bound to be affected.

There will be a constant endeavor to reshape acceptance frameworks on a continuous basis so that they are functional within the backdrop of changing technological and societal forces.

6.2 Conclusion

The purpose of the current study was to analyze consumer reaction to human service assistants versus AI-based assistants across two industries, hotel and banking, based on the degree of task involvement propelling their usage of these services and the type of assistant concerned. The study was theoretically grounded in a robust theoretical base, which was borrowed from the TAM, UTAUT, sRAM, and the ELM, all in one way or another, unveiling rational and affective determinants of consumer behavior in technology-mediated service interactions.

There is evidence supporting a generalizable human assistant preference across industries in favor of Hypothesis 1 and toward existing literature contributing to determinants of emotional bonding, trust, and perceived competence in the service encounter. Customers in both banking and hospitality were much more likely to utilize human assistants, which aligns strongly with the author’s expectation and in cases of low-involvement activities where AI potentially could have monopolized. Contrary to what would otherwise be the case, task involvement per sector (Hypothesis 2) did not have a direct influence on consumer intentions to use AI-based assistants, contrary to the author's expectation. A result that refutes earlier ELM hypotheses that low cognitive effort will make one more accepting of automation. However, findings suggest the direction of social presence, trust, and affective comfort, the highest TAM and sRAM constructs being the best predictors of acceptance, and not cognitive effort or task complexity.

On the other hand, the most prominent assistant type by task involvement interaction effect was in banking, in the sense that consumer liking is greatest for low-involvement tasks. This is opposite to other research in the AI literature and implies the unique nature of consumer risk aversion and trust to function in high-sensitivity information-rich environments such as finance. At the same time, the hospitality industry also saw a global requirement for human assistance in task complexity towards facilitating affective expectations of hedonic services.

Using aggregate reports draws a bleak scenario for the adoption of AI. They point out that context is important, customers equate service technologies on affective, relational, and trust-based as much as utilitarian grounds. Although AI has the potential to maximize efficiency and personalization, it remains defeated where affective warmth, social signals, or perceived risk are at stake.

With the addition of empirical evidence gathered in two service settings, this thesis offers theoretical and practical management guidance. The enterprise poses companies a challenge to think beyond task type, but also emotion and expectation of trust imposed by customers on service encounters, a challenge that will remain relevant as AI technologies advance.

Direct answer to lead research question: "How does the type of assistant and level of involvement influence consumers' acceptance of using AI-powered service assistants?" The assistant type is found to be the highest opportunity maker, with human assistants preferred in all settings, especially in emotionally charged or socially sensitive settings. AI assistants are permitted to some degree, primarily in banking, low-involvement instrumental work, but more particularly in the banking example, where functional capability outweighs the technical richness of the relationship. Task involvement, although primarily initially postulated as a facilitator, did not necessarily account for readiness to accept AI usage but rather constructs such as trust, social presence, and affective comfort. Therefore, the involvement level is a less strong predictor of acceptance than the type of assistant, and consumers' relational and affective expectations are the primary mediators of AI use.

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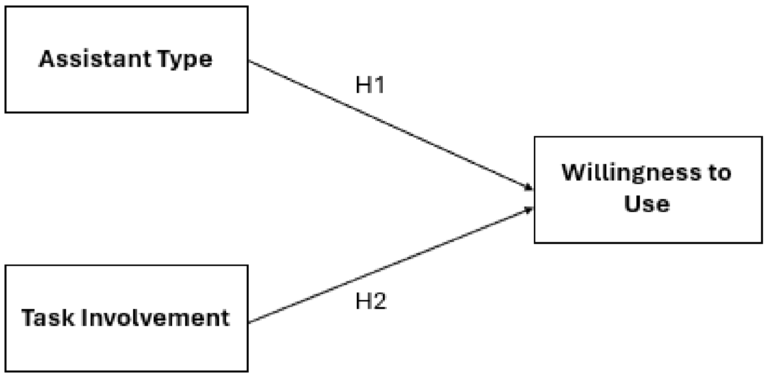
APPENDIX A: Conceptual Model and Survey Questions

Figure A1: The conceptual model



Survey Questions:

Customer Acceptance of AI Robot Services or Assistants in Banking & Hospitality.

Welcome!

In this short survey, you will read a few situations where a person or a robot assistant helps you with a simple task at the bank or in a hotel. After each situation, you'll be asked how you would feel or respond in that moment. Please answer honestly based on your personal thoughts and feelings. There are no right or wrong answers.

Thank you for your time!

Your participation is entirely voluntary, and you are free to withdraw from the survey at any time. The survey should take approximately 7-10 minutes to complete.

Instructions for Participants:

1. Read the scenario carefully and imagine yourself in that situation.
2. Answer a series of questions about your experience.
3. At the end, you will be asked questions about yourself (like age, gender, and if you have used an AI service before).

There are no right or wrong answers.

Please answer honestly. Your responses will help me learn more about how people feel about new service technologies.

Consent:

Please confirm that you agree to participate in this study

I have read the information above and voluntarily agree to participate in this study.

By ticking this box, you agree that the data collected via this survey can be used for scientific research.

- Yes, I agree to participate
- No, I do not agree to participate

Demographics:

Age

How old are you?

- 18-25
- 26-35
- 36-45
- 45+

Gender

What is your gender?

- Male
- Female
- Non-binary/third gender
- Prefer not to say

Education

What is your highest level of education?

- High school diploma or equivalent
- Bachelor’s degree
- Master’s degree
- Doctorate
- Other

AI Usage

Have you ever used an AI service assistant (e.g., chatbots, self-check-in, hotel self-service kiosks…)?

- Yes
- No

Residency

What type of area do you currently live in?

- A large city or urban area
- A rural area or countryside

Scenario Descriptions

1. Banking – Utilitarian – Low-Involvement – Robot Assistant

Context: You want to check available investment options for a savings plan and visit your bank. You contact an AI assistant that gives you personalized recommendations.

Interaction: The AI assistant asks questions about your income and risk preference. It suggests matching investment plans and explains them clearly. You can ask questions using a chat function.

2. Banking – Utilitarian – Low-Involvement – Human Assistant

Context: You want to check available investment options for a savings plan and visit your bank. You contact a human assistant who gives you personalized recommendations.
Interaction: The assistant asks questions about your income and risk preference. It suggests matching investment plans and explains them clearly. You can ask questions throughout the conversation.

3. Banking – Utilitarian – High-Involvement – Robot Assistant

Context: You are applying for a home loan and visit your bank. An AI assistant is available to help you with personalized recommendations.

Interaction: The AI asks for your financial details and preferred loan amount. It shows different loan options and compares interest rates, monthly payments, and terms. You can adjust inputs to update the recommendations, but it does not provide emotional reassurance or personalized advice.

4. Banking – Utilitarian – High-Involvement – Human Assistant

Context: You are applying for a home loan and visit your bank. A human assistant is available to help you with personalized recommendations.

Interaction: The assistant asks about your financial details and preferred loan amount. They show different loan options and compare interest rates, monthly payments, and terms. The assistant reassures you, answers your questions by providing emotional reassurance and personalized advice.

5. Hospitality – Hedonic – Low-Involvement – Robot Front Desk Employee/Server

Context: You check into a hotel and want to request extra amenities (extra towels, late checkout). An AI assistant at the front desk is available to help you.

Interaction: The assistant greets you, and you make your request using a touchscreen or voice command. The request is confirmed and processed right away.

6. Hospitality – Hedonic – Low-Involvement – Human Front Desk Employee

Context: You check into a hotel and want to request extra amenities (extra towels, late checkout). A human assistant at the front desk is available to help you.

Interaction: The employee greets you, listens to your request, and personally assures you that they will handle it. They provide additional information about hotel services and assist with further needs.

7. Hospitality – Hedonic – High-Involvement – Robot Front Desk Employee

Context: You are planning a unique vacation and want activities and dining options suggestions. An **AI assistant** is available to help you.

Interaction: The AI assistant asks about your preferences and shows options with descriptions, maps, and booking links. but does not provide emotional reassurance or personalized insights.

8. Hospitality – Hedonic – High-Involvement – Human Front Desk Employee

Context: You are planning a unique vacation and want activities and dining options suggestions. A human assistant is available to help you.

Interaction: The concierge asks about your preferences and engages in conversation to better understand your interests. They offer personalized recommendations and give personal insights into the best places. The human assistant provides emotional reassurance and personalized insights.

Scenario Related Questions:

Willingness to Use

- I will use this assistant in a similar situation.
- I will choose this assistant over other service options.
- I will recommend this assistant to others.
- I will feel comfortable using this assistant regularly.
- If I have a choice, I would prefer this assistant over an alternative.

Perceived Usefulness

- This assistant would improve the efficiency of the service
- The assistant would help me accomplish my task more effectively.
- Using this assistant would save me time.
- The assistant makes the process easier.

Ease of Use

- Using this assistant would be simple and intuitive.
- I would understand the assistant's instructions easily.
- I would not need extra help to complete the task.
- The assistant would quickly respond to my needs.
- I would find the assistant's interface (voice, touchscreen, etc.) easy to use.

Trust the Assistant

- I would trust this assistant to complete the task correctly.
- This assistant would provide accurate and reliable service.
- I would feel comfortable relying on this assistant in a real-life setting.
- This assistant would perform consistently well over time.
- This assistant would make unbiased decisions.

Comfort Level

- I am comfortable interacting with this assistant.
- The assistant's behavior and responses are natural to me.

- I would readily use this assistant in a public place.
- I would feel less nervous using this assistant than other options.
- The assistant would make the service experience more enjoyable.

We thank you for your time spent taking this survey.

Your response has been recorded.

APPENDIX B: SPSS Tables

Data Source: Researcher's Collected Data 2025

Hospitality:

The Number of Respondents:

Between-Subjects Factors

		Value Label	N
Assistanttype	1	AI	58
	2	HA	57
Involvementlevel	1	High involvement	60
	2	Low involvement	55

Two-way ANOVA:

Tests of Between-Subjects Effects

Dependent Variable: Mean Willingness of use

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	11.374[a]	3	3.791	3.178	.027
Intercept	1331.731	1	1331.731	1116.265	<.001
Assistanttype	7.790	1	7.790	6.530	.012
Involvementlevel	2.692	1	2.692	2.257	.136
Assistanttype * Involvementlevel	.725	1	.725	.607	.437
Error	132.426	111	1.193		
Total	1471.840	115			
Corrected Total	143.800	114			

a. R Squared = .079 (Adjusted R Squared = .054)

The Interaction Between the Independent Variables:

Estimated Marginal Means

Assistanttype * Involvementlevel

Dependent Variable: Mean Willingness of use

Assistanttype	Involvementlevel	Mean	Std. Error	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
AI	High involvement	2.913	.199	2.518	3.308
	Low involvement	3.379	.206	2.970	3.788
HA	High involvement	3.593	.199	3.198	3.988
	Low involvement	3.741	.210	3.324	4.157

Banking:

The Number of Respondents:

Between-Subjects Factors

		Value Label	N
Assistanttype	1	AI	55
	2	HA	65
Involvementlevel	1	High involvement	61
	2	Low involvement	59

Two-way ANOVA:

Tests of Between-Subjects Effects

Dependent Variable: Mean Willingness of use

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	27.198[a]	3	9.066	7.372	<.001
Intercept	1264.900	1	1264.900	1028.557	<.001
Assistanttype	22.191	1	22.191	18.045	<.001
Involvementlevel	.040	1	.040	.033	.857
Assistanttype * Involvementlevel	5.500	1	5.500	4.472	.037
Error	142.655	116	1.230		
Total	1504.520	120			
Corrected Total	169.853	119			

a. R Squared = .160 (Adjusted R Squared = .138)

The Interaction Between the Independent Variables:

Estimated Marginal Means

3. Assistanttype * Involvementlevel

Dependent Variable: Mean Willingness of use

Assistanttype	Involvementlevel	Mean	Std. Error	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
AI	High involvement	3.077	.199	2.683	3.472
	Low involvement	2.608	.226	2.160	3.057
HA	High involvement	3.513	.202	3.112	3.914
	Low involvement	3.909	.187	3.537	4.280