Exploring Ethical Implications of Adopting Autonomous Service Robots (ASRs) in Hospitality: A Mixed-Methods Study

by

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ABSTRACT

Since the pandemic accelerated the penetration of AI-based autonomous service robots (ASRs) in hospitality and tourism, people are more likely to experience these service innovations, which raises critical ethical concerns from consumers' perspectives. This dissertation focuses on the ethics of ASRs in hospitality and aims to 1) explore consumers' ethical perceptions of ASRs, 2) investigate factors that can affect consumers' intention to adopt ASRs in a post-pandemic context, and 3) examine how initial trust can mediate the relationship between consumers' ethical perceptions and facilitate the intention to adopt ASRs. This dissertation conducted two studies using the exploratory mixed methods approach to achieve these goals. Study one explored the consumers' ethical perceptions of ASRs, driven by various ethical theories, such as teleology and deontology. Using triangulation methodology, data collection proceeded through semi-structured interviews, focus groups, and on-site interviews. The findings revealed eight themes of consumers' perceived ethical issues of ASRs. These themes were categorized into two dimensions: ethical issues that arise during interactions and ethical issues that are inherent to the characteristics of ASRs. Therefore, a total of 16 ethical issues were identified. Study two further developed measurements of consumers' perceived ethical issues of ASRs by conducting two rounds of online surveys. A second-order model based on Technology Acceptance Model and Initial Trust Model was built to understand better the relationship between consumers' ethical perceptions and their intention to adopt ASRs.

By utilizing second-order confirmatory factor analysis and partial least square structural equation modeling, the main results demonstrated the relationships between the two dimensions of consumers' perceived ethical issues, perceived usefulness, perceived ease of use, initial trust, and behavioral intention. Furthermore, initial trust significantly mediated the relationship between consumers' ethical perceptions and behavioral intention, while personal innovativeness moderated the relationship between initial trust and behavioral intention. This study is the first to empirically explore, measure, and validate a framework regarding consumers' ethical perceptions of ASRs in hospitality. The findings contribute to the literature on ethics studies in business and information technology and provide valuable implications for managers in tourism and hospitality, policymakers, and those implementing ASRs in broader service contexts.

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CHAPTER 1

INTRODUCTION

1.1 Research Background

Technological innovation is the most vital driver of service innovation, referring to a process in which innovative ideas are embodied in tools, devices, or procedures that have practical value to society (National Research Council, 1992). In the tourism context, technological innovation indicates not just the technical development of new service functions but also the integration of technologies into tourists' holistic experiences (Huang & Hsu, 2010). Specifically, visitors can search for information about a destination to have a prior travel experience and reserve hotels and activities on different travel platforms, such as TripAdvisor and Expedia. Some hotels have adopted digital devices, including service robots and self-check-in/out kiosks, to offer innovative services. Hence, innovative technologies can provide unprecedented experiences to tourists, drive innovation in service, and bring new opportunities to the tourism and hospitality industry (Buhalis et al., 2019).

With technological advancement, intelligent technology, as one of the vital technological innovations, has revolutionized the service industry. Intelligence means changing its state or actions in response to varying situations and requirements (Li et al., 2017). Hence, intelligent technology can be widely defined as a new technology with intelligence that can make autonomous decisions based on the data to provide timely services to users in different contexts. Intelligent technology emphasizes its intuitive self-learning capabilities and interconnectivity with other intelligent agents, so it can make independent judgments and respond in varying situations (Li et al., 2017). For instance, like Siri and Alexa, virtual assistants can learn users' preferences and perform autonomous tasks or services. Thus, it is no doubt that these intelligent technologies play critical roles in altering consumer behaviors and revamping marketing strategies (Buhalis et al., 2019).

Artificial intelligence (AI), the core of intelligent technology, is a learning system that can learn, sense, reason, and act (Stanford, 2016). AI can analyze massive amounts of data and has been used as a decision-support tool to perform various administrative tasks related to consumer service (Wirtz et al., 2018). In the context of the tourism field, a rising trend of integrating AI into the service delivery process exists. AI-based systems on tourism websites can offer suggestions to help with consumers' basic requests. For example, Kayak is a travel tool and search engine which uses AI to process thousands of reviews to show consumers the best travel options and alternatives to the destinations with the best prices, travel times, and even vacation packages (German, 2023). Moreover, one of the essential functions of AI is that it enables a machine to be intelligent. Owing to the development of AI, the emergence of autonomous agents, such as service robots, drones, and automated vehicles, has dramatically increased the scope of the service sectors, provided convenience and efficiency, and substituted human labor in a range of tasks (Buhalis et al., 2019). Hence, these intelligent innovations transform the model of traditional human service into an innovative way of service delivery.

Especially in the hospitality industry, service robots have directly served consumers through social interactions while making autonomous decisions without human interventions (Ivanov et al., 2017). Multiple definitions of service robots exist in the literature. Service robots are physically or virtually independent and adaptable machines that interact with and deliver consumer services (Wirtz et al., 2018). Bowen and Morosan (2018) attached the intelligent feature to service robots and stated that service robots become physically embodied intelligent agents that can take action and affect the world. Later, scholars stressed the social functions of service robots presenting service robots as social roles with a relatively high level of intelligence that can interact with humans in an acceptable manner (Zeng et al., 2020). Thus, social robots are designed to have human likenesses, such as appearance and voice, and are also known as humanoid service robots (Lu et al., 2019). These features have triggered the perception that service robots should be treated as social entities with human-like social skills and autonomous decision-making abilities to interact with consumers directly (van Doorn et al., 2017). In this dissertation, to emphasize the AI-based feature of service robots, the concept of autonomous service robots (ASRs) is applied to highlight the core feature of autonomy. As a result, ASRs in this study are defined as AI-based service robots that can actively collect, store, and transmit private data and further learn from the environment while making autonomous decisions to interact with humans and serve consumers in hospitality.

During COVID-19, many hotels adopted ASRs as effective tools to beat the pandemic and provide contactless services (Seyitoglu & Ivanov, 2020). Coronavirus can be spread by close person-to-person contact and touching surfaces contaminated with the virus. Thus, the hospitality industry implemented social distancing procedures and adopted multiple types of ASRs to reduce the possibility of infection during the pandemic. For example, the South African Hotel adopted distinctive ASRs during the pandemic, including delivery robots for room service and luggage robots for taking luggage up to guestrooms (Pillay, 2021). The Westin Houston Medical Center Hospitality used housekeeping robots to automatically clean the floor and disinfect the air via germ-zapping UV light (Glusac, 2020). A few studies have investigated COVID-19 as a catalyst that promotes the adoption of service robots in hospitality (Gursoy & Chi, 2020; Seyitoğlu & Ivanov, 2020; Zeng et al., 2020). Currently, consumers are getting familiar with ASRs and have more opportunities to interact with these new applications in the hospitality industry. Therefore, the outbreak of the pandemic has accelerated the penetration of ASRs adoption and shifted consumers' attitudes and behaviors toward ASRs services.

1.2 Problem Statement

Consumers were forced to use the ASRs to reduce human contact during the pandemic. One study revealed that consumers had a positive attitude toward robot-staffed hotels when COVID-19 was significant (Kim et al., 2021). However, whether consumers are willing to embrace these innovations in the post-pandemic age is still being determined. In other words, as an increasing number of hotels and restaurants start to use ASRs to provide services when consumers can choose services provided by either human beings or ASRs without the threat of the pandemic, it is doubtful whether consumers will accept and adopt ASRs, especially in the hospitality industry. The impact of the pandemic has lasted for a long time, but little research on consumers' intentions to adopt ASRs in the post-pandemic period can be found.

An increasing number of hotels have adopted ASRs, but only a few grand hotels have adopted them. Hence, only a few consumers have had direct experiences with these robots in hospitality. As such, consumers may know about these service robots through online resources and others' experiences. However, owing to a lack of direct personal interactions with and basic knowledge about the functions of ASRs, they may generate uncomfortable feelings, ethical concerns, and moral issues about ASRs (Seyitoglu & Invanov, 2020). The ethical problems possibly influence their intention to use and lead to unethical outcomes, such as ethical issues related to responsibility, safety, and privacy (Siau & Wang, 2020). Hence, increasing chances for consumers to use ASRs exist, but consumers' ethical concerns may lead to resistance to these innovative services in the hospitality industry. As consumers play central roles in using and evaluating ASRs, it is imperative to understand their ethical concerns about ASRs, which are largely neglected in the previous literature.

Regarding the ethics studies of intelligent technology, the existing studies have primarily targeted the ethics of AI because ethics is involved in the whole autonomous decision-making process (Chi et al., 2020; Siau & Wang, 2020; Wirtz et al., 2018). The ethical challenges of AI focus not only on the moral behaviors of the humans who design, operate, and use AI but also on the ethics of AI itself, such as data security and transparency. Despite the growing literature on the ethics of AI, ethics studies about specific AI applications, like ASRs in the hospitality industry, still need to be explored. From the literature about service robots, only a few review papers theoretically point out the importance of the ethics of service robots in the hospitality industry (Chi et al., 2020; Siau & Wang, 2020). Hence, more empirical research is needed about the ethical issues of ASRs. For the specific ethical issues of service robots, extant studies have targeted information security, responsibility, and personal privacy as the dominant ethical concerns of service robots (Lin & Mattila, 2021; Tussyadiah & Miller, 2019). Thus, other underlying ethical challenges of ASRs, such as dehumanization and fairness, have failed to gain sufficient attention in the literature (Chi et al., 2020; Wirtz et al., 2018), and the impact of different ethical issues on the adoption of ASRs has rarely been given a chance to receive the attention. Therefore, a comprehensive understanding of consumers' ethical perceptions of ASRs is critical in hospitality.

Previous literature on information technology has examined that building trust is a critical antecedent of risk-taking behaviors because trust can reduce perceived uncertainty and drive consumers to accept and use innovative technologies (Chi et al., 2020; Tussyadiah et al., 2020). For this reason, consumers who build trust in ASRs will likely eliminate their ethical concerns and accept these innovations. Hence, a need exists to investigate the framework for examining how consumers build trust that reduces ethical concerns about ASRs and facilitates the consumers' intentions to adopt ASRs in the hospitality industry. Current literature has examined how trust affects the intention of service robot adoption (Fuentes-Moraleda et al., 2020; Tussyadiah et al., 2020; Wirtz et al., 2018), but how trust mediates the relationship between consumers' ethical perceptions and behavioral intention has been less discussed. In addition, trust-building is a dynamic process that begins with initial trust and develops into continuous trust (Siau & Shen, 2003). Initial trust presumes users have no reliable information before encountering a new technology (Li et al., 2008). Since most consumers may have no or little direct experience with ASRs, the concept of initial trust is more appropriate than trust to apply in this study. Hence, it is essential to investigate the importance of initial trust-building in the pre-adoption phase of ASRs in the hospitality industry.

1.3 Research Purpose

Consumers may be unlikely to use ASRs in particular situations because of various ethical concerns. Thus, it is vital to understand how consumers perceive these innovations from ethical perspectives and identify potential ethical issues of multiple ASRs. Building trust can significantly reduce concerns and drives adoption behaviors related to new technologies (Chi et al., 2020). Hence, it is necessary to investigate how to build initial trust for inexperienced consumers toward ASRs in hospitality. Once consumers build initial trust toward the ASRs, the ethical concerns may be reduced so that consumers may adopt these new services in the hospitality field. For these reasons, this dissertation employs an exploratory sequential mixed methods approach to achieve the goals. The exploratory sequential mixed methods can develop contextualized instruments by acquiring qualitative data and validating them via a quantitative study. Thus, utilizing the results from the initial qualitative phase to build the quantitative scales is a significant point in an exploratory sequential design (Creswell & Creswell, 2018). The mixed methods are chosen for three reasons. Firstly, there is insufficient literature on consumers' ethical concerns toward ASRs in hospitality. Secondly, the quantitative approach can further confirm the qualitative results, increasing the findings' validity. Thirdly, integrating qualitative with quantitative methods into one study can improve our understanding of complex phenomena and minimize the limitations of both methods (Malterud, 2001).

This dissertation is separated into two studies based on the exploratory sequential mixed methods. Study one aims to empirically explore consumers' perceived ethical issues of ASRs in the hospitality industry to comprehensively understand consumers' ethical perceptions. Study one uses the methodological triangulation approach, which collects triangulated data to enrich the dataset and reduce underlying bias. Study Two aims to establish a hypothesized model based on the qualitative findings about consumers' ethical perceptions toward ASRs and examine whether initial trust can reduce consumers’ ethical concerns and facilitate the intention to adopt ASRs in hospitality.

More specifically, study one utilizes the qualitative approach to comprehensively explore consumers' ethical perceptions of ASRs in hospitality via triangulated methods, including semi-structured individual interviews, focus groups, and on-site interviews. This triangulated approach can effectively increase the validity and reliability of the findings. Since consumers may have limited knowledge of and inexperience with ASRs, they evaluate the service based on their own ethical values and judgment. Ethical theories embody moral values that help to explain consumers’ ethical judgment toward ASRs in hospitality. Scholars have addressed that an individual’s ethical judgment may function with multiple ethical theories (Brunk, 2012). Hence, consumers may perceive different ethical issues of distinctive ASRs. Therefore, this study one aims to gain empirical and comprehensive explanations of various ethical concerns from consumers’ perspectives in a variety of ethical scenarios of using ASRs in hospitality.

Under a quantitative approach, study two aims to develop a hypothesized model and then examine how consumers’ ethical perceptions affect their behavioral intention and how to build initial trust to reduce ethical perceptions and increase adoption behaviors. The first step is to develop measurements of consumers’ ethical perceptions of ASRs based on the qualitative results. Then, grounded in the Technology Acceptance Model (TAM) and Initial Trust Model (ITM) (Davis, 1989; McKnight et al., 1998), the hypothesized relationship in the model is established. TAM measures the impact of perceived usefulness and perceived ease of use on consumers’ behavioral intentions via attitude (Davis, 1989). The previous literature has applied TAM to examine robot adoption in the general service contexts (Go et al., 2020; Kao & Huang, 2023; Parvez et al., 2022). ITM categorizes three dimensions that form initial trust: institutional, personal, and environmental dimensions (McKnight et al.,1998). Since consumers have few direct experiences with ASRs in hospitality, it is valuable to examine how the initial trust formation mitigates the impact of consumers' ethical concerns on behavioral intention in the context of ASRs in hospitality. Therefore, this dissertation integrates consumers' ethical perceptions with TAM and ITM to establish the model. The dependent variable in this model is the intention to adopt ASRs in hospitality.

Additionally, previous literature examined initial trust as a critical predictor of behavioral intention (Kim et al., 2009; Talwar et al., 2020). Initial trust is crucial to reducing the consumers' uncertainty, forming the first impression, and driving behavioral intention (Siau & Wang, 2018), so initial trust-building plays a mediating role between the consumers' ethical perceptions and the intention of ASRs adoption in hospitality. For moderators, previous studies have examined the moderating impact (e.g., age, familiarity, and innovativeness) on new technology adoption in different contexts, like digital wallets, social networking sites, and online shopping (Chang et al., 2016; Lee, 2022; Shetu et al., 2022). Therefore, these moderators are investigated in the context of ASRs in hospitality.

In summary, this dissertation aims to 1) comprehensively explore consumers' ethical perceptions of ASRs, 2) develop measurements of consumers' perceived ethical issues of ASRs, 3) examine the influence of TAM constructs and consumers' ethical perceptions of ASRs on initial trust and behavioral intention respectively, 4) investigate the mediating impact of initial trust between antecedents and outcomes regarding ASRs adoption, and 5) identify the moderating impact of age, familiarity, and innovativeness on the relationship between initial trust and behavioral intention.

1.4 Research Questions

To fill the identified gap in the literature, this study integrates TAM and ITM with consumers' ethical perceptions to investigate the impact on the consumers' intention to adopt ASRs in hospitality in the post-pandemic age. Therefore, the overarching research questions are postulated to address in this dissertation:

RQ1: What are consumers' ethical perceptions toward ASRs adoption in hospitality?

RQ2: How do consumers' ethical perceptions influence their intention to adopt ASRs in hospitality in the post-pandemic age?

RQ3: How does building initial trust mediate the relationship between consumers' ethical perceptions and the intention to adopt ASRs in hospitality?

1.5 Significance of Study

This dissertation has several contributions to both academia and industry. Theoretically, this dissertation contributes to the literature by identifying consumers' ethical perceptions of ASRs in different service contexts (study one) and examining the relationships in the hypothesized model consisting of consumers' perceived ethical issues, perceived usefulness, perceived ease of use, initial trust, and intention of adoption regarding ASRs in hospitality (study two). Consequently, the results can provide empirical evidence about consumers' ethical perceptions of ASRs and examine how the ethical perceptions affect the intention to adopt ASRs in hospitality in the post-pandemic age. The findings also emphasize the mediating impact of initial trust regarding ethical concerns and behavioral intention since the previous studies mainly treat trust as an independent variable and ignore its mediating impact (Kim et al., 2009). With increasing intelligent technologies appearing, studying the concept of initial trust is essential to facilitate adoption for inexperienced users. In addition, this dissertation represents the first study of ASRs adoption in hospitality from an ethical perspective using mixed methods. The measurements of consumers' ethical perceptions are validated in both qualitative and quantitative methods.

For managerial contributions, this study provides valuable insights for both managers and policymakers seeking to understand consumers' ethical concerns toward ASRs. Through our empirical exploration, managers can implement corresponding practices to reduce the consumers' ethical concerns and increase adoption behaviors regarding ASRs. Policymakers can determine the regulations and laws to protect the benefits and rights of consumers regarding using ASRs. Moreover, this study delineates a series of salient factors that influence the initial trust and behavioral intention regarding ASRs. Thus, a door is opened for hospitality managers to cultivate consumers' initial trust, overcome their ethical concerns, and drive acceptance and usage of ASRs. Lastly, examining the intention to adopt ASRs in hospitality in the post-pandemic period can guide hospitality managers and designers of ASRs to formulate marketing strategies, successfully invest in these innovative services, and improve the consumers' experience with these innovative services in the future.

1.6 Outline of Chapters

This dissertation follows the exploratory sequential mixed methods approach, separated into two studies. Each study with specific research purposes includes four sections: literature review, method, findings, and discussion. Study one reviews the literature about ethics, ethical theory, and ethics of AI and robotics, particularly consumers' perceived ethical issues of ASRs in hospitality. This study adopts a qualitative approach to collect data through three steps (i.e., semi-structured individual interviews, focus groups, and on-site interviews). Data is analyzed via content and thematic analysis. The discussion concerns consumers' ethical perceptions and their implications for academia and industry.

Study two firstly reviews the literature about each variable in the model, including previous studies about ASRs adoption, TAM, and ITM. The model is established based on the theory, and hypotheses are proposed based on the existing studies. Then, the measurements of consumers' perceived ethical issues are developed through qualitative results and tested in the two rounds of surveys. Data are collected via online surveys to examine the model via factor analysis and partial least squares-structural equation modeling. The discussion targets the implication of causal relationships in the model. The final section concludes this dissertation, focusing on the summary, theoretical and practical implications, limitations, and recommendations for future study.

STUDY ONE

CHAPTER 2

LITERATURE REVIEW

2.1 Ethics

The concept of ethics, also called moral philosophy, is complex and broad (MacKinnon & Fiala, 2014). Morality is often used as a synonym for ethics, but there is a difference between these two terms. Morality refers to the actual content of right and wrong, while ethics involves the entire process of determining what is right and wrong (Bartneck et al., 2021). In other words, the concept of ethics provides the basis for morality. Hence, ethics is broader than morality, widely used in academia.

Scholars have conceptualized ethics from various perspectives, so there is no universally settled definition. As a subfield within philosophy, *philosophers* believe ethics concentrates on the concepts and principles that guide individuals or groups in determining what behaviors help or harm sentient creatures (Paul & Elder, 2006). Due to conflicts and disagreements, people need a philosophical inquiry into basic ethical questions and a consensus on certain social things, such as fairness and no harm to humans (MacKinnon & Fiala, 2014). The purpose of ethics study can significantly guide ethical judgment and moral obligations for human beings. Thus, ethics is a rational and systematic discipline of the standards of what principles, rules, and guidelines are correct (Kazim & Koshiyama, 2021). *Psychologists* focus on ethics from the individual perspective and study the formation of personal ethical values and the impact on personal choices when confronted with a situation. In this domain, ethics refers to a capacity to think critically about values that direct individual actions (Churchill, 1999). Personal moral values are largely internalized from own life experience, family, society, religion, law, and workplace setting, so people may interpret the values and make judgments differently in various contexts. Personal ethical values are employed to make choices and evaluations involving the whole process of decision-making (Des Jardins & McCall, 2014).

From a *social* perspective, ethics concerns general norms and principles instead of personal ethical values. Thus, ethics is regarded as a norm for distinguishing between acceptable and unacceptable behaviors (David & Resnik, 2020). Ethics is usually discussed with laws in a social context. Society has specific regulations and laws to govern human behaviors, but ethical norms tend to be broader and more informal than laws (David & Resnik, 2020). Thus, ethics becomes a kind of soft law regulating human behaviors. *Practically*, some scholars define ethics as a method for deciding how to analyze complex real-life problems (David & Resnik, 2020). The method can be applied to solve the ethical dilemma, so multiple perspectives are considered, such as political, economic, and environmental. This study conducts under the psychological aspect to understand ethics from personal values.

The literature on ethics has utilized various approaches, including descriptive, normative, meta, and applied ethics (Beauchamp et al., 2004; Caldero & Crank,2004). Firstly, the descriptive approach focuses on the descriptions of ethical terms, such as right/wrong, good/bad, just/unjust, and virtuous/vicious. Scholars also describe specific moral beliefs or behaviors. Secondly, normative ethics attempts to formulate general ethical theories to explain and guide what humans ought to do (Evans & Macmillan, 2014). These theories commonly treat specific ethical problems in practice, such as fairness, responsibility, and discrimination. The difference between descriptive and normative ethics is that the former focuses on what is valued, whereas the latter is concerned with what should be valued (Des Jardins & McCall, 2014). The empirical insights form the basis of descriptive ethics, which provides essential input for normative ethics (Bartneck et al., 2021). Thirdly, like the theory of normative ethics, meta-ethics concerns moral ontology and epistemology (Bartneck et al., 2021). In other words, meta-ethics deeply discusses the origin and the nature of ethics. Pollock (2021) further explained meta-ethics as a discipline investigating whether ethical systems are relative, universal, self-constructed, or independent of human creation. Simply, meta-ethics is the way we understand and evaluate normative ethical theories. Last, applied ethics emphasizes applying normative ethical theories to solve controversial problems in specific fields (Evans & Macmillan, 2014). As the interactions increase between humans, between humans and machines, and even between machines, ethical theories have been applied to various real-life situations to solve different ethical dilemmas, such as marketing and machine ethics (Siau & Wang, 2020). In this sense, applied ethics cannot be entirely distinguished from normative ethics. Hence, applied ethics is much more complicated than normative ethics and needs to investigate specific ethical issues in certain fields. In the following section, different ethical theories under normative ethics are interpreted.

2.2 Ethical Theory

Utilizing the approach of normative ethics, the primary concern is identifying the theory to explain individuals' ethical judgments about proper actions (Michaelidou et al., 2021). Ethical judgment refers to an individual evaluation of how a behavior is ethical or unethical (Hopkins & Deepa, 2018). According to this, scholars establish a rationally justifiable basis by investigating ethical theories. Ethical theory refers to a systematic exposition of a particular view about the nature and basis of good or right (MacKinnon & Fiala, 2014). Ethical theories can provide ethical principles that embody specific moral values and offer a clear and comprehensive framework for individual ethical judgment in practice.

The literature on ethical theories has two dominant traditional ethical theories: teleology and deontology (Barnett et al., 2005). *Teleology* is formulated by weighing the consequences of actions, which means an act is considered ethically correct if it leads to better results. This school of thought emphasizes that an action is ethical if it leads to the best possible balance of maximizing positive outcomes and minimizing harm (Kimmel, 1988). Utilitarianism is one of the teleological theories and maintains the principle of utility that promotes the greatest happiness, well-being, satisfaction, welfare, etc., for all related parties (Beauchamp et al., 2004). The numerous interpretations of utilitarianism can be divided into act and rule utilitarianism (Kazim & Koshiyama, 2021). Act utilitarianism directly judges the outcomes of each alternative act in a situation of choices, whereas rule utilitarianism builds a promise and evaluates the results by following or breaking the promise. However, critics of teleology believe that it is only concerned with the consequences of actions, regardless of the act itself (Beauchamp et al., 2004). For example, positive effects could be achieved from unethical activities. Ethical behaviors could result in unforeseen adverse outcomes in the long term. When ethical decisions benefit the majority at the expense of the minority, the minority's rights may not be considered, enabling the action to be unethical (Caldero & Crank, 2004).

Deontology focuses on ethical motivations instead of the results of actions in teleology (Des Jardins & McCall, 2014). Kant is one of the most influential contributors to deontological theories. He stated that an act could be considered right if it follows the moral duties that are essential, absolute, and applied to everyone equally (Kant, 2006). Even if it sometimes produces a wrong consequence, deontological theories frame specific duties and rules that people must follow, such as human dignity and civil rights, (Kimmel, 1988). Human dignity is inviolable of being human (e.g., respect and no harm), and civil rights are fundamental to the political community (e.g., benevolence and fairness) (Kazim & Koshiyama, 2021). However, while Kant emphasized universal obligations, critics have argued that ethics is inadequate concerning handling particular responsibilities in various problems and the possibility of conflicts of different duties in our lives (Des Jardins & McCall, 2014).

In line with previous ethical theories, scholars have developed other theories to guide human behaviors, such as virtue ethics and social contract. *Virtue ethics* highlights an individual's character development regarding understanding moral actions (Caldero & Crank, 2004). This theory believes that cultivating virtuous characteristics (e.g., wisdom, courage, temperance, and justice) is viewed as the primary function of ethics. Simply, we ought to be virtuous people, so we are likely to act ethically. However, one weakness of virtue ethics is that a person's adverse change in moral character is not taken into account. For example, a scientist may change from an ethical to an unethical character for a purposeful and profitable intent in the short term. Furthermore, *social contract theory* stresses the importance of moral rules and laws in society (Caldero & Crank, 2004). The selfish nature of humans may increase risks to our lives, families, and properties. Hence, the social contract theory is a collective consensus about a solution that ensures societal safety, such as no killing or destruction. This theory provides a basis for understanding why societies or organizations have implemented rules, regulations, and laws. Still, it does not guide how people ought to behave in a particular situation (Caldero & Crank, 2004).

In summary, each ethical theory attempts to use insights to shed light on different aspects of particular ethical issues and explain individual ethical judgments. Scholars have addressed that an individual's ethical judgment may function with various ethical theories (Brunk, 2012). Hence, these ethical theories can provide a theoretical foundation to explain different consumers' ethical judgments. The following section is going to review the literature regarding applied ethics in the field of AI and robotics.

2.3 Ethics of AI and Robotics

AI has widely penetrated our lives. For example, Siri of Apple and the recommendation systems of TikTok are AI-based. AI is a learning system that can learn, sense, reason, and act (Stanford, 2016). AI can synthesize sophisticated software and hardware with large databases to allow the machine to make decisions at the human level of intelligence and perform more complicated tasks than prior technologies (GeeksforGeeks, 2020). Thus, AI has become the core of making machines intelligent. However, researchers recognize apparent ethical concerns as to advancements in AI technology. Therefore, studies of AI ethics have been divided into AI ethics, robot ethics, and machine ethics. AI and robot ethics refer to the moral behaviors of how humans design, construct, use, and treat AI systems and robots, respectively (Veruggio & Operto, 2020). These areas are related to ethics studies of humans surrounding AI systems and robotics design. Machine ethics is concerned with giving machines ethical procedures for discovering a way to resolve the ethical dilemmas that machines might encounter, enabling them to function in an ethically responsible manner through their ethical decision-making (Siau & Wang, 2020). In other words, machine ethics emphasize the ethics of the machine itself, such as algorithms and data. According to the above categories, Siau and Wang (2020) distinguished ethical AI from the ethics of AI. Specifically, the ethics of AI deal with ethical issues that arise when designing, developing, and using AI, while ethical AI targets analysis processes and ethical/unethical outcomes of AI.

In terms of the ethics of AI, many institutions and governments discuss and establish AI frameworks to guide AI development. The institution of electrical and electronics engineers builds ethical principles for AI and robotics development, including awareness of misuse, accountability, and data transparency (IEEE, 2019). The ethical guidelines for trustworthy artificial intelligence of the European Union include seven essential requirements: human oversight, technical robustness and safety, privacy and data governance, transparency, diversity, non-discrimination and fairness, societal and environmental well-being, and accountability (European Commission, 2019). These ethical principles can serve as a valuable structure for securing the ethical outcomes of AI and robots. These institutions prioritize the ethical issues of responsibility, privacy, and transparency in their ethical framework. Floridi et al. (2018) proposed an AI4People framework by applying human ethical principles (non-maleficence, beneficence, autonomy, and fairness) into the context of AI and adding another dimension of explicability. Precisely, ethical AI should follow the ethical principles of humans, for example, not physically harm individuals, promote human well-being and dignity, strike a balance of the power of decision-making between humans and AI, and facilitate fair outcomes of social justice. The additive principle of explicability means AI must be understandable to humans and responsible for its actions (Floridi & Cowls, 2021). Since there is overlap across the global consensus on AI ethical principles, Jobin et al. (2019) summarized the current regulations of AI ethics and revealed a global convergence on five ethical guidelines: transparency of algorithms, justice of results, non-maleficence of human rights, the responsibility of actions, and privacy of data. With the advancement of AI, the higher level of intelligence has received more attention to technical restrictions and moral arguments (Huang & Rust, 2018).

Regarding specific ethical issues of AI, three dimensions have been categorized by Siau and Wang (2020): technical features, human factors, and social impact. First, the *technical features* of AI may cause three ethical challenges: transparency, data security, and personal privacy. Specifically, AI should be transparent to everyone, but even for experts, the algorithms take a long time to understand, so people cannot easily know how AI works (Siau & Wang, 2020). The misuse of data and the issues related to protecting personal information can increase the risks of using AI. Second, *human bias*, such as gender and race bias, may integrate into the AI systems, resulting in unethical outcomes. The morality of humans may not be seen as perfect because humans cannot recognize all ethical problems and solve all identified ethical issues (Siau & Wang, 2020). Hence, AI could generate bias due to the origins of programmers, operators, and users. Third, the *social impact* of AI mainly focuses on technological job replacement. Most scholars debated whether AI would lead to workforce disruptions, while some argued that new AI-related jobs could be created in the future (Siau et al., 2019; Wang and Siau, 2019). Besides, accessibility is another issue as it is unclear whether AI is available and suitable for vulnerable people, including the elderly and disabled groups. Therefore, these ethical issues of AI are urgent to solve before it is widely applied in practice.

In conclusion, the previous ethics studies on AI and robotics mainly focus on two streams. One direction is formulating the ethical principles that direct the use and development of AI and robotics. The other direction is investigating the potential ethical issues regarding AI and other AI-based applications. Recognition of specific ethical issues of AI can mitigate the potential risks and increase the benefits of AI usage. ASRs, as one type of AI-based application, may contain all the ethical problems of AI. Thus, the following section reviews the literature on the underlying ethical issues of ASRs, especially in the hospitality industry.

2.4 Ethical Issues of ASRs in Hospitality

The studies of the ethics of ASRs are still in the infancy stage. The ethics of ASRs is more complicated than that of AI because ASRs consist of both the features of AI and the functions of service contexts. The different service scenarios of ASRs may generate specific ethical issues. Except for one recent quantitative paper that examines the impact of the ethical problems of human-robot interactions, the rest of the articles are review papers that address the theoretical significance of studying the ethics of ASRs, including data security and privacy, fairness, responsibility, job replacement, and dehumanization (Siau & Wang, 2020; Wirtz et al., 2019). The summarized current literature on the ethics of service robots is presented in Appendix A. A total of 11 papers were published through the end of 2022.

Each ethical issue is delineated as follows. The first issue is *data security and privacy*. ASRs can collect and store consumers' data, which is helpful for management and operation in hospitality (Siau & Wang, 2018). However, if the data is not appropriately protected, its misuse and malicious use could harm the consumers personally and financially. For example, cybercriminals can steal sensitive information (e.g., ID and credit card) from corporations and efficiently use the information for illegal activities. The recorded metadata, including personal behaviors, locations, and voices, could allow others to impersonate consumers for fraud activities. Voice impersonation fraud rose by 350% between 2013 and 2017 (Livni, 2019). If these situations were to occur, consumers might face potential deception issues. Moreover, as service robots with multiple cameras and sensors can monitor and record the consumers' behaviors, voices, and locations, this type of surveillance may cause consumers uncomfortable feelings as it can infringe on their freedom and right to privacy (Tussyadiah et al., 2020). Thus, it is essential to consider what should be recorded and who can access the data (Siau & Wang, 2020).

Moreover, the *fairness* issue is an ethical concern caused by using ASRs. Human bias can inevitably lead to the tendency of intelligent agents (Siau & Wang, 2020). Hence, ASRs can be developed based on incomplete or skewed datasets and algorithms, which may lead to biased results. For instance, a facial recognition system primarily serves Caucasians and may not accurately recognize other ethnic people (Zou & Schiebinger, 2018). Therefore, unintentional ethnic bias could result in critical justice issues (Chi et al., 2020). Moreover, increasingly sophisticated ASRs should take responsibility for their social roles and actions. Since only some consumers have prior experience with service robots, consumers cannot respond appropriately and immediately to a service failure (Leo & Huh, 2020). If consumers would have gotten hurt during the ASRs services, who should take responsibility is still a debated argument (Um, Kim, & Chung, 2020). The failure of the service robots takes a different form compared with general human service failures. Thus, consumers without experience may worry about mistakes during interactions and whether multiple solutions are available.

In addition, from a social aspect, employees are concerned about whether ASRs can lead to *job replacement* (Wirtz et al., 2018). Due to the pandemic, some jobs have been replaced by ASRs to avoid workplace infections of COVID-19 and keep operating costs low, especially in the hospitality industry (Semuels, 2020). Some repetitive and low-skilled tasks have been given to ASRs, such as delivery and luggage robots (Nourbakhsh, 2015). Thus, there were increased ethical concerns about job security. Nevertheless, some scholars have argued that high-level creative and emotional work, such as building a relationship with consumers, cannot be automated because humans still possess a competitive advantage of empathy (Nourbakhsh, 2015). Lastly, the dehumanized algorithm of ASRs would lead to consumers' social isolation. ASRs can connect with other AI agents to offer a series of services without human contact. Currently, ASRs cannot meet the consumers' emotional demands, which could lead to severe psychological loneliness (Veruggio et al., 2016). For example, the reviews from the Henn-na Hotel describe that the robot services are cold, eliminating a feeling of welcome and care (Bhimasta & Kuo, 2019).

The above ethical issues have been discussed in the literature, but no empirical studies comprehensively investigate specific ethical issues of ASRs in the hospitality industry. When ASRs are applied in the service industry, we argue that the ethical problems of ASRs could arise not only from the characteristics of ASRs themselves but also during service interactions. Hence, this paper conducts from the consumers' perspectives and comprehensively explores their ethical perceptions of ASRs in the hospitality industry.

2.5 Consumers' Ethical Perceptions of ASRs

Consumers' ethical perceptions are mainly discussed in marketing ethics. Marketing ethics is a systematic study of how moral standards are applied to the behaviors of humans and organizations (Nadeem et al., 2021). Agag et al. (2016) summarized five streams of marketing ethics: ethics in marketing strategy (e.g., price and promotion) (Bakir & Vitell, 2010; Tsalikis and Seaton, 2008), specialized fields of marketing ethics (e.g., education in marketing) (Gioia, 2002), companies' social responsibility (O'Fallon & Butterfield, 2005), ethical consumption (e.g., unethical behaviors of consumers identification) (Kallis et al., 1986), and consumers' perceptions of corporate marketing ethicality) (e.g., consumers' perceived ethical issues of online shopping) (Román, 2007). Thus, consumers' ethical perceptions toward firms are significant in marketing ethics. Brunk (2012) proposed that the business perspectives of ethical/unethical actions of firms could be incongruent with consumers' perceptions. Hence, the ethical perceptions of consumers' views should receive special attention.

The concept of consumers' ethical perceptions has been examined in different arenas. In marketing, consumers believe sales behaviors should conform to social norms, such as honesty, full disclosure, and fairness (Ou et al., 2015). Agag et al. (2016) defined buyers' ethical perceptions of sellers in the context of online retailing as "positive perceptions about the behavior of e-retailers that handle consumers in a confidential, fair, honest, and sincere manner that ultimately protects consumers' interests." They identified six dimensions of buyer perceptions of seller ethics: privacy, security, reliability, non-deception, service recovery, and shared value. Moreover, in the field of information and communications technology (ICT), as technologies facilitate the performance of services, consumers generate ethical perceptions towards advanced technologies employed in companies. For example, the determinants of consumers' ethical perceptions toward sharing economy platforms are privacy, security, shared value, reliability, and service recovery (Nadeem et al., 2021). Therefore, consumers can generate ethical perceptions toward sales and technologies during the services. ASRs, as an emergent intelligent technology, can provide unique services unfamiliar to consumers. ASRs can be treated as social identities with autonomous ability to perform particular tasks like human beings (Ivanov et al., 2017). Thus, consumers' ethical perceptions of ASRs are much more complicated than human services because ASRs can be treated as service providers and technologies.

Consumers can form different ethical perceptions about specific behaviors, which reflect their subjective ethical judgments. Hence, consumers' ethical perceptions of ASRs are defined in this dissertation as the consumers' subjective beliefs of righteousness/wrongness of ASRs' behaviors related to specific services in hospitality. Thus, consumers could engender diverse ethical perceptions regarding the various actions of different types of ASRs. The aforementioned ethical theories (e.g., deontology and teleology) could be applied to explain consumers' diverse ethical judgments. Hence, this study concentrates on the consumers' ethical perceptions of ASRs by recognizing the consumers' perceived ethical issues of ASRs in the hospitality industry.

CHAPTER 3
METHOD

3.1 Research Design

Huang and Rust (2021) proposed three levels of AI: mechanical, thinking, and feeling intelligence. Given the different levels of AI, ASRs can be categorized to perform various tasks owing to their distinct capabilities. Firstly, *mechanical intelligence* is the lowest level that can limit robots' ability to perform simple, standardized, routine, and repetitive tasks. For example, delivery robots with mechanical intelligence like "Dash" at the Crowne Plaza Hospitality can only perform simple jobs with limited consumer interactions, such as product delivery to guests' rooms (Social Tables, 2020). Secondly, *thinking intelligence* is relatively higher because it follows rule-based learning and performs complex, systemic, and predictable tasks. For instance, robot ambassadors with a high level of thinking intelligence, like "Pepper" in Mandarin Hospitality, can be applied to greet consumers with personalized communications, accurately answer property-specific questions, provide check-in/out services, and make recommendations and reservations (Newsdesk, 2017). Lastly, *feeling intelligence* is the highest level of AI that can be used to complete robots' emotional and humanlike interactive tasks. However, feeling intelligence is infancy, so AI applications can barely read and react to individuals' emotions. Emotional demands remain the territory of human employees (Huang & Rust, 2021).

Based on the levels of AI, dominant ASRs in the hospitality industry can be classified into two groups. One group consists of highly interactive ASRs with thinking intelligence (e.g., robot concierges and chatbots) that perform complex services, such as giving hospitality-related information, providing multiple complex services, and communicating with consumers. The other group of ASRs with mechanical intelligence (e.g., robot bartenders, cooking robots, cleaning robots, and delivery robots) barely communicate with consumers and only offer simple tasks. For instance, food delivery and luggage robots can deliver products and luggage to guest rooms, respectively. In the hospitality industry, these low intelligent ASRs are applied broader and easier to operate in different service contexts than the highly interactive ASRs.

Methodological triangulation is a method design in which multiple methods and data sources are integrated to develop a comprehensive understanding of phenomena (Carter et al., 2014). Methodological triangulation is advantageous for confirming the results, providing more comprehensive data, increasing validity, and developing various aspects of understanding a complex phenomenon (Bekhet & Zauszniewski, 2012). Owing to the two types of ASRs with different levels of intelligence in the hospitality industry, consumers may perceive various ethical concerns regarding different ASRs. Hence, this study adopts three steps under a qualitative triangulated approach to comprehensively investigate the consumers' ethical perceptions of various ASRs in the hospitality industry.

3.2 Data Collection

The process of data collection is divided into three steps. The first step is semi-structured individual interviews, which are exploratory to identify different ethical scenarios of various service robots in the hospitality industry. Then, three focus groups explore ethical issues in consumers' perceived ethical scenarios of three specific service robots (e.g., delivery robots, robot bartenders, and chatbots). Last, the on-site interviews recognize ethical issues based on consumers' actual experience of the corresponding three

ASRs in Las Vegas. The interview protocols and consent forms are shown in Appendix B and C, respectively.

Step 1: *Semi-structured Individual Interviews*. The semi-structured interview is more flexible than the structured interview since interviewers can modify questions based on the answers and explore an in-depth understanding of responses (Bernard et al., 2016). Considering that the number of individuals with direct experience with ASRs in the hospitality industry is relatively minor (Lu et al., 2020), a purposive sampling strategy was used to recruit people both with and without experience regarding ASRs in hospitality. In addition, the researchers summarized a table with the current dominant roles of ASRs in the hospitality industry (shown in Appendix D), enabling the participants to understand the functions and roles of different ASRs in hospitality.

Before the interviews, participants had been informed of the purpose of this study, the interview process, and the requirement for audio recording. During the discussions, participants first introduced themselves, such as age, race, profession, and description of past experience with ASRs. Then, they reviewed the table containing different ASRs in hospitality. The interviewers also helped with describing the various functions of these ASRs. After introducing distinctive ASRs, interviewees answered questions following the interview protocol, including a series of open-ended questions. Three pilot interviews were performed to refine and finalize the interview protocol. The interview questions were created depending on consumers' past experience with or without ASRs in the hospitality industry. For example, "Can you describe your experience with service robots in a hospitality and/or restaurant?" which is asked for experienced participants; on the other hand, "If you were to go to a hotel or restaurant with a service robot, what experience might you perceive?” which is asked for non-experienced participants. The primary interviews were conducted via Zoom platform, phone call, or in person in the spring of 2022. The process of each individual interview lasted for approximately 25-30 minutes. The number of participants is decided based on the principle of saturation, which means the data collection process should stop when there is no additional valuable information (Charmaz, 2006).

Step 2: *Focus Groups*. Participants in this step have no experience with ASRs because this step aims to explore the consumers’ perceived ethical scenarios of ASRs in hospitality. Young generations may have experience with ASRs, have more information and knowledge about ASRs, or at least watch videos related ASRs. Thus, we recruited relatively older generations for these focus groups. Convenient and snowball sampling strategies were used to recruit participants. The appropriate size of a focus group is around six to eight interviewees (Creswell & Creswell, 2018). Three focus groups targeted three different ASRs in this study, including delivery robots, robot bartenders, and chatbots. The reasons for selecting these three ASRs are 1) these ASRs have been practically applied in the hospitality industry and 2) these three robots covering diverse characteristics can represent the service robots. For example, delivery robots and robot bartenders have a low level of interaction and physical appearance, while chatbots have a high level of interaction and virtual status. Since low interactive ASRs are more widely used in hospitality than high intelligent ASRs, two ASRs with machinal intelligence (i.e., delivery robots and robot bartenders) and one ASR with thinking intelligence (i.e., chatbots) were selected. Thus, these three case studies could be employed to understand consumers’ ethical perceptions and generalize the findings comprehensively.

Before the focus groups, participants had been informed of the purpose of this study, the process of discussion, and the requirement for video recording through email. Participants consented to attend the focus group by sending back their personal information. $15 for each person was provided as compensation. Participants first watched a short video about how a specific ASR functions and provides services in each focus group. Then answered five open-ended questions following the protocol, such as "What are your feelings about using this service robot?" and "How likely would you want to use this service robot in a hotel or restaurant setting?" Participants were encouraged to elaborate on each question during the discussion freely. The three focus groups were conducted via the Zoom platform in the spring and summer of 2022. Each focus group lasted for over one hour.

Step 3: *On-site interviews*. In this stage, participants were recruited at the site. Hence, all interviewees have direct interactions with specific ASRs and meet the goal of this phase, which aims to explore consumers' perceived ethical issues from actual experience. Purposive sampling was employed to maintain the diversity of interviewees. The number of participants meets the principle of saturation. Corresponding to the three different types of ASRs in focus groups, three ASRs in hospitality were chosen for on-site interviews: the delivery robot "Elvis" in Renaissance Hotel (delivering food to consumers' tables in restaurant or guest rooms), the robot bartender "Tipsy" in Planet Hollywood Hotel (making customized drinks in 90 seconds), and the chatbot "Rose" in Cosmopolitan Hotel (answering questions and making recommendations via text messages). These ASRs are all located in Las Vegas hotels in the United States.

Before the interviews, interviewers declared the purpose of this study and asked for their willingness to attend the interview and permission for audio recording. During the interviews, interviewees answered the questions based on the protocol, such as “How likely would you want to use this service robot in a hospitality or restaurant setting again?” and “What potential ethical issues are you worried about?” The three on-site interviews were conducted in the summer of 2022. The average time of each on-site interview is around 15 minutes.

3.3 Data Analysis

All individual answers were fully transcribed from the recording files in the data analysis process. The audio was played three times to confirm the wording and completeness. Since the Zoom platform has the function of transcribing the conversation automatically, the transcriptions on Zoom were double-checked verbatim with the audio files. For individual interviews in Chinese, one interviewer was responsible for translating it into English and ensuring the correctness of the meaning. All transcriptions were English versions as the basis for subsequent content analysis. The researchers looked through the transcriptions back and forth several times. Proper sentences and codes were highlighted and related to the themes to analyze the data. The analysis process considered the frequency, extensiveness, internal consistency of the words, the specificity of the responses, and the significant ideas conveyed (Rabiee, 2004). The qualitative data were classified via thematic analysis to identify the themes (Braun & Clarke, 2006). The multiple triangulations of verification and validation of the findings can minimize potential bias in interpreting data (Creswell & Creswell, 2018). For example, the triangulated data recourses and member checking can increase the accuracy of the qualitative findings. For reliability, the researchers checked the transcriptions several times to avoid mistakes and agreed on the codes and themes among the researchers.

CHAPTER 4

FINDINGS

4.1 Demographics

The demographics of 57 participants are presented in Appendix E. Seventeen (29.8%) participants participated in the semi-structured individual interviews. A total of 22 (38.6%) participants attended the focus groups. There were 18 (31.6%) interviewees involved in the on-site interviews. Participants have diverse cultures and backgrounds. Specifically, there were 29 (50.9%) males and 28 (49.1%) females; the age range of interviewees was from 20 to 60; 24 (42.1%) participants had experience with ASRs, whereas 33 (57.9%) interviewees had no experience with ASRs; 36 (63.2%) interviewees were likely to use ASRs in hospitality.

4.2 Qualitative Results

The analytical process reveals that consumers' ethical perceptions of ASRs in the hospitality industry emerged with eight themes of ethical issues: privacy, security, transparency, fairness, safety, socialization, autonomy, and responsibility. Each theme can be explained from two perspectives: ethical issues possibly arise during interaction with ASRs (e.g., ubiquitous surveillance, data excessiveness, unknown risks, full disclosure, inaccessibility, dehumanization, selection of services, service recovery), and ethical issues can be possibly raised from characteristics of ASRs (e.g., privacy infringement, malicious use, malfunctions, untrust, bias, job replacement, inflexibility, self-solved solutions). These issues are summarized in Table 1 below and explained in detail in the following sections.

Each ethical issue with corresponding one quote from the interviewees is presented in Appendix F.

Table 1

Consumers' perceived ethical issues of ASRs in hospitality

	Ethical issues arise during interaction with ASRs	Ethical issues can be raised from characteristics of ASRs
Privacy	Ubiquitous Surveillance	Privacy Infringement
Security	Data Excessiveness	Malicious Use
Safety	Unknown Risks	Malfunctions
Transparency	Full Disclosure	Untrust
Fairness	Inaccessibility	Bias
Socialization	Dehumanization	Job Replacement
Autonomy	Selection of Services	Inflexibility
Responsibility	Service Recovery	Self-Solved Solutions

4.2.1 Ethical Issues Arise during Interaction with ASRs

Ubiquitous Surveillance. Ubiquitous surveillance involves monitoring and recording consumers' behaviors and communications without their consent. Participants are concerned about any forms of surveillance under the ASRs. Some ASRs, like delivery and security robots, have built-in cameras and sensors to monitor human behaviors and detect potential risks. When consumers use these robots, their behaviors and conversations can be surveilled. Even other consumers who do not use ASRs can be unconsciously monitored. This type of surveillance can happen all the time. The responses showed, “If there are cameras on the robots, we should be notified. My behaviors may be restricted because every action is recorded, so I may feel uncomfortable and lose freedom of myself" (P5). "Informed consent should be acquired about the videotape all the time" (P10). "The robots may have cameras in them. People may not have any choices to be taken photos" (P21). In addition, especially when ASRs are in guest rooms, these robots can record consumers' private conversations. People must move or turn off the robots during sensitive or private conversations. One interviewee claimed, "I have an Alex in my room. I know a lot of people would say it's listening to us all the time. If we have a robot in the guestroom in hotels, it may record our words and gather the information that we wouldn't want to, so this is something I know, a big concern for a lot of people" (P34). Hence, the surveillance can cause consumer dissatisfaction and further legal issues, so informed consent for surveillance should be acquired from consumers before using the specific ASRs.

Data Excessiveness. Excessive data collection means that a large amount of consumer information is needed to initiate hotel ASR services, such as address, ID, credit card, etc. In certain situations, consumers have to input various information to use ASRs, such as age, address, email, phone number, ID, credit card, etc. Participants indicated that this process needs clarification because some information is irrelevant to a specific service. Respondents said, "The chatbots in hotels ask for too much information from me. I have to input a lot for processing, but I don't know how these data to be used, so I don't feel secure" (P6). "When I use chatbots, I feel that they ask a lot of information" (P11). Moreover, several ASRs require consumers to input information to process. Once mistakes happen, ASRs will repeat the previous steps. Participants argued that "I prefer to go human services so that it won't take a long time to go through the process that had been designed. Because robots are controlled by programs with a certain process, step by step. You have to go to this one first, then go next and next. I have to choose or type a lot of information, but if I have a human service, I talk to a server, and the server will know what I need and jump to the right point" (P36). Thus, when users input the data repeatedly, the ASRs may still not solve the problems, which results in timewasting and inefficiency.

Unknown Risks. Unknown risks mean potential negative consequences or hazards associated with ASR services that are not fully identified. Participants are worried about potential physical injuries and unknown risks. As ASRs are controlled by programs, technical issues may lead to ASRs losing control and harming consumers. We are still determining what is going to happen when ASRs lose control. Participants mentioned, "I don't know how robots work. I am afraid robots will cause sudden physical damage to me. For example, robot bartender may not hold the cup tightly when shaking the drink, or the delivery robot can crash on me" (P3). Additionally, different ASRs may have their own distinctive unknown risks in specific situations. Taking the delivery robot as an example, some potential dangers were revealed in the following responses: "Cross-contamination of food delivery. If somebody is allergic to peanuts, do hotels have to get cleaned robots between users, especially lots of people are touching it?" (P16). "What if someone just follows the delivery robot to take the elevator without the key card? The criminals can easily follow the robots to the guest rooms. Human staff may identify something wrong, but robots cannot feel criminals" (18). "How security the items robot delivers and what did robots do to make sure to the correct place they are intended" (P19). "When you ask for food and beverage, does anyone ever interact with the delivery robot within that timeframe? How do you make sure that your food and beverage are always safe, and no one changes them? (P22)”. Hence, various may generate different uncertain risks, and these potential risks can significantly influence consumers’ experience in certain situations.

Full Disclosure. Full disclosure of ASR services is defined as providing consumers with clear and transparent information about ASRs, including their purposes, capabilities, limitations, potential risks, whether extra fees are required, and whether personal data will be collected. As most people have yet to gain experience with ASRs in hospitality, the employees or front desk staff should comprehensively introduce the details and explain the functions of robot services to all consumers. For example, how to access the ASRs, what functions of ASRs, what services ASRs can provide, and whether extra fees are needed. ASRs are a novelty with various advantages, such as efficiency and convenience, but some consumers still need to learn to use ASRs. Hence, it is essential to get consent from consumers before directly providing the robot services. Respondents said, "If hotels have robot services, they need to disclaim them to customers clearly. If I am assigned to robot services, I would question why I serve by robots without notifications” (P5). “The hotels must declare the details of robot services. It is critical to know whether human service is available simultaneously. I would argue if I were assigned to robot services without notice because I would be disappointed if only robots served me.” (P13). As a result, if the service delivery process is conducted only by ASRs, the consumers should be informed first.

Inaccessibility. Inaccessibility refers to the design and implementation of ASR services that certain groups cannot access and use. Participants believed inaccessibility is an ethical issue of ASRs service. Consumers are afraid to touch them because people need more knowledge of ASRs. Thus, the assumption is that ASRs are challenging to access and not helpful for services. One respondent claimed, “I guess that even though the chatbot seems sophisticated, it can only answer pretty basic and easy questions" (P28). Other interviewees declared the language problem. For example, "For some people with dialects or accents, their language may not be recognized" (P5). "Las Vegas is an international city. The hospitality is really kind of restricting the people that can interact with this chatbot if they are only offering English. The challenge is there for people who don't speak English" (P28). In addition, participants consider how ASRs treat vulnerable groups of people. The responses show concerns, "All services are standard, so the minority may not feel more caring and friendly" (P5). "How do service robots treat disabled groups? There should be special considerations for these groups of people" (P13). "What if people from some areas and countries unfamiliar with these new technologies, they may run into some problems quickly" (P18). "Like older people, they may not understand how to use a robot like that, and they may sometimes be confused about what to do next" (P21). Thus, ASRs may not currently provide suitable services for these vulnerable groups.

Dehumanization. Dehumanization refers to treating consumers as less than human, denying their fundamental rights and dignity. Most participants argued that ASRs lack human contact because robots cannot meet the social demands of humans currently. There are no emotions involved in the service-providing process by ASRs, so interacting with these ASRs can result in severe psychological loneliness and dehumanization. Several responses expressed this point: "Robot services lack intimacy like humans, so psychological issues may arise" (P1). "Robots do not have emotions, so they cannot understand our feelings and humor" (P3). "Hospitality means friendliness and caring, so a person or interaction is very important, but I'm not sure about these robots. There is no personal interaction. Staff can share their personal experience, but robots only provide hospitality-related information” (P4). “The robot services are cold and less welcome” (P5). “I don’t think I would be comfortable with complete automation, like robots” (P7). “I should be greeted and treated very well by human staff in hotels. These robots make hotels less warm and caring” (P8). “A person can pick up the emotional response and address a sort of specific needs. However, robots may come across as insensitive when people are dealing with particularly hard issues” (P15). “Image how often we interact with humans daily, like basic interactions you have. If you eliminate those and substitute them with service robots in restaurants, for example, it would be less interesting. It influences my emotions and my psychological status. If I feel moody, the staff smiling at me can make me feel better immediately, you know, that's due to human contact” (P23). “You cannot express your emotions if you're talking to a robot. I would probably feel annoyed and angry. That's the only thing I can feel, but when we are with someone, we can feel emotions from them. So, robots cannot replace human factors” (P29). “If this kind of robot is used in servicing areas, I would say that some people may fear losing their social needs. Because some people will go to the coffee shop, they expect to communicate with someone having a conversation” (P36). The current level of ASRs cannot meet the social demands of consumers. For example, the robot bartender cannot provide a chance for a conversation as a bartender does. In certain situations, consumers may expect to have a conversation happen, so it tends to be depressed if there is no human interaction during the services. Therefore, ASRs may not reach the nature of hospitality.

Selection of Services. Foremost autonomy represents the freedom to select service providers between humans and ASRs to meet consumers’ needs. Interviewees thought consumers should be free to select services offered by humans or ASRs. During COVID-

19, consumers are forced to use ASRs in hospitality to maintain social distance and reduce human contact. However, in the post-pandemic age, people should have the right to choose services provided by either humans or ASRs. Respondents said, “If hotels have robot services, customers have the right to choose to be served by either robots or humans” (P5). “The hospitality industry should provide the options served by robots or humans. I would argue if I was assigned to robot services. I would be disappointed if only robots serve me” (P13). “I think having the robots is a good thing as long as I have the option to have human services… If someone is intimidated by the robot, they can have their other choices to have interactions with people” (19). As services from humans or ASRs have their advantages, the hospitality industry could offer the selection of both service providers for consumers. For example, if people are hurrying to get a drink, robot bartenders are probably much more efficient than humans. If consumers would like to have a conversation with bartenders about local attractions and their experiences, robots cannot replace the role of humans. Hence, both services should be available for people for different purposes.

Service Recovery. Service recovery refers to how hotels identify and resolve service failures. Consumers without experience with ASRs cannot immediately and appropriately respond to a service failure. Participants indicated that technical assistance and human support should be available. As participants addressed, “I wonder if the hotels have technical support when robots mess up the service” (12). “The delivery robots might get stuck when delivering food to guest rooms. If this happens, hotels may not solve the situation quickly and efficiently” (P17). “I think, what if I say something that the robot doesn't understand? What happens then? There's no other contact, and what should I do… A human may not know how to answer your questions, but they can refer you to someone else or call someone else to answer your questions, but the robot may not provide valid solutions” (18). “Maybe something was wrong, so you need to see a person to talk about and handle the situation and take responsibility for that problem. In the end, we need a real person. I think it shouldn't be just everything in artificial intelligence” (26). “I wonder if the chatbot is in a difficult situation, the chatbot cannot answer my questions, so is there any way to connect a real person” (P27). To some degree, ASRs are helpful for consumers. Once mistakes or errors happen, it may be a big accident that the hotels cannot take responsibility for providing alternative solutions quickly and efficiently.

4.2.2 Ethical Issues can be Raised from Characteristics of ASRs

Privacy Infringement. Privacy infringement refers to informational exposure without unauthorized access. Participants emphasized the importance of their privacy. Several participants have concerns about the infringement of their personal data, “There is an information security problem. Robots can easily leak my data and be hacked by others” (P3). “Robots can record personal information, so I don't feel secure enough to interact with robots” (P4). “ID is very sensitive, especially when I go abroad. I think if I put my passport number or my ID number on the chatbot, whether anyone can get all of my personal information, so someone can know my name, gender, date of birth, and all of the information they want” (P30). “One of the most common issues is concerned about privacy when you have more interactions with the robots… People don't want to share or want robots to have access to certain information, for example, information about credit cards” (P34). Moreover, the ASRs in hospitality can record the history of consumption, conversations, behaviors, etc. The exposure of this data, especially including sensitive and private information, is a serious ethical issue. One participant claimed, “When you're online and using the chatbot, your conversations will be saved, so you will get some records. If it includes sensitive stuff, I do not want someone else to see it” (P24). Consumers may feel uncomfortable and not trust ASRs when they cannot control their data. For example, errors in ASRs are possible to publicize consumer information. One respondent said, “Your information goes through somewhere which you don't know. It doesn't show up, and you don't know what is going on with the information, privacy, and data that you just put into the chatbot. You can go for one person, or you are talking with the whole company, and that's really big (26).” Intrusions into personal information privacy have become a serious ethical issue, so data protection is significant for hospitality. Interviewees said that “Robots may have more and more data. Is there a corresponding protection measure to prevent information leakage” (P2)? “How is personal data stored safely and destroyed? Whether robots record all information without permission, such as our conversations and consumption history? (P5)” Therefore, the hospitality industry should find a way to secure customers' personal information.

Malicious Use. Malicious use is defined as the intentional and harmful exploitation of consumer information for other purposes. Participants are concerned about not only the exposure of their data but also how the hotels or organizations use their data. Participants stated, “Will they sell the personal information to other companies” (P5)? “It is critical to figure out where hotels store my information and videos. It is very easy for companies to sell it to third parties without permission” (P8). “I feel one concern for me personally is that you don't understand or know how exactly they're (hotels and designed company) using this chatbot with the information that you put…the way they will use for the hospitality or other purposes. After using the chatbot sometimes, you would get, like an advertisement on Facebook, what we've never gotten before visiting Las Vegas. They might leverage data for advertising or for other uses which they don't have my consent for (29)". In addition, many organizations with data systems can be attacked by hackers. Hackers can enter the system and acquire consumer data for other purposes. If personal data is inappropriately protected, its malicious use can harm consumers financially. Participants asserted, "The hotels should find a way to make sure that the personal information of customers stays secure. I wouldn't want it to get hacked if they have my financial information" (P10). "I don't know to what extent they will abuse my information, and how the results will affect my life is a significant ethical issue" (P19). As a consequence, the malicious use of personal data is a vital ethical issue.

Malfunctions. Malfunctions are defined as unexpected interruptions in functions or systematic errors in the service delivery process, which may frequently happen in hotels as the advancement is still in infancy (Leo & Huh, 2020). Various malfunctions of ASRs can frequently happen in hospitality. Participants described malfunctions of different ASRs, for example, "Can delivery robot function correctly? What if the delivery robot delivers something wrong, like products, or delivers to the wrong rooms? That can be a serious problem" (3). "If somebody has an accent in the way that they speak, they may struggle with the robots" (P15). "If I try to ask some questions that are not simple, chatbots may not respond clearly and give me the correct answers… so the chatbot cannot get enough keywords I ask, and I cannot guess what the chatbot wants, what keywords it exactly catches" (P30). "What if the robot bartender gives me the wrong drink that I already paid for? If it's a human server, I can say you charge me for those I've not ordered, and the server can fix it. What if it's a robot, if it gives me the wrong drink and charges on my card, who I should tell this is wrong" (P32)? Hence, it is a high possibility that the ASRs may misunderstand the consumers' requests, or the words consumers intend to say. In addition, the technological robustness of ASRs should be given priority by hospitality. Participants said, "Once the robots cannot follow the pre-designed program, nobody knows what would happen. They can stop services immediately, or event hurt people" (P1). "I guess it becomes more frustrating for guests if robots stop working or give the wrong information" (P3). "I am worried that robots can get stuck. Once the malfunctions of robots occur, the efficiency of service can be significantly influenced" (P5). "I am afraid chatbots are not efficient and waste my time. When the system goes wrong, it takes longer if I start over, and I may still not get the accurate results" (P7). "I am afraid robots have technological malfunctions and stop suddenly" (P8). "The chatbots will not understand me if my information is different from the US citizens, so I need a real person there" (P11). "The robots may have bugs. The hotels need to fix the bugs. Otherwise, they will influence the consequences of my requests" (27). Therefore, malfunction is an essential ethical issue affecting consumers' experiences and service quality.

Untrust. Untrust means a lack of transparency in ASRs because consumers barely know the working process of ASRs, even complex functions, rationales, and algorithms. Participants do not trust ASRs because it is mysterious. People have limited knowledge about back algorithms and logic, so how ASRs work and deliver service is unknown. Participants stated, "When AI reaches a certain level, will robots be dangerous to humans or hurt people" (P2). "This new technology, we don't know how it's going to be looked like in the near future, what other functions, and what they are capable to do. So, we don't trust robots. In general, many people don't trust robots because they are not human. Simply, maybe they are less dangerous than humans, but you don't know what they are doing. We simply don't trust them" (P34). Especially for some functions, consumers barely understand the process and know whether the results are best for them. One participant argued, "When I ask for recommendations of restaurants and activities, I don't know exactly how I get the result from the chatbot. Even with the check-out service via chatbot, I cannot confirm if I have checked out and identified the bill. I have to ask the staff to double-check" (P14). What if the ASRs provide recommendations that enable consumers to be unsatisfied, they may consider why others get better results. Hence, ASRs can provide transparent and understandable explanations of the working process. As one respondent suggested: "It will be great to present an introduction about robots' functions and the rationale for the services. Guests have the right to know these, even if some might not be interested" (P1). Moreover, even the staff may not fully understand how ASRs work. For example, a delivery robot may take a few minutes to finish its tasks. After the robot departs to the guest room, the staff has no idea where it is. If a consumer asks for the robot delivery service, the employee cannot give an accurate timeframe for how long it will return. Once the delivery robot is stuck somewhere, staff cannot recognize it immediately. However, respondents do not trust the ASRs. "If somebody really wants to know how the information is used and process of service, the robots should provide specific information" (P3). "I would use my phone to get information since I would read more different opinions than from service robots" (P3). "I doubt the ability to accomplish services" (P5). "There may be errors when robots do not have enough data to train the model" (P7). "I would like to use my phone to get the same information that robots can provide" (P10). "I don't trust these robots because they are easily hacked" (P11). As a result, consumers do not believe ASRs can solve any problems and do not trust them.

Bias. Bias means attributes of ASRs that may lead to unfair or discriminatory outcomes in the services, such as appearance, algorithms, decision-making, and behaviors. The algorithm of ASRs can be biased. ASRs can be developed based on skewed datasets, which leads to biased results. Participants were afraid of potential discrimination and negative consequences. "We do not know what behaviors of robots should be coded. What and how should ethical situations be coded? Humans cannot pre-design every decision making for robots" (P3). "I wonder what kind of appearance of robots would present. Male or female? Caucasian or other races? These may lead to discrimination issues" (P3). "Customers may be curious whether the algorithms are fair and how robots provide services. For example, how to decide who should be served first" (P6). "White-centric features of the dataset may cause a potentially discriminatory issue towards people of color" (P8). "The hotels need to make sure that the robots are not going to become racists over time. It seems like the program is designed by the people, so those people should not have bias. I would worry that robots would give us inaccurate or prejudiced results" (P10). "The ethical guidelines within ASRs' codes could be able to discriminate against people. I am not just saying by gender or color, but by interaction with a different experience. The thing is that you don't know how AI will grow and discriminate one from another. Maybe it will give me an experience that is worse than someone else when I know that someone else got VIP passes or stuff like that, just because of the algorithm of AI. The AI figured out a way to help them out more than I did. This will make me feel worse at the end (P29)". "There is any what we call disparate impact. So, it looks like we're treating everybody fairly, but there's a disproportionate impact on certain groups, so monitoring would be important. You know the unintended consequences of using something like this chatbot and looking at whom is it benefiting and who is it not (24).” Hence, the algorithm of ASRs should be fair for anyone and any services. Therefore, it is apparent that the hotels must ensure that the ASRs will not become racist and give prejudiced results over time.

Job Replacement. Job replacement means using ASRs to perform tasks previously done by humans, ranging from simple and repetitive jobs to complex consumer services. Most participants were concerned that ASRs might reduce the opportunities for jobs for humans. The responses showed, “Employment for humans is important, but I am not sure how significantly these robots affect the labor market” (P5). “I feel like these robots may replace some human jobs. In Japan, they develop robots because of the small number of populations, but so many people need jobs in Mexico. I am worried about these robots’ replacing humans in the future” (P9). “If these robots can serve most guests, I think the hotels do not need to hire many people” (P10). “If service robots take over, I won't be able to find a job. That is a bit troubling for people who are not advanced at the educational level. They really need the service job, but they're not able to find one” (P23). Once these service robots possibly replace humans’ labor resources, the dignity and well-being of humans will be violated. In addition, once the mass ASRs are applied in the service industry, people not just lose their jobs but also influence their paychecks. This could lead to a serious social issue. The income of hundreds of people will be condensed so that this money may be distributed to big establishments, such as Tesla and Amazon. Participants argued, “Most labor may be replaced by robots, such as delivery” (P1). “When jobs would be replaced by robots, the employment rate could decrease significantly. The job could be more competitive" (P2). "Robots will take a lot of jobs from humans, which will affect the employment of the labor market" (P4). "People need jobs. These robots may replace human jobs" (P11). "At that point, you've got much less revenue spread amongst people, and you're just going to create a further divide in the class system" (P20). Thus, the social impact of job replacement raised by ASRs is critical.

Inflexibility. Inflexibility is defined as the limited ability of ASRs to adapt to changes in new tasks outside their pre-programmed capabilities. Participants argued that ASRs could not meet consumers' unique demands or give solutions in a particular context. Even if machine learning enables smart ASRs, ASRs are still pre-programmed so that flexibility is limited to meet specific requests from consumers. Participants claimed that "Robots are all standard, so they cannot treat a specific situation. Robots cannot take all situations into account" (P1). "Robots cannot provide customized services, so people may lose their loyalty. The standard process of service wastes more time to solve the issues and contact human service" (P2). "I am worried about the special requests for services. If my requests are outside the scope of the pre-designed program, the robots cannot solve the problems and waste time in the end" (P3). "The words and attitudes of a person can be adjusted according to the different customers you are talking to. For example, a more gentle and friendly conversation could make disabled persons feel more comfortable. However, robots serve people equally so that it doesn't offer caring to minorities" (P4). "Robots are programmed without living experience. I would like to know more about a personal experience related to the destinations or resorts, but the robots might only provide predesigned hospitality-related information" (P8). "Robots have limited capability to deal with emergency" (P5). "Because the robot gives you five choices, so you're about to choose only within these five choices. Let's say you want a service that demands more complicated, or I want to modify a bit of my service, how this robot will provide the service if there is no human intervention" (P23). "Something cut to me for customers would like special food needs, you can say, please do not add this ingredient to my hamburger because I'm allergic to the food, and then they know how to take care of the special order. Some people who are religious could require that they cannot eat certain foods. Like people who are vegan or have a particular medical requirement and other special biases, they will definitely feel more comfortable with a human than a robot" (P32). "If you feel unsafe to tell this word to the bartender or the waitress or waiter, they will help you, but I don't know that will not work with the robot bartender" (P32). "I think humans can do better personalization and services. They have intelligence but robots still don't have it. So, in personalization and many aspects of the service itself, I mean when you talk to humans, they understand you the way better than the robot understands you, so they can personalize your service in a better way in general (P34)". Hence, the inflexibility of ASRs cannot meet the demands of consumers.

Self-Solved Solutions. Self-solved solutions mean solutions that are recognized by ASRs themselves. Participants were concerned whether ASRs could identify and solve the error by themselves. Participants addressed that "Robots may face different kinds of scenarios to make decisions. Can robots identify their own stuck problems and make autonomous urgent reactions?" (P1). "What if robots have errors and malfunctions, I don't know what will happen and whether they can be resolved by themselves" (P16). With the advancement of ASRs, it is possible that they become more intelligent and can provide self-identified solutions for potential risks and issues. However, consumers still worry about any mistakes in service delivery.

4.2.3 Discussion on Ethical Issues of ASRs

From the participants' point of view, for ASRs with mechanical intelligence, participants primarily target ethical issues from functional and social perspectives. Specifically, ASRs are still in the infancy stage, so they possibly have many errors or bugs that influence the service quality. This study has identified several potential problems, such as unknown risks, inflexibility, malfunctions, and service recovery. These types of ASRs mainly serve consumers in a simple and standardized way. Once these ASRs cannot complete their tasks with many mistakes, this can lead to a negative experience for consumers. Hence, consumers may not accept and use these innovative services in the future. In addition, a commonly mentioned ethical issue is job replacement. Even if most participants believed ASRs could take humans' jobs, other respondents argued that other jobs were being created related to ASRs, so the total number of jobs may not decrease. Due to the nature of hospitality, it is mostly about personal interactions and the human touch. Some mechanical functions that occupy only a small part of the hospitality industry can be substituted by ASRs, but other tasks in a service delivery process still need humans. As one participant addressed, "I think, finally, this will happen, and robots will take jobs from humans, but I think that's going to take a long time, and everything will be different. Compared with now, how jobs are different from 50 years ago. Computers have replaced many of the jobs that humans used to do manually. I think now the jobs are different from even ten years ago and humans are adjusting to the new technologies. I personally think this will happen, but at that time, everything will be different, so it will not be an issue or a problem for employment. Because the types of jobs are going to be different for humans, we are adjusting the skill sets of employees. We need to learn as we move forward and adjust ourselves" (P34).

Regarding ASRs with thinking intelligence, participants not only consider the ethical issues from functional and social perspectives but also focus more on the informational and emotional sides. Hence, highly interactive ASRs have more ethical issues than low interactive ASRs. On the one side, people are worried about their information security and personal privacy, which have been emphasized in the previous literature (Ioannou et al., 2021). Because ASRs need consumers' data to provide the services, this study has recognized the ethical issues of privacy infringement, malicious use, and data excessiveness. In the age of big data, people continuously produce data and information. Consumers already have a sense of data protection. Hence, the hospitality industry should take action to store and use the consumers' data safely and carefully. On the other said, participants claimed that emotional demands could not be met by ASRs services because consumers need human contact during the services. However, some respondents argue that introverted people may struggle with socializing. These ASRs can solve their social anxiety and problems with speaking language. Hence, ASRs services have sort of advantages for these groups of people. Probably, there is a poll for consumers to choose either human or ASRs services. If ASRs are the only options, there still should have alternative ways to socialize with real people.

4.2.4 Consumers' Willingness of ASRs Adoption in Hospitality

Regarding adopting ASRs in hospitality, more than half of the participants without experience are likely to adopt ASRs for the first time because of curiosity. However, for the second time, participants are hesitant due to different ethical concerns. Several interviewees with experience are likely to continuously use ASRs because of previously satisfied experience. However, once ASRs leave a negative experience, participants hesitate to use them again. Hence, the first image of ASR services is crucial for consumers to build relationships with ASRs.

Moreover, most interviewees believed the intention to adopt ASRs in hospitality is situational based on consumers' demands and the purpose of the trip. As one participant mentioned, "I think it really depends on the purpose of the trip. For example, if you are doing more of a business trip, like a conference, having robot services will probably be faster and more convenient. Still, if you are going just for vacation, it is nice to have that human touch, be able to speak to somebody, and get an understanding of the community around your environment" (P21).

Lastly, in the previous study, the young generations are more willing to adopt innovative technology than the old generations, such as smartphones (Yoo et al., 2021). However, in this study, some young interviewees hesitate to use ASRs even for the first time, whereas relatively older participants are highly likely to interact with different ASRs. Hence, this study finds an exceptional result in the context of ASRs in hospitality. Given the above aspects, it is essential to quantitatively examine whether age can significantly influence consumers' intention to adopt ASRs in hospitality.

People are still determining how robots will develop and apply in the future because ASRs will be increasingly intelligent and autonomous. Most participants believed that a model of co-work, a service combination of humans with ASRs, would be the optimal result in the future. The ASRs perform repeated and routine jobs while humans oversee consumer interactions. As one participant stated, "The robots can help humans to pre-prepare, and then the human completes the process in some way, like the human interactions. It is like a complement to each other” (P32). Another interviewee commented, “I wonder if it will go full circle where all hospitality in the past had people, and now we're in this kind of transition period where we've got people and artificial intelligence. It might become where hotels only have robots in the future. Human service becomes a luxury experience at that time” (28). No matter what kind of service, the satisfaction of consumers is the most critical thing in the hospitality industry. With more ASRs adopted in hospitality, we need to think thoughtfully about these aforementioned ethical issues before their wide applications in the hospitality industry.

CHAPTER 5

DISCUSSION

Study one empirically explores consumers' ethical perceptions of ASRs in hospitality, which fulfills the goal of overarching question one. The findings emerge eight themes of consumers' perceived ethical issues of ASRs, including privacy, security, transparency, fairness, safety, socialization, autonomy, and responsibility. Each theme can be explained from two perspectives: ethical issues possibly arise during interaction with ASRs (e.g., ubiquitous surveillance, data excessiveness, unknown risks, full disclosure, inaccessibility, dehumanization, selection of services, service recovery), and ethical issues can be possibly raised from characteristics of ASRs (e.g., privacy infringement, malicious use, malfunctions, untrust, bias, job replacement, inflexibility, self-solved solutions). Therefore, a total of 16 specific ethical issues from two dimensions have been recognized from consumers' perspectives. These results demonstrate the following insights, which contribute significantly to the literature.

Firstly, this study conceptualizes the concept of consumers' ethical perceptions by identifying the underlying ethical issues of ASRs from consumers' perspectives in the context of hospitality. The concept of consumers' ethical perceptions has been applied in different fields, such as marketing and ICT (Nadeem et al., 2021; Ou et al., 2015). The concept of consumers' ethical perceptions in marketing literature mainly targets the ethics of service providers, while this concept in ICT literature primarily focuses on the ethics of using certain technology. Because of the features of ASRs, consumers can treat ASRs as humans and technologies simultaneously. Thus, this concept is redefined as related to ASRs adoption in hospitality based on previous ethical theories, such as teleology and deontology. Theoretically, this conceptualization can be helpful in a comprehensive understanding of consumers' ethical perceptions, not just the ASRs in hospitality but also the intelligent technologies in the border context. Thus, as increasing intelligent technologies enter the service industry, this study can pave the way to conceptualize the ethics of different intelligent technologies.

Moreover, this study extends the literature on the ethics of AI applications, particularly ASRs, by presenting consumers' ethical perceptions of ASRs based on qualitative inquiries. The findings explain eight themes, including privacy, security, safety, transparency, fairness, socialization, autonomy, and responsibility, which provide a comprehensive understanding of ethical issues of ASRs from consumers' perspectives in hotels. The results further uncover two dimensions of consumers' perceived ethical issues, which propose two ethics of ASRs in hospitality. Most prior papers focus on the ethics of AI and robotics and identify the possible ethical issues, such as ethical issues related to technical features, human bias, and social impact (Chi et al., 2020; Siau & Wang, 2020; Tussyadiah et al., 2020; Wang & Siau, 2019). These ethical issues also need to consider for ASRs. Thus, eight themes of ethical issues are concluded related ASRs. However, this study further explains these eight themes in two dimensions. One dimension (consumers' perceived ethical issues that can be raised from characteristics of ASRs) is in line with the previous studies. However, as ASRs are applied in the service contexts, ethical issues possibly arise during service interactions, such as ubiquitous surveillance, inaccessibility, and dehumanization. These ethical issues should receive more attention in the service industry, barely discussed in the previous literature. As ASRs directly serve consumers, these ethical concerns can significantly affect consumers' experience and service quality.

Once negative experiences with ASRs happen, consumers may lose confidence in these innovations and generate negative feelings about the brand image and reputation. Therefore, this study is the first to reveal two dimensions of ethical issues of ASRs from consumers' perspectives. The findings contribute to the literature by recognizing two dimensions of consumers' perceived ethical issues of ASRs in hospitality. As the previous studies only theoretically emphasize the importance of the ethics of service robots (Chi et al., 2020; Siau & Wang, 2020), this research fills the gap by providing empirical evidence to present two dimensions of ethical issues of ASRs in hospitality. The approach of methodological triangulation can increase the validity of these findings. Hence, this study proposes two dimensions of ethics of ASRs when applied in the service industry and emphasizes the importance of ethics during service interactions. The results are further classified into ethical issues driven by human-robot interaction and those driven by ASRs characteristics, which provide a theoretical foundation for other ethics studies of AI applications.

Lastly, this study shows a total of 16 consumers' perceived ethical issues, which can provide a comprehensive understanding of the ethics of ASRs from consumers' perspectives. In previous papers, many papers have investigated the ethical issues related to AI and robotics, such as information security, personal privacy, and responsibility (Lin & Mattila, 2021; Siau & Wang, 2020; Tussyadiah & Park, 2018; Tussyadiah & Miller, 2019). Some theoretical papers have addressed the ethical issues of ASRs, like dehumanization, fairness, and ubiquitous surveillance (Siau & Wang, 2020; Wirtz et al., 2018). The findings in this study separate the ethical issues based on the two dimensions of consumers' perceived ethical issues and expand each dimension to eight ethical issues with empirical evidence. These findings can enhance the understanding of the ethics of

ASRs from consumers' perspectives and extend the literature about business ethics and service robots on the ethics of ASRs.

From a practical way, this study provides valuable insights for hospitality managers and the whole service industry. The findings of this study can enhance comprehension of consumers' perceived ethical issues of ASRs in the hospitality industry. Even if there are debates on some ethical issues, all these ethical issues need to receive more attention. On the one hand, ethics about ASRs themselves have been identified in previous studies, but consumers may not realize and even understand those issues. Thus, the hospitality industry should consider all these issues before wide applications. For example, service robots must operate safely and reliably to prevent harm to guests or staff. Ethical considerations involve addressing technical limitations and potential risks, conducting regular maintenance and safety checks, and establishing protocols for handling malfunctions or emergencies. For privacy and data protection, service robots in hotels may collect and store sensitive guest data, such as personal preferences, habits, and biometric information. Ethical considerations arise regarding the collection, use, and protection of this data. It is crucial to ensure robust data security measures, obtain informed consent, and provide transparency in handling the data. In terms of workforce displacement, introducing service robots in hotels can lead to concerns about job displacement and unemployment among human workers. Ethical considerations include ensuring fair transition plans for affected employees, providing retraining opportunities, and creating new job roles that complement the work of robots rather than completely replacing human workers.

On the other hand, ethics during service interaction should receive more attention in the hospitality industry because ASRs directly serve consumers. Consumers are more likely to realize the ethical issues, especially when they meet particular situations. For example, some service robots are designed to mimic human behavior and interactions. This raises ethical questions about the potential for deception or manipulation. It is essential to establish clear guidelines and disclosure mechanisms to ensure that guests understand they are interacting with a machine and can make informed decisions about the level of trust they place in these robots. For accessibility, service robots should be designed to accommodate the needs of all guests, including those with disabilities or special requirements. Ethical considerations involve ensuring equal access, usability, and inclusivity in the design and implementation of these robots. Additionally, in situations where service robots interact with guests autonomously, questions of accountability and liability may arise in the event of accidents, errors, or damages. It is important to establish clear guidelines for responsibility and liability, outlining the roles of hospitality, robot manufacturers, and third-party service providers. Therefore, ethical considerations include studying the social acceptance of these robots, considering the broader societal and moral implications of their introduction and use, and aiming to ensure responsible and beneficial integration of robots in the hospitality industry while addressing potential ethical concerns.

Through our empirical exploration, the results can provide insightful suggestions for hospitality managers who are seeking to identify consumers' ethical perceptions toward ASRs in hospitality. For example, managers must make ethical decisions regarding deploying and using service robots. This includes determining which tasks are appropriate for robots to handle and which require human intervention. Managers should consider the potential consequences of their decisions on employees, guests, and other stakeholders. Hospitality managers also should have a responsibility to provide exceptional guest experiences. Ethical considerations arise when integrating service robots, as managers need to ensure that the use of robots enhances rather than detracts from the overall guest experience. This involves carefully selecting robot functionalities, maintaining human interaction where necessary, and monitoring guest feedback to ensure their needs and preferences are met. When sourcing service robots, managers should consider the ethical practices of the robot manufacturers and suppliers and strive to work with partners who align with their ethical values, assessing factors such as labor practices, environmental sustainability, and adherence to ethical guidelines. Lastly, hospitality managers need to consider the long-term implications of service robots. Ethical considerations involve evaluating the potential societal impacts, such as job market shifts and the broader implications for the hospitality industry. Managers should actively engage in discussions and collaborations to address these concerns and ensure sustainable and ethical implementation of robots. Therefore, managers can implement corresponding practices to reduce the consumers' ethical concerns and increase acceptance and usage of ASRs in hospitality, for example, protection of personal privacy and information, reduction of malfunctions and unknown risks, transparent and fair services, and available options for both ASRs and human services. Hospitality managers can develop strategies for promoting innovative services and developing consumers' experiences. By studying these ethical implications, hospitality managers can make informed decisions and develop strategies that prioritize the well-being of employees, guests, and other stakeholders, while effectively integrating service robots into their operations. These implications are relevant to the hospitality industry but generally to a broader range of service industries.

STUDY TWO

CHAPTER 6

LITERATURE REVIEW

6.1 ASRs Adoption in Hospitality

As a front-line service industry, hospitality has adopted ASRs in the early stage, such as a concierge robot at Hilton Hotel and a delivery robot at Savioke Hotel (Jong, 2017). Recently, much attention has been paid to ASRs in academia and industry. The positive views toward these innovations are evident. From the hospitality managers' perspectives, these innovations can solve labor shortages, reduce operating and labor costs, expand service capacity, and implement repetitive work efficiently and productively (Bowen & Morosan, 2018; Ivanov & Webster, 2017; Tussyadiah, 2020). Regarding consumer aspects, these new services can provide identical service quality, communicate in different languages, deliver enjoyable and entertaining service, and operate for 24 hours (Ivanov & Webster, 2017; Wirtz et al., 2018).

However, the ASRs can benefit all stakeholders, but the drawbacks of ASRs can inhibit the adoption of these innovations, especially in hospitality. Due to the high operation and maintenance costs, only some brand properties can afford these new services (Ivanov & Webster, 2017). Utilizing these innovative services would burden small and medium hotels heavily. Significantly, the staff is concerned about being gradually replaced by these innovations, given the work efficiency and speed of ASRs, which threatens job security (Ivanov & Webster, 2017). Thus, hospitality employees must learn and train how to use ASRs forcefully. From the consumers' aspect, they may experience anxiety and loneliness due to the loss of human contact and social support (Tussyadiah, 2020).

Consumers may hesitate to engage with ASRs due to a lack of knowledge and experience (Bowen & Morosan, 2018; Ivanov et al., 2017; Wirtz et al., 2018). Therefore, there is a continuing discourse on adopting ASRs in the hospitality industry among managers, employees, and consumers.

The COVID-19 pandemic accelerates the use of ASRs in the hospitality and tourism fields (Seyitoğlu & Ivanov, 2020; Zeng et al., 2020), so the research on ASRs adoption has been increasing quickly. Several studies have unveiled that the pandemic significantly affected consumers' acceptance of hotel service robots (Jiang & Wen, 2020; Wang &Wang, 2021). The papers from 2019 - 2022 related to AI-based applications adoption in tourism and hospitality are summarized in Appendix G. A total of 17 papers were published through the end of 2022.

Given that organizations aim to adopt ASRs to gain the above advantages, most studies were conducted from organizational perspectives and focused on the impact of COVID-19 (Bowen & Morosan, 2018; Xu et al., 2020). Pizam et al. (2022) proposed a technology-organization-environment framework (TOE) to examine managers' intention to adopt robotic technologies in hotels. The data across different countries indicated that hospitality managers' intention to adopt robotic technologies was positively influenced by their perceived relative advantage, competitive pressure, and top management support, whereas negatively affected by their perceived complexity of the technology.

However, as consumers are prominent in interacting with ASRs directly, their perceptions of ASRs significantly affect their acceptance of ASRs and guide the improvement of ASRs in hospitality. From the consumers' perspectives, prior studies have examined the different direct or indirect antecedents of behavioral intention toward service robots. For a direct impact on ASRs adoption, Cain et al. (2019) review the service robot acceptance model (sRAM) developed by Wirtz et al. (2018) and the Technology Acceptance Model (TAM) to summarize three dimensions of influencing factors on technology adoption: functional (e.g., perceived ease of use, perceived usefulness, and subjective social norms), social (e.g., perceived humanness, perceived social interactivity, and perceived social presence), and relational dimensions (e.g., trust and rapport). Fernandes and Oliveira (2021) further tested the sRAM and found that perceived social presence, perceived usefulness, trust, and rapport positively influence millennials' acceptance of digital voice assistance. Hence, functional and relational dimensions are essential to driving adoption behaviors. Regarding the indirect effect, Gursoy et al. (2019) proposed the AIDUA framework based on three steps of cognitive appraisal. The first step includes performance and effort expectance, which evoke the consumers' emotions. The elicited emotion in the second step can affect the intention to accept AI devices in the last step. Lin et al. (2020) extended the AIDUA model by including three additional antecedents: social influence, hedonic motivation, and anthropomorphism. Chi et al. (2022) further tested the AIDUA framework in different service contexts (airline and hotel) and trip purposes (leisure and business). Thus, the mediator is mainly emotional factors.

Concerning theory, Technology Acceptance Model (TAM) has been widely used in several studies as a theoretical basis to develop models, and two constructs in TAM have been tested positively affect the intention to use AI-based devices (Go et al., 2020; de Kervenoael et al., 2020; Lin & Mattila, 2021; Pillai & Sivathanu, 2020; Zhong et al., 2020). Melián-González et al. (2021) applied the United Theory of Acceptance and Use of Technology (UTAUT) to determine the factors influencing the intention to use chatbots while traveling. These factors included performance expectancy, effort expectancy, social influence, hedonism, habit, anthropomorphism, and perceived innovativeness. Lu et al. (2019) developed the Service Robot Integration Willingness (SRIW) scale for consumers' long-term views, which incorporated performance efficacy, anthropomorphism, social influence, facilitating conditions, intrinsic motivation, and emotion. Recent studies in the hospitality field have identified several features of service robots that can directly influence the intention of adoption, such as perceived usefulness, perceived ease of use, perceived innovativeness, trust, social influence, and hedonism (Abou-Shoul et al., 2021; Melián-González et al., 2021; Goel et a., 2022; Liu et al., 2022; Kim et al., 2022).

While most research on adopting ASRs has examined the positive factors, only two recent papers are related to the negative aspects of factors. Jang and Lee (2020) found that the perceived risks negatively influence the intention to use service robots in restaurants; Lin and Mattila (2021) only considered the impact of perceived privacy on the acceptance of humanoid service robots in hotels. Perceived risk has been tested as a critical factor influencing the intention to adopt new technology (Hwang & Choe, 2019). Especially for ethical issues, they have been mentioned by an increasing number of scholars. Hence, more than privacy risk is represented as the ethical risks of using ASRs. Etemad-Sajadi et al. (2022) summarized the ethical issues of service robots, including social cues, job replacement, autonomy, trust and safety, responsibility, privacy, and data protection. They found that only job replacement and autonomy do not impact users' intention to use a service robot in general service contexts. As scholars have highly emphasized ethical issues, it is urgent to test the impact of ethical concerns on consumers' intention to adopt ASRs, especially in the hospitality and tourism industry. As two dimensions of consumers' ethical perceptions have been found in the qualitative results of study one, the current study aims to test how the two dimensions of consumers' ethical perceptions influence their intention to adopt ASRs in hospitality. As TAM has been widely applied as a theoretical foundation to build the model, this study extends TAM by adding consumers' ethical perceptions and initial trust, which are reviewed in the following sections.

6.2 Technology Acceptance Model (TAM)

Literature targeting the acceptance and use of innovative technologies has lasted two decades, so studies on adopting new technologies have become increasingly mature. The Technology Acceptance Model (TAM) (David, 1989) has been widely used as a theoretical basis by which to examine the intention of new technology adoption toward various technologies, such as autonomous driverless cars, smartphones, wearable devices, etc. (Koul & Eydgahi, 2018; Sakkthivel & Ramu, 2018; Wang et al., 2020). TAM identifies various external variables (e.g., user characteristics and technology features) that can influence attitude and behavioral intention mediated by perceived usefulness (PU) and perceived ease of use (PEU), which further has an impact on behavioral intention and actual use. PU is defined as the degree to which a person believes that using a particular technology could enhance performance, while PEU refers to the degree to which a person believes that using a particular technology could be free from effort (David, 1989). As actual usage is tough to measure, literature mainly regards behavioral intention as the dependent variable. Behavioral intention (BI) refers to the strength of a personal intention to perform a specific behavior (David, 1989).

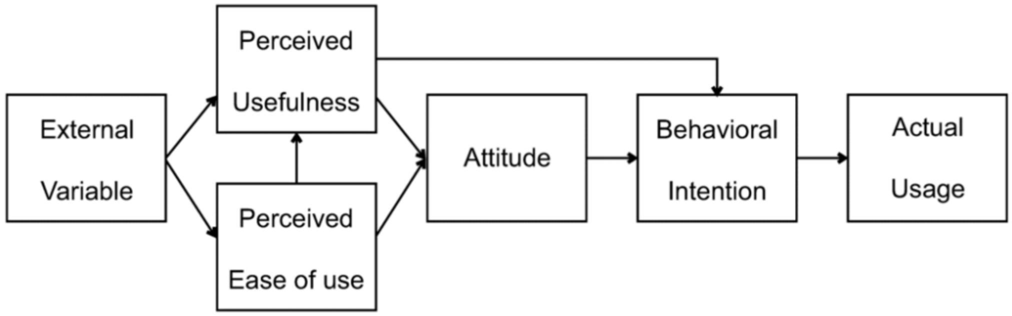

Figure 1 Technology Acceptance Model (David, 1989)

TAM has widely served as a baseline model. Still, TAM only took the relationship between attitude and behavioral intention into account in predicting actual behavior, so scholars argued that TAM is not sufficient to elaborate on the external factors and only explains 40% of the variance in individuals' intention to use technology (Venkatesh & Bala, 2008). As a result, there are two ways of model development. Some scholars have tried to extend the TAM by adding different variables in the various context of innovative technologies. For instance, perceived trust and social capital were added to TAM to investigate their positive impact on travelers' intentions to use social media (Singh & Srivastava, 2019). Another example is the study by de Kervenoael et al. (2020), which extended TAM for service robots by adding two dimensions from human-robot interaction (i.e., empathy and information sharing) and service quality dimensions related to perceived value. Pillai and Sivathanu (2020) extended TAM to uncover the predictors of chatbot adoption intention, including perceived trust, perceived intelligence, and anthropomorphism.

Meanwhile, other scholars have combined TAM with different theories or models to identify better factors influencing technology adoption. For example, Lin and Mattila (2021) built the model upon several frameworks, including the theory of consumption values, value-attitude-behavior theory, technology acceptance model, service robot acceptance model, self-service technology acceptance model, and the congruency theory. Their findings indicate that perceived privacy, functional benefits, and robot appearance positively influence consumers' attitudes toward adopting service robots. Functional benefits and novelty influence the individuals' anticipated overall experience. Attitude and anticipated overall experience, in turn, enhance consumers' acceptance of service robots. Zhong et al. (2020) integrated the theory of planned behavior and the perceived value-based acceptance model with TAM to unveil that attitude, perceived usefulness, and perceived value have the most significant impact on acceptance, with gender and educational level playing a moderating role in the acceptance of hotel robot services. From the literature, TAM is appropriate for this study to employ as a theoretical foundation for establishing a model. Since most people have no experience with ASRs, building trust is a significant step to overcoming potential risks and encouraging behavioral intention (Tussyadiah et al., 2020). For this reason, the following section reviews trust building in terms of ASRs in hospitality.

6.3 Trust of ASRs

Various conceptualizations of trust exist in the literature. The concept of trust was initially studied in the context of interpersonal relationships, with scholars defining it as a positive belief, expectation, or willingness to evaluate specific attributes of an individual and its impact on personal behaviors (Mayer et al., 1995). Later studies applied this conceptualization of trust to the area of information and communications technology (ICT) as a critical element in affecting users' acceptance of new technologies. The trustees change from humans to various technologies. In the ICT literature, scholars defined trust as a user's expectation that a specific technology can achieve the expected task outcomes (Tussyadiah et al., 2020). Trust reflects users' capability to make judgments about the trustworthiness of technologies. Thus, building trust is costly and time-consuming because trust is formed via long-term interactions (McKnight et al., 1998). Cumulative experiences can increase the trustees' knowledge and emotion, significantly impacting their trust levels (Kim et al., 2009). However, users barely have relevant experience or knowledge of new technology, so trust cannot be built based on knowledge, experience, and emotion. Hence, building consumers' trust in new technology is critically challenging.

To this end, Schaefer et al. (2016) proposed three dimensions to determine trust in new technology adoption: human, environmental, and technological factors. Kaplan et al. (2021) applied meta-analysis and confirmed that these three factors could predict trust in service robot adoption. Specifically, given that humans are the primary users of ASRs, human-related factors, including personal ability and personality, are critical for trust development. Environmental factors, such as team collaboration and task-related factors, can also affect trust in service robots (Goodrich & Schultz, 2008). Although human and environmental factors can be similar across different technologies, technological factors, such as performance, process, and purpose, can vary for distinctive technologies. For example, ASRs differ from traditional technologies due to their unique features like autonomy and sociality (Siau & Wang, 2020). These new features enable ASRs to communicate with consumers actively, make decisions to serve consumers autonomously, and replace human services. As a result, trust in ASRs may have distinctive attributes (Siau

& Wang, 2018; Tussyadiah et al., 2020). Unlike traditional technologies that are primarily tools for promoting productivity, ASRs are treated as social identities with social and autonomous abilities. Therefore, consumers can evaluate ASRs from multiple angles, such as robotic embodiment, human-oriented features, and social levels (Gursoy et al., 2019; Yu, 2020). Hence, trust in ASRs is likely a combination of trust in ICT and humans (Chi et al., 2020).

Moreover, another conceptualization views trust as a significant determinant in reducing perceived risks and increasing acceptance of new technologies. Trust is defined as an attitude that a person can help achieve an individual's goal in a situation characterized by uncertainty and vulnerability (Lee & See, 2004). This definition implies that risks and uncertainty are necessary for trust, which can influence the user's trust in new technologies (Park, 2020). Regarding ASRs, it is reasonable to assume that consumers may have perceived risks relevant to adopting ASRs, particularly ethical concerns. Consequently, establishing trust becomes essential to reduce ethical concerns, especially among consumers who lack experience and knowledge of ASRs. Hence, this conceptualization of trust is employed in this dissertation. Recent studies have examined that trust can mediate the impact between perceived risks and acceptance of AI-based technology. For example, Kaur and Rampersad (2018) tested that perceived risks (security and privacy risks) could be antecedents of trust and indirectly affect adoption through trust in the context of automated vehicle adoption. Similarly, Vimalkumar et al. (2021) indicated that consumers' perceived privacy risk does not directly affect the intention to adopt voice-based digital assistants but is mediated through trust. Therefore, building trust in ASRs is essential to alleviate consumers' ethical concerns and foster acceptance of ASRs services in the hospitality industry.

The nature of trust-building is a dynamic process that begins with initial trust and moves through continuous trust development (Siau & Wang, 2018). Initial trust pertains to a consumer's initial level of trust in technology, characterized by a willingness to fulfill a need without prior experience or credible, meaningful information (Kim & Prabhakar, 2004). Simply, initial trust means to trust in an unknown entity. Initial trust presumes that consumers have no credible and meaningful information, so it can set a basis for future relationships and trigger the belief of continuous development. The strength of future trust can be solidified or weakened during ongoing interactions, so the initial trust in ASRs is crucial in informing the first impression. Hence, given that consumers have few experiences with ASRs, initial trust is more appropriate to employ in this study than the concept of trust.

In this dissertation, initial trust in ASRs is defined as consumers' attitude to take ethical risks to accept ASRs-produced information and services and follow the suggestions provided by ASRs without any prior experience. While initial trust has been studied concerning various technologies such as e-commerce, mobile banking, and mobile payment (Kim et al., 2009; Stouthuysen et al., 2018; Talwar et al., 2020), initial trust remains unexplored in the context of intelligent technology and service industry. Given that consumers have no experience with ASRs, it is possible to argue that building initial trust is essential to reduce their perceived ethical concerns and affect their adoption intentions toward ASRs in hospitality. To measure initial trust, the initial trust model is reviewed in the next section.

6.4 Initial Trust Model (ITM)

The initial trust model (ITM) proposed by McKnight et al. (1998) conceptualized three dimensions to form initial trust: institutional, personal, and environmental attributes. Specifically, institutional dimensions are the organization-related characteristics, such as the role in the marketplace, firm reputation, brand image, and the company's capability (McKnight et al., 2002). Personal dimensions involve personalities, such as the propensity to trust and a trusting stance (Gefen et al., 2003). Environmental dimensions are relevant to enhancing trustworthiness, such as structural assurance, social influence, privacy policies, endorsement, third-party recognition, and service guarantees (McKnight et al., 2002). Initial trust cannot be built based on cumulative prior experience but on cognitive, institutional, and personal cues (Li et al., 2008). Thus, initial trust in ASRs can be explained from the above dimensions.

In line with previous literature, firm reputation, propensity to trust, and structural assurances are the representative antecedents of initial trust regarding innovative technologies (Kim & Prabhakar, 2004; Oliveria et al., 2014; Tussyadiah et al., 2020). Specifically, *firm reputation* reflects a cognitive process about familiarity with the vendors or organizations which use certain technologies. When lacking information, people will establish their cognitive familiarity based on second-hand knowledge, impressions, and cognitive cues (Gefen et al., 2003). A firm reputation can help build familiarity and trustworthiness when there is no experience or confirmed information (Li et al., 2008). Word-of-mouth can affect consumers' initial perceptions of service quality in an organization (Kim & Prabhakar, 2004). Thus, consumers can initially perceive a firm's ability to deliver services based on reputation or word-of-mouth. A good reputation assures organizational service quality, enhancing trust when consumers do not have experience and knowledge of a firm (Lohse & Spiller, 1998). In hospitality, the reputation of hotels or restaurants plays a significant role in building consumers' initial confidence and trust in their overall service quality, including the service quality of ASRs. If a hotel's reputation is well-recognized, consumers may believe that ASRs in that hotel can also provide high-quality services.

Secondly, users' *propensity to trust* means a consistent tendency of personality to rely on technology across various situations (Oliveria et al., 2014). It is deeply rooted in a person's character and psychological development in an early stage of life (Lee & Turban, 2001). Two constructs under the propensity to trust are faith in general technology and the trusting stance (McKnight et al., 2004). Faith in general technology means users' belief about attributes of technology in general, which is comparable to faith in humanity; a trusting stance refers to users' tendency to believe that relying on technologies can generate positive outcomes (Tussyadiah et al., 2020). Thus, users who have a higher faith in technology and are more likely to use technology until given reasons not to will affect their trust belief toward a technology. Empirical studies have shown that the propensity to trust can positively affect trust formation and users' belief in the trustworthiness of the technology (Chen, 2006). Therefore, the high propensity to trust general technology may impact their initial trust-building toward AI-based applications. Besides, consumers are more likely to trust and adopt new technologies may be easier to trust and use ASRs in hospitality.

Lastly, *structural assurances* are different forms of agreements, regulations, and guarantees to enhance initial trust in a relationship (McKnight et al., 2004). This institutional trust focuses on the situation and structures that affect trust belief. In institutional-based trust, one believes that favorable conditions are in place that are beneficial to institutional success and initial trust-building. Information asymmetry makes it possible to have uncertainty and risks associated with services. Hence, the availability of formalized structural assurances is vital to building consumers' initial trust. There are two aspects of structural assurances, technical and organizational assurances. Technical assurances are viewed as safeguards to ensure the development and usage of technology appropriately and legally, such as encryption, protections and regulations in the development processes and procedures, third-party certifications, feedback mechanisms, access controls, data backup, etc.; organizational assurances include organizational policies, relevant regulations, and even legal means to protect the results of particular technology adoption (Li et al., 2008; McCole et al., 2019; Sarkar et al., 2020). Technical and organizational assurances are critical for maintaining the integrity and reliability of particular technologies. Concerning ASRs in hospitality, the technical and organizational assurances of ASRs possibly include built-in safety features to prevent accidents or injuries, maintenance to ensure optimal performance, AI and robotics development framework, ASRs policies in hospitality, warranties from manufactories, which can ensure ASRs operate smoothly, minimize the risks of technical or safety issues, and provide values and experience to guests.

The above three antecedents of initial trust (i.e., firm reputation, propensity to trust, and structural assurances) are employed to measure the consumers' initial trust toward

ASRs in the hospitality industry. As a result, in this dissertation, TAM and ITM are integrated with consumers' ethical perceptions of ASRs to build the hypothesized model, described in the next section.

6.5 Theoretical Framework and Hypotheses Development

As Technology Acceptance Model (TAM) has been widely used to investigate technology adoption, TAM is drawn as a theoretical foundation to describe the factors that affect the intention of ASRs adoption. Consumers may generate ethical concerns before using ASRs, which may resist their adoption of ASRs in the hospitality industry. Previous research has suggested that building trust is a crucial step to facilitate the individual acceptance of innovative technology when perceived risks exist (Arfi et al., 2021; Tussyadiah et al., 2019). More importantly, the initial stage of trust is more appropriate than trust to use in this study for consumers without prior experience. Thus, the study argues that building initial trust is critical in reducing consumers' ethical concerns and facilitating adoption, particularly for consumers without prior experience with ASRs in the hospitality industry. As Technology Acceptance Model (TAM) has been widely used to investigate technology adoption, TAM is drawn as a theoretical foundation to describe the factors that affect the intention of ASRs adoption. Integration TAM with initial trust, the two constructs in TAM, perceived usefulness (PU) and perceived ease of use (PEU), can influence behavioral intention (BI) through initial trust (IT). Thus, initial trust is employed as a mediator in this study. The initial trust model (ITM) proposed three dimensions to measure initial trust, including firm reputation (FR), propensity to trust (PT), and structural assurances (SA). From the qualitative findings, consumers' ethical perceptions of ASRs can be classified into two dimensions: consumers' perceived ethical issues that arise during interaction with ASRs (EIDI) and consumers' perceived ethical issues that can be raised from the characteristics of ASRs (EIFC). Hence, the variables of two dimensions of consumers' ethical perceptions (i.e., EIDI and EIFC) and initial trust are second-order variables.

Concerning moderating roles, age is included in the study because the qualitative results in study one show that age's impact on behavior intention is inconsistent with prior studies. Thus, a further moderating test of age is necessary. Schaefer et al. (2016) proposed that the personal dimension significantly affects initial trust. Hence, from the personal attributes, familiarity and innovativeness are selected as moderators in this study to test their impact on the relationship between initial trust and behavioral intention since familiarity and innovativeness in previous studies have been examined as moderating roles in accepting innovative technology (Lin & Mattila, 2021; Zhong et al., 2020). The different levels of familiarity with ASRs and the personal innovativeness of participants present different responses in qualitative results in study one. Given these aspects, this study integrates the TAM and ITM with consumers' ethical perceptions to create a hypothesized model as a second-order model with moderators of age, familiarity, and innovativeness, as shown in Figure 2.

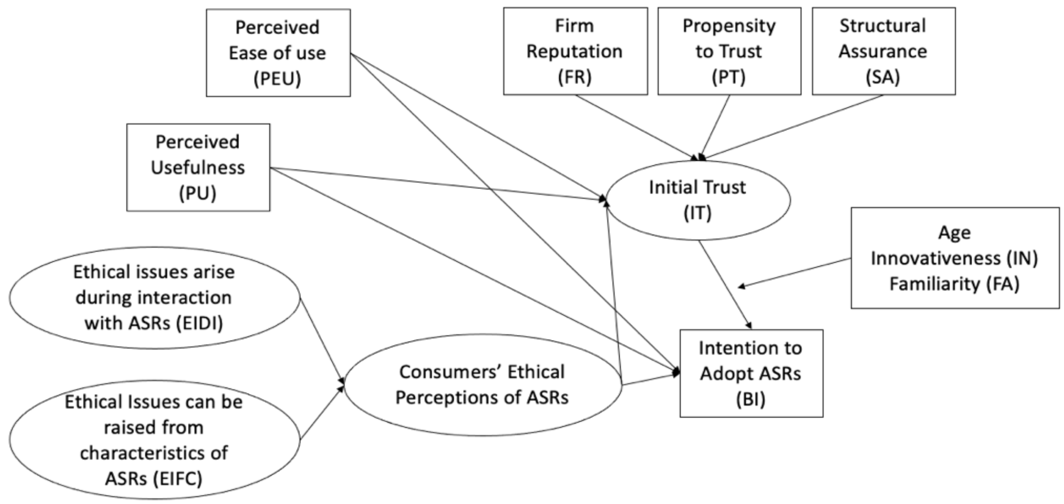

Figure 2 Hypothesized Model

The overall research questions are developed to investigate how constructs PU and PEU in TAM, and EIDI and EIFC of consumers' ethical perceptions influence initial trust (IT) and behavioral intention (BI), respectively. Further, this study examines whether initial trust mediates the relationship between antecedents of initial trust and behavioral intentions toward adopting ASRs in hospitality. Lastly, the moderating impact of age, familiarity, and innovativeness are tested between initial trust and behavioral intention.

Antecedents of Initial Trust and Behavioral Intention

Perceived usefulness, initial trust, and behavioral intention. Perceived usefulness (PU) is defined as the degree to which individuals believe that using ASRs in hospitality is helpful for consumers in service interactions. For consumers, ASRs offer advantages in hospitality, such as convenient accessibility, 24-hour availability, and an entertaining way of delivering services (Ivanov & Webster, 2017; Wirtz et al., 2018). Consumers can recognize the underlying beneficial performance of these innovations. Besides, the initial trust could be formed when consumers find usefulness in ASRs services. Previous studies have unveiled that perceived usefulness can influence initial trust and behavioral intention, respectively, in using mobile banking, automated vehicles, service robots, and chatbots (Abou-Shouk et al., 2021; Mostafa & Kasamani, 2022; Oliveira et al., 2014; Pillai & Sivathanu, 2020; Zhang et al., 2020). Thus, the perceived usefulness of ASRs may affect initial trust and behavioral intention in adopting ASRs in hospitality. Therefore, the hypotheses are postulated:

H1a: Perceived usefulness has a positive impact on initial trust.

H1b: Perceived usefulness positively affects the intention to adopt ASRs in hospitality.

Perceived ease of use, initial trust, and behavioral intention. Perceived ease of use (PEU)in this study is defined as the degree of ease of using ASRs in hospitality. The acceptance of new technology is significantly influenced by perceived ease of use (Cimperman et al., 2016). The autonomy feature of ASRs enables consumers to access ASRs easily and conveniently, leading them to perceive ASRs as ease of use. Besides, when consumers perceive to adopt ASRs without any effort or learning process, it may be helpful to build consumers' confidence in using ASRs in hospitality. In the previous study, perceived ease of use can influence trust and behavioral intention, respectively, in using mobile banking, automated vehicles, and service robots (Abou-Shouk et al., 2021; Mostafa & Kasamani, 2022; Pillai & Sivathanu, 2020; Ramos et al., 2018; Zhang et al., 2020). As a result, the perceived ease of use of ASRs may affect initial trust and behavioral intention in adopting ASRs in hospitality. This study proposed the following hypotheses:

H2a: Perceived ease of use has a positive impact on initial trust.

H2b: Perceived ease of use positively affects the intention to adopt ASRs in hospitality.

Consumers' ethical perceptions, initial trust, and behavioral intention. Consumers' ethical perceptions can be regarded as one type of perceived risk relevant to using ASRs. Perceived risks, like privacy and safety risks, have been examined to affect trust and behavioral intention (Hwang & Choe, 2019). Thus, more than these risks are found in the study one about consumers' ethical perceptions about using ASRs in hospitality, which are measured by consumers' perceived ethical issues related to ASRs adoption. Based on qualitative results, consumers' ethical perceptions consist of two dimensions: consumers' perceived ethical issues that arise during interaction with ASRs (EIDI) and consumers' perceived ethical issues that can be raised from the characteristics of ASRs (EIFC). Ethical issues related to intelligent technologies have been argued to affect consumers' trust in previous research (Siau & Wang, 2018; Wirtz et al., 2018). The qualitative findings present consistent evidence that consumers' perceived ethical issues can negatively impact participants' trust and the intention to adopt ASRs in hospitality. Another study about ethical concerns of mobile purchases has tested that consumers' ethical concerns negatively affected users' trust (Gao et al., 2015). Etemad-Sajadi et al. (2022) have examined that the ethical issues of service robots, such as safety and responsibility, significantly impact behavioral intention during human-robot interaction. As a result, the two dimensions of consumers' ethical perceptions of ASRs may affect initial trust and behavioral intention regarding using ASRs in hospitality. Hence, the following four hypotheses are posited:

H3a: Consumers' perceived ethical issues that arise during interaction with ASRs have a negative impact on initial trust.

H3b: Consumers' perceived ethical issues that arise during interaction with ASRs negatively affect the intention to adopt ASRs in hospitality.

H4a: Consumers' perceived ethical issues that can be raised from characteristics of ASRs have a negative impact on initial trust.

H4b: Consumers' perceived ethical issues that can be raised from characteristics of ASRs negatively affect the intention to adopt ASRs in hospitality.

Initial trust and behavioral intention. Most consumers have yet to gain experience with ASRs in hospitality, so building initial trust is critical to convince consumers to use new ASRs services. In the literature, initial trust has been tested to affect the behavioral intention of using general technology (Kim et al., 2009). The results from some studies demonstrated that initial trust could positively affect the acceptance and use of different innovative technologies, such as mobile banking, online services, mobile payment, and chatbots (Li et al., 2008; Mostafa & Kasamani, 2022; Oliveira et al., 2014; Silic & Ruf, 2018; Talwar et al., 2020). Therefore, behavioral intention can be the outcome of initial trust. The initial trust may positively impact the intention to adopt ASRs in hospitality. Thus, the hypothesis is proposed:

H5: Initial trust positively impacts the intention to adopt ASRs in hospitality.

Mediating Effects of Initial Trust

Based on the definition of trust, perceived risks are the pre-conditions of trust. Prior studies have found that trust can mediate the relationship between perceived risks and behavioral intention in different contexts, such as online buying behaviors and automated vehicle adoption (Casey& Wilson, 2012; Mostafa & Kasamani, 2022; Pappas, 2016; Talwar et al., 2020; Zhang et al., 2020). Ioannou et al. (2021) tested that trust has a mediating impact on the relationship between consumers' privacy concerns and willingness to share information. Besides, previous studies have extended TAM with trust and identified that trust mediates the relationship between perceived usefulness and perceived ease of use and behavioral intention in different contexts, such as online shopping, mobile wallet, and digital transaction (Iqbal et al., 2018; Sawitri & Giantari, 2020; Singh & Sinha, 2020; Syaharani & Yasa, 2022).

Initial trust. Gao and Waechter (2017) investigated how initial trust can mediate valances and usage intention of mobile payment services. Talwar et al. (2020) examined how initial trust can mediate its inhibitors (e.g., perceived uncertainty and perceived information quality) and continuation intention in mobile payment. When building initial trust in ASRs, consumers' perceived ethical issues could be reduced, thereby facilitating ASRs adoption. The initial trust may mediate the relationship between the antecedents (i.e., perceived usefulness, perceived ease of use, and consumers' ethical perceptions) and the outcome (i.e., intention to adopt ASRs). Therefore, initial trust is proposed in this study as a mediator between consumers' ethical perceptions and the intention to adopt ASRs in hospitality. Hence, the following hypotheses are developed:

H6a: Initial trust mediates the relationship between perceived usefulness and intention to adopt ASRs in hospitality.

H6b: Initial trust mediates the relationship between perceived ease of use and intention to adopt ASRs in hospitality.

H6c: Initial trust mediates the relationship between consumers' perceived ethical issues that arise during interaction with ASRs and intention to adopt ASRs in hospitality.

H6d: Initial trust mediates the relationship between consumers' perceived ethical issues that can be raised from characteristics of ASRs and intention to adopt ASRs in hospitality.

Moderating Effects of Age, Familiarity, and Innovativeness

Age. Age is a significant predictor of technology adoption, measured as a moderator in TAM (Griebel et al., 2013). Older adults may face more challenges when adopting new technologies than younger people (Hoff & Bashir, 2015). Previous studies have shown that young generations have higher levels of trust and greater intention toward innovative technologies adoption than older adults, such as the Internet of Things and mobile services (Arfi et al., 2021; Warsame & Ireri, 2018). Based on the literature, the following hypothesis is proposed:

H7a: Age significantly moderates the relationship between initial trust and intention to adopt ASRs in hospitality.

Familiarity. Familiarity is the degree of a person's understanding of a particular object (Chi et al., 2020). In general, familiarity can help reduce uncertainty and promote the accumulation of trust. The qualitative results show that people who have experience with ASRs are positive in building trust and driving their behavioral intention. When consumers are more familiar with ASRs (e.g., have a background in intelligence technology, learning engineering or computer science, and watching videos and reading articles related to ASRs), they can generate more positive feelings and attitudes. In previous studies, Shareef et al.

(2020) examined that familiarity with social media significantly mediates the relationship between initial trust and behavioral intention. Familiarity with technology has been investigated as a moderator in prior studies influencing behavioral intention in online shopping (Chang et al., 2016). Familiarity with AI social robots has been tested to improve consumer trust and drive adoption behaviors (Chi et al., 2020). A higher level of familiarity with ASRs may lead to a higher level of initial trust in the acceptance of ASRs. Thus, the hypothesis is proposed:

H7b: Familiarity significantly moderates the relationship between initial trust and intention to adopt ASRs.

Innovativeness. Innovativeness refers to the degree to which an individual is relatively earlier in adopting new ideas than other members of his social system (San & Herrero, 2012). Personal innovativeness as a personality trait can be high or low, which influences cognitive and decision-making processes, such as accepting and using innovative technologies. Previous studies have highlighted that the innovativeness of technologies is an essential moderator in the ICT context. For example, San Martin and Herrero (2012) have confirmed that innovativeness significantly moderates the relationship between trust and online purchase intention. San Martin and Herrero (2012) emphasized the moderating impact of innovativeness in the context of online shopping. The qualitative findings reveal that participants' curiosity is the main reason for initially using ASRs in hospitality. In other words, the higher level of an individual’s innovativeness in ASRs, the higher level of initial trust in acceptance of ASRs. Hence, the hypothesis is as follows:

H7c: Innovativeness significantly moderates the relationship between initial trust and intention to adopt ASR.

CHAPTER 7

METHOD

7.1 Sample and Data Collection

The population of this study is the consumer who has no experience with ASRs in hospitality. The targeted samples were selected from individuals who have stayed in hotels or visited restaurants as consumers in the last year but have no interaction with ASRs. These participants possess a basic understanding of the service functions in the hospitality industry but have yet to be directly experienced with robot services.

Under the quantitative approach, the online survey is the primary method to collect data. The survey is designed and administrated on the Qualtrics platform. This platform is an essential tool with a user-friendly interface for designing and conducting surveys. At the beginning of the questionnaire, an introduction with the background and purpose of this survey was shown to the participants. Participants clicked the next page button means they agreed to participate in the survey. The screening questions on the next page were essential to ensure that participants were over 18 years old and had yet to experience with ASRs in hotels or restaurants as consumers in the 12 months. These screen questions were used to maintain qualified participants and avoid misrepresenting ineligible samples. Then, the survey showed participants full descriptions and pictures of two types of ASRs (i.e., a delivery robot in the Vdara Hotel and a chatbot in the Cosmopolitan Hotel) to fully understand the roles and service scope of ASRs in hospitality. After reviewing these examples, the participants started to rate each question in the central part of the survey. The primary part of the survey includes six sections of questions: 1) ethical issues that arise during the service interactions with service robots, 2) ethical issues can be raised by the characteristics of service robots, 3) perceived usefulness and perceived ease of use regarding service robots, 4) initial trust in service robots, 5) innovativeness, familiarity, and intention to use service robots in hotels in the future, and 6) demographics. The questionnaire is shown in Appendix H.

Before sending out the survey, the original statements in the survey were assessed by five graduate students. They provided comments and evaluated the content and wording of each item. The data collection consisted of two steps. In the pre-test phase, the first survey was sent out among college students with convenience sampling in January 2023. The questionnaire in this phase only included sections 1 and 2 related to consumers' perceived ethical issues and section 6 about demographics. This pre-test aims to develop the measurements of consumers' ethical perceptions and verify the survey process. After refining the statements based on the results from the pre-test, the main questionnaire is finalized. The cross-sectional survey was sent out in the spring of 2023 via the Prolific platform with a small incentive ($2). Scholars have argued the issues related to data quality across different platforms, such as Amazon Mechanical Turk (MTurk), Prolific, and Qualtrics. MTurk has been shown as having the lowest data quality, while Prolific provides high data quality on all measures (Eyal et al., 2021). Therefore, Prolific is an appropriate platform for data collection in this study. There were several standards in the system of Prolific to prescreen the participants for the main survey: 1) over 18 years old, 2) an approval rate equal to or higher than 100, and 3) the number of previous submissions equal to or higher than 100. These standards can ensure a high response quality.

7.2 Measurements

All measurements of variables were measured on five-point Likert scales, ranging from 1 = "strongly disagree" to 5 = "strongly agree." The items of consumers' perceived ethical issues were generated based on qualitative findings and developed based on the results from the pre-test. Specifically, the variables of consumers' ethical perceptions consist of two dimensions of consumers' perceived ethical issues (i.e., ethical issues that arise during interactions with ASRs (EIDI) and ethical issues that can be raised from the characteristics of ASRs (EIFC)). From the qualitative findings, each dimension of consumers' perceived ethical issues has eight themes. Each theme initially generated five items, meaning 80 statements of consumers' perceived ethical issues. After the assessment by five graduate students, 21 items were removed. The rest of the 59 statements about consumers' perceived ethical issues were tested in the pre-test survey. Based on the results of the pre-test survey, 24 items for EIDI and 25 items for EIFC were revised for the main survey. After testing these items in the main survey, the measurements of consumers' perceived ethical issues were finalized, 22 items for EIDI and 23 items for EIFC.

The measurements of other variables in the model were adopted from the previous literature and modified to fit into the context of this study. Each construct was measured by four items, except behavioral intention measured by three items. More specifically, the variables in the hypothesized model in this study include three variables in TAM (i.e., perceived usefulness (PU), perceived ease of use (PEU), and behavioral intention (BI)), three constructs of ITM (i.e., firm reputation (FR), propensity to trust (PT), and structural assurance (SA)), and moderators (i.e., age, familiarity (FA), and innovativeness (IN)). The measurements of three variables in TAM were adopted from the literature and modified in this study's context (de Kervenoael et al., 2020; Venkatesh et al., 2003; Lu et al., 2019;

Chi et al., 2020). The measurements of three constructs of ITM were adopted from previous literature (Kim et al., 2009; Oliveira et al., 2014; Tussyadiah et al., 2020). The moderators of familiarity and innovativeness were borrowed from literature (Chang et al., 2016; San Martin & Herrero, 2012). For the demographics part, some questions related to qualitative findings were added, including the preference for using different types of ASRs (e.g., delivery robots and chatbots), how many times actively gather information about ASRs (i.e., from never to more than five times), different trip purposes of ASRs adoption (i.e., leisure or business trips), having technology related background (i.e., yes or no).

7.3 Data Analysis

7.3.1 Pre-test

The pre-test stage aimed to develop the measurements of consumers' perceived ethical issues (i.e., EIDI and EIFC). The first step of the analysis was to test the normality and sampling adequacy of the data. The normality was examined via skewness< 3.0 and kurtosis<10.0 (Kline, 2015). The Kaiser-Meyer-Olkin (KMO) and Bartlett's Test of Sphericity tested the sampling adequacy. The KMO should be above 0.7, and Bartlett's Test of Sphericity needs to be significant (Brown, 2015). Then, the exploratory factor analysis (EFA) was adopted to merge the possible factors under each dimension of consumers' perceived ethical issues. EFA was conducted separately for two dimensions via principal component analysis (PCA) with varimax rotation to evaluate the measurements via SPSS 27. The results of EFA were determined using an eigenvalue higher than 1, and items were removed for having higher cross-loadings than 0.5 and lower factor loading than 0.5 (Kaiser, 1960).

7.3.2 Second-Order Model

The first step of analysis of the main survey is data cleaning, which is followed by several criteria: 1) uncompleted survey, 2) failure of attention check, 3) rushed work, 4) same IP address, and 5) failure of screen questions. Next, the measurements of consumers' perceived ethical issues were further refined. EFA was employed in the main survey via SPSS 27, following the same steps of EFA in the pre-test to evaluate each construct of consumers' perceived ethical issues. Thus, the constructs of EIDI and EIFC were finalized.

Since the variables of EIDI, EIFC, and initial trust were second-order constructs, the hypothesized model in this dissertation was specified as a second-order model. To analyze the higher-order model, there are two dominant approaches. The first repeated indicators approach is easy to apply because all indicators of the lower-order components are assigned to the higher-order factors, which are analyzed in a whole model. However, all indicators are repeated to identify the higher-order constructs, so it is impossible for other antecedents that are not part of the higher-order constructs to explain any variance (Sarstedt et al., 2019). The second approach is the disjoint two-stage approach (Sarstedt et al., 2019). Following this approach, the first stage considers all lower-order components of the higher-order constructs and links them with other constructs. Then, the researchers need to save the construct scores of those lower-order components and rebuild the model. Stage two is to test the causal relationships of higher-order constructs and other factors. Because initial trust is a second-order variable as a mediator in the model, other variables, like PU and PEU, cannot explain the variance of initial trust following the repeated indicators approach. Thus, the analysis process in this dissertation followed the disjoint two-stage approach.

Under the disjoint two-stage approach, the validation of measurements was needed to separately evaluate the measurement model of the lower-order components and the measurement model of the higher-order construct as a whole. Thus, the first lower-order model concluded all measurements of consumers' perceived ethical issues and initial trust, PE, PEU, and behavioral intention. The higher-order model only contained second-order constructs of consumers' perceived ethical issues and initial trust and other variables (i.e., PE, PEU, behavioral intention, and moderators).

Moreover, confirmatory factor analysis (CFA) was employed on SmartPLS (version 3.2.9) to evaluate the measurement model. CFA aims to test the hypothesized structure between observed indicators and latent constructs against the data. Validity involves convergent and discriminant validity. There are several criteria to evaluate the measurement model. The model fit should be assessed based on the Normed Fit Index (NFI close to 1) and standardized root mean residual (SRMR< 0.08) (Bentler, 1990; Henseler et al., 2016; Wui et al., 2009). Multicollinearity can be checked by the variance inflation factor (VIF), which is acceptable under 10.0 (García et al., 2015; Gómez et al., 2021). Factor loadings (FL) refer to "the extent to which each of the items in the correlation matrix correlates with the given principal components" (Pett et al., 2003, p.299). A high FL means a high correlation of the items with the underlying factor, which should be over 0.5 (Brown, 2015).

Next is to test the validity and reliability of constructs. Validity is the accumulation of evidence to support interpreting what a measure reflects. Construct validity refers to the extent that the instrument measures what it was designed to measure (Creswell & Creswell, 2018). Convergent and discriminant validity are the two subtypes of construct validity.

Convergent validity is indicated by evidence that different indicators of theoretically similar or overlapping constructs are strongly interrelated (Brown, 2015). Convergent validity can be assessed by examining the significance of items to factor loadings and the average variance extracted (AVE values greater than 0.5). Discriminant validity reflects the extent to which a measure can distinguish between different constructs (Brown, 2015). Simply, discriminant validity assesses whether a measurement measures what it intends to measure. Discriminant validity can be tested in two ways: 1) values in Heterotrait-monotrait ratio (HTMT) below the threshold of 0.9, and 2) tested by correlations between each pair of dimensions and inter-correlations between constructs smaller than the square root of AVE for all constructs, named Fornell-Larcker criterion (Brown, 2015; Henseler et al., 2016). In addition, reliability refers to the consistency or repeatability of instruments, which is tested via composite reliability and Cronbach's alpha value (Creswell & Creswell, 2018). The scores of composite reliability (CR) should be higher than 0.8, and Cronbach's alpha (α) values range between 0 and 1, with optimal values between .7 and .9 (Brown, 2015; Creswell & Creswell, 2018; Fornell & Larcker, 1981). Following the above standards of testing the measurement model, both lower-order and higher-order measurement models were evaluated.

The next step was to test the hypotheses in the structural model via the structural equation model (SEM). SEM can typically represent theories that explain attributes of measured variables, including variances, covariances, and means (Kline, 2015). One advantage of SEM is that all measurements can be tested simultaneously in one statistical estimation procedure. However, the traditional technique of SEM is covariance-based (CB-SEM), which can be used to identify patterns of covariances among a set of observed variables and explain as much of their variances as possible within the hypothesized model. Compared with traditional CB-SEM, partial least squares-structural equation modeling (PLS-SEM) has several advantages. PLS-SEM aims to maximize the explained variance of the latent constructs and has the advantage of lacking normality of distribution and minimum sample sizes (Park et al., 2019). PLS-SEM is widely known as a non-parametric method, which features a higher level of statistical power (Hair et al., 2016). PLS-SEM is robust to small sample sizes and can be used for a single-item construct (Hair et al., 2016). Thus, this study employed PLS-SEM as the main analysis method via SmartPLS (version 3.2.9).

The causal relationships based on the hypotheses were tested via PLS-SEM. The goodness of fit measure in PLS-SEM does not exist, so bootstrapping and blindfolding techniques were used. The number of bootstrap samples should be larger than the number of valid observations in the original data set (Hair et al., 2016), so 5000 samples were selected for bootstrap and blindfolding. R^2 means the coefficient of determination, which indicates an explained amount of variance by predictors. The value of Q^2 is a measure of the model's out-of-sample predictive power, which was used to assess the predictive relevance of the model (Hair et al., 2016). PLS-SEM examines each causal relationship between endogenous and exogenous variables, which means all direct and indirect effects among the factors can be present in the hypothesized model. For direct effect, PLS-SEM can demonstrate each result of the hypothesis in the model. In other words, the direct impacts of variables were examined via β coefficient and p-value to test whether the hypotheses were supported or rejected.

7.3.3 Mediating and Moderating Effects

A mediator is a variable that causes mediation in the dependent and the independent variables. In other words, indirect or mediated effects assume a sequence of relationships in which an antecedent variable affects a mediating variable, which in turn affects a dependent variable. For the mediating effects, there are three types of mediation (Nadeem & AI-Imamy, 2020). The first is complementary mediation, which means when the direct impact is significant, and its direction is as same as the indirect effect. The second is competitive mediation occurs when the direct impact is significant but points in the opposite direction. The last one is full or indirect mediation, which means the direct impact may or may not be significant, but the indirect effect is significant. In this dissertation, as initial trust was the mediator in the model, the mediating effect was examined via testing whether antecedents of initial trust have an indirect effect on behavioral intention through the initial trust.

For the moderating effect, the interaction effect was tested when the moderator is a continuous variable (e.g., familiarity and innovativeness). The change of moderator can affect the relationship between independent and dependent variables. The interaction effect can be analyzed by adding an interaction variable in the multiple regression analysis. The interaction effects assume that all relationships (i.e., dependent, independent, and moderator variables) should have a linear relationship.

Moreover, the moderator as a categorical variable can split data into two different datasets (e.g., gender and IT background). Comparison in two groups about the relationship between initial trust and behavioral intention can be conducted via multi-group analysis (MGA). MGA is mainly an invariance test that aims to confirm whether a set of indicators assess the same variables across different groups, which ultimately enhances the validity of the measurement model (Kline, 2015). Measurement invariance determines if the measurement models specify measures of the same attribute under different conditions, which is significant to be addressed at first. All measurement indicators must be included in the constructs across all groups. Then, the focus is to determine if the path coefficients of initial trust's effect on the two groups' behavioral intentions are significantly different. Comparison of the path coefficients in the model can be evaluated through fit comparison with a robust S-B chi-square difference test. The last step is to interpret the results on whether differences exist between the two groups.

CHAPTER 8

FINDINGS

8.1 Pre-test

8.1.1 Sample

Out of 184 responses, 153 valid samples (83.15%) were retained. Others were removed due to uncompleted surveys and the failure of screen questions. For the demographics of the pre-test, 71.2% were between 20-29 years old because the samples were college students. 75.8% were female, and 22.9% were male, so female students dominated tourism and hospitality majors. 60.8% were white, and 82.4% were undergraduate students. 25.5% have a full-time job, while 30.1% were part-time employees. For income, 61.4% were less than $25,000. Regarding preference for willingness to use various ASRs in hotels, 19% selected robot bartenders, 17.6% chose chatbots, 58.2% picked delivery robots, and 31.4% never wanted to use these innovations. Regarding the willingness to use ASRs for different purposes of hotel trips, 19% selected vacations, 13.1% chose business trips, 32.7% selected both trip purposes, and 35.3% decided never to use ASRs during the trips. From these results, a large percentage of young generations were still unwilling to use ASRs. The sample profiles are presented in Appendix I.

8.1.2 Measurement Purification

Before examining the measurements of consumers' perceived ethical issues, the data normality and sampling adequacy were tested. The distributions of skewness (ranging from -1.483 to 0.403) and kurtosis (ranging from -1.296 to 2.764) were acceptable because the cutoff values are skewness< 3.0 and kurtosis<10.0 (Kline, 2015). Thus, the normal distribution was confirmed. The sampling adequacy was tested via Kaiser-Meyer-Olkin (KMO) (above 0.7) and Bartlett's Test of Sphericity ($p<0.5$) (Brown, 2015). For measurements of EIDI and EIFC, the KMO is 0.971 and 0.970, respectively. Both p-values in two constructs are 0.000 in Bartlett's Test of Sphericity. Hence, the data could be used for factor analysis.

Next, EFA was conducted separately to identify the underlying dimensions of EIDI and EIFC. The variance explained was 67.673% for EIDI and 70.89% for EIFC. The measurements were discarded due to higher cross-loadings than 0.5 or lower factor loading than 0.5 (Kaiser, 1960). Therefore, based on an eigenvalue higher than 1, EIDI was grouped into four factors containing 24 items, while EIFC was grouped into five factors comprising 25 items. These measurements were further validated in the main survey.

8.2 Main Test

8.2.1 Sample

A sufficient number of responses, usually over 300, is essential to ensure a significant statistical level, such as an alpha value over .05 and a level of power over .8 (Greenland et al., 2016). In the main survey, a total of 529 responses were collected. The useable sample size was 504 (95.27%) after removing the cases owing to the failure of an attention-check question, uncompleted surveys, disqualified participants, and duplicate responses. Among responses, 37.9 % of respondents were male, and 61.3% were female; 35.9% were between the ages of 30 to 39, and 22.6% were between 40-40 years old; 93.5% were white, 42.1% had a bachelor's degree, and 18.5% had a mater or higher degree, 58.1% were employed full-time, and 20.0% were part-time employees; 40.7% reported income from $25001 to

$75000. For information related to ASRs, 84.9% did not have a technology-related or engineering background; 87.7% had never gathered information about ASRs; 59.5% resisted to use ASRs in hotels, but delivery robots (27.8%) had the highest likelihood of adoption among all types of ASRs; 54.2% chose never to use ASRs during the trips, but 27.6% would like to use ASRs during the leisure trip. The table of the demographic profile of the main survey is shown in Appendix J.

8.2.2 Measurement Refinement

This step aimed to refine the measurements of consumers' perceived ethical issues. Following the same procedures of EFA in the pre-test, the measurements were examined in a larger sample data size. The distributions of skewness (ranging from -1.337 to 1.946) and kurtosis (ranging from -1.258 to 3.806) were acceptable since the cutoff values of normality were skewness< 3.0 and kurtosis<10.0 (Kline, 2015). The sampling adequacy was satisfactory for factor analysis via testing the Kaiser-Meyer-Olkin (KMO) and Bartlett's Test of Sphericity. Both KMO values for EIDI (0.946) and EIFC (0.915) were greater than 0.8, and both Bartlett's Test of Sphericity results are significant ($p = 0.000$). The EFA was conducted separately for EIDI and EIFC via a principal component analysis with the varimax rotation method (SPSS 27) to refine the measurements in the pre-test. The results of EFA were determined using an eigenvalue higher than 1 (Kaiser, 1960). The results indicated that four factors (i.e., personal privacy, disclosure, dehumanization, and service failure) were generated under the EIDI (explaining 63.438% of the variance), while EIFC presented a five-dimensional structure (i.e., informational security, untrustworthiness, bias, job replacement, and inflexibility) (explaining 62.558% of the variance), which is as same as the results in the pre-test. After the EFA test, two measurements from each variable were removed because of higher cross-loadings than 0.5 or lower factor loading than 0.5 (Kaiser, 1960). Specifically, two items related to EIDI were removed (i.e., one item from the selection of services and one item from the inaccessibility). Two items related to EIFC were discarded, including two items of malfunctions. Thus, the measurements of EIDI and EIFC were finalized (See in Appendix K). Each factor is explained below.

Both EIDI and EIFC originally had eight themes from the qualitative results. After the EFA test, some themes were combined under one construct. More specifically, four constructs were under EIDI. The first construct is personal privacy, which consists of three measurements of ubiquitous surveillance, two measurements of data excessiveness, and one measurement of selection of services. Personal privacy refers to the right of individuals to control access to confidential information and the ability to maintain a level of anonymity or seclusion from others. The importance of personal privacy has become increasingly apparent with the rise of intelligent technologies. Consumers are concerned about inputting too much personal information to initiate services and their behaviors and conversations being recorded or monitored. Consumers should be able to select ASRs services and be notified about the cameras or CCTV. Thus, this new construct relates to the privacy issue of personal information and surveillance during service interactions. The second construct is the disclosure, which comprises two measurements of unknown risks, two measurements of full disclosure, and one measurement of inaccessibility. Disclosure means the practice of informing consumers about comprehensive information related to ASRS, such as whether consumers are only served by ASRs, any potential risks and mistakes, and functional limitations and restrictions during interactions with ASRs. The disclosure of ASRs service is essential to promote transparency and build trust between consumers and the hotel/restaurants, which can reduce potential risks and miscommunications. The third construct is dehumanization, which includes four dehumanization measurements and one inaccessibility measurement. Dehumanization means the service process of treating people as if they are less than human or denying their human dignity. Consumers have complained about this issue as cold service without empathy and feelings. The current ASRs can only provide basic and simple services, which needs to be more welcoming in hospitality. The last construct is named service failure, consisting of three measurements of service recovery and one measurement of each qualitative theme, selection of services, full disclosure, and inaccessibility. Service failure means any situation in which ASRs fail to meet consumers' expectations or requirements. Since consumers have yet to gain prior experience, they are afraid to handle the challenging situation of service failures generated by ASRs during service interactions. They also have concerns at the beginning of accessing and selecting the ASRs services because of the difficulty and unfamiliarity. Thus, service failure contains various forms of failures throughout the entire service encounters with ASRs in hospitality.

On the other hand, EIFC has five constructs (i.e., informational security, untrustworthiness, bias, job replacement, and inflexibility), which are quite similar to qualitative results. Specifically, the first construct is informational security, combining the three measurements from each qualitative theme: privacy infringement and malicious use. Information security refers to the practice of protecting consumers’ digital information from unauthorized access, use, disclosure, disruption, modification, or destruction. Information security is essential for all individuals, businesses, and organizations. Still, consumers can be concerned about how the data is safely stored and who can access and use it for other purposes. For example, hackers can use consumer data for illegal purposes, and organizations can leverage consumer data for marketing or other business purposes. Adequate information security requires ongoing monitoring and assessment for all stakeholders. The second construct is untrustworthiness, which is contained three measurements of untrust and one measurement of malfunctions. The untrustworthiness of ASRs demonstrates a lack of reliability and credibility from consumers. It is no doubt that consumers are worried about any issues related to malfunctions of ASRs and do not trust an intelligent agent to provide services. With the increasing advancement of ASRs, people, not just consumers, have concerns about how AI will control the world. As most consumers barely have knowledge about AI or ASRs, persuading them to trust and adopt ASRs is dramatically challenging. The third construct is inflexibility, combined with the three measurements of each qualitative theme: inflexibility and self-identified solutions. The inflexibility of ASRs is evident as a lack of adaptability or the inability to change in response to new or changing circumstances. ASRs must follow the pre-designed programming to provide services, and it is hard to make a change that requests from consumers. Consumers also have concerns about whether ASRs can identify and solve their own errors. The inflexibility explains that ASRs are unable to meet changing demands and recognize mistakes during service interactions in hospitality. The last two constructs are not changed from qualitative themes as bias and job replacement maintain their three same measurements. These two constructs retain the same definitions as qualitative results. The bias is about the effects of ASRs services that are systematically inaccurate, unfair, or discriminatory. Job replacement refers to the possibility of the process by which ASRs replace human workers. These two concerns are critical as consumers' ethical perceptions.

In summary, EIDI is measured from four constructs of a total of 22 items: personal privacy (6 items), disclosure (5 items), dehumanization (5 items), and service failure (6 items). EIDI contains five constructs of a total of 23 items: informational security (6 items), untrustworthiness (5 items), bias (3 items), job replacement (3 items), and inflexibility (6 items).

8.2.3 Measurement Model of Lower-Order Model

The variables of consumers' perceived ethical issues that arise during interactions with ASRs (EIDI), ethical issues that can be raised from the characteristics of ASRs (EIFC), and initial trust (IT) have second-order constructs, so the analysis process followed the disjoint two-stage approach. This first step was focused on the measurement model of the lower-order model to test the validity and reliability of constructs via confirmatory factor analysis (CFA). In the lower-order model, the independent variables contained a total of nine constructs of EIDI and EIFC (i.e., personal privacy, disclosure, dehumanization, service failure, informational security, untrustworthiness, bias, job replacement, and inflexibility), two constructs in TAM (i.e., PU, and PEU). The mediator is initial trust with the three constructs (i.e., firm reputation, the propensity to trust, and structural assurance). The dependent variable is the intention to adopt ASRs in hospitality. All these variables were correlated in the lower-order model.

The model fit was first checked. The results showed that the goodness of fit statistics of the measurement mode was acceptable (SRMR = 0.054 < 0.08 and NFI=0.789). Next, multicollinearity was assessed by the variance inflation factor (VIF). The VIF values, ranging from 1.317 to 7.400, were acceptable under the threshold of 10.0 (García et al., 2015; Gómez et al., 2021). Additionally, the factor loading (FL) of items lower than 0.5 should be removed for better reliability (Hair et al., 2021). The results of FL of all measurements were above 0.5. No cross-loadings were found amongst constructs. Thus, all measurements were retained to measure the respective latent variables.

The next step was testing the validity and reliability of constructs in the lower-order model. Specifically, the convergent validity was tested via average variance extracted (AVE). The results showed that all AVE values exceeded the threshold of AVE > 0.5 (Brown, 2015). The discriminant validity was tested via the Heterotrait-monotrait ratio (HTMT) and the Fornell-Larcker criterion. The results indicated that the values of HTMT were less than the cutoff values of 0.9 (Henseler et al., 2016), and all AVE values' square roots were larger than the correlations among latent variables (Fornell & Larcker, 1981). The reliability was tested via composite reliability (CR) and Cronbach's alpha values. All CR values were higher than 0.8, and Cronbach's alpha (α) values ranged over 0.7 (Fornell & Larcker, 1981). Therefore, these results demonstrated satisfactory validity and reliability of each construct in the lower-order model, summarized in Appendix L.

8.2.4 Measurement Model of Higher-Order Model

This step was to validate the constructs in the higher-order model. After the validation of constructs in the lower-order model, the scores of those lower-order latent variables were saved as new variables to rebuild the second-order model. Thus, in this model, the second-order constructs of EIDI, EIFC, and initial trust consisted of respective constructs. The exogenous variables were EIDI, EIFC, PU, and PEU; the mediator was initial trust; the endogenous variable was behavioral intention; and the moderator was age, familiarity, and innovativeness.

The validity and reliability of constructs in the second-order model were tested. The steps were followed as construct validation in the lower-order model. The model fit was acceptable (SRMR = 0.061 < 0.08 and NFI=0.829). The VIF values (ranging from 1.259 to 5.32) were under the threshold of 10 (García et al., 2015; Gómez et al., 2021). For validity and reliability, the results presented that all construct scores of FL > 0.5, AVE > 0.5, CR > 0.8, and Cronbach's alpha (α) values > 0.7 (Brown, 2015; Fornell & Larcker, 1981; Henseler et al., 2016). All HTMT scores were smaller than 0.9. The square root of AVE was greater than its correlation with other constructs in this study, which strongly supported the establishment of discriminant validity via the Fornell-Larcker criterion (Fornell & Larcker, 1981). Thus, the second-order measurement model was considered satisfactory and provided sufficient evidence of validity and reliability, as shown in Appendix M.

8.2.5 Structural Model of Second-Order Model

The structural model was evaluated by using a set of standard assessment criteria. R^2 value, regarded as the coefficient of determination, reveals the predictive power of independent variables on the dependent variable. R^2 of initial trust and intention showed 65.8% and 64.8% variance can be explained by the predictors, respectively. The value of Q^2 is a measure of the model's out-of-sample predictive power, which was used to assess the predictive relevance of the model (Hair et al., 2016). The Q^2 uncovered predictive relevance via the blindfolding technique. Q^2 values were positive for all constructs, ranging from 0.355 to 0.685, indicating the structural model's high predictive accuracy (Henseler et al., 2016).

The hypotheses in the model were evaluated by bootstrapping technique with 5000 samples. Most hypotheses were supported, which is present in Figure 3 below. The results suggested that PU (β = 0.468, t = 8.555, p = 0.000 < 0.001), PEU (β = 0.175, t = 4.277, p = 0.000 < 0.001), EIDI (β = -0.139, t = 2.650, p = 0.008 < 0.01), and EIFC (β = -0.190, t = 3.840, p = 0.000< 0.001), could significantly influence the initial trust. Therefore, H1a, H2a, H3a, and H4a were supported. The effects of PU (β = 0.192, t = 4.279, p = 0.000 < 0.001) and EIFC (β = -0.1292, t = 2.642, p = 0.008 < 0.01) on BI were significant. Thus, the H1b and H4b were supported. However, PEU (β = 0.018, t = 0.457, p = 0.648 > 0.05) and EIDI (β = -0.045, t = 0.861, p = 0.389 > 0.05) had no significant impact on BI, so the H2b and H3b were rejected. The initial trust positively impacted the BI (β = 0.365, t = 3.186, p = 0.001 < 0.05). All results of SEM, including direct, indirect, and interaction effects, are summarized in Appendix N.

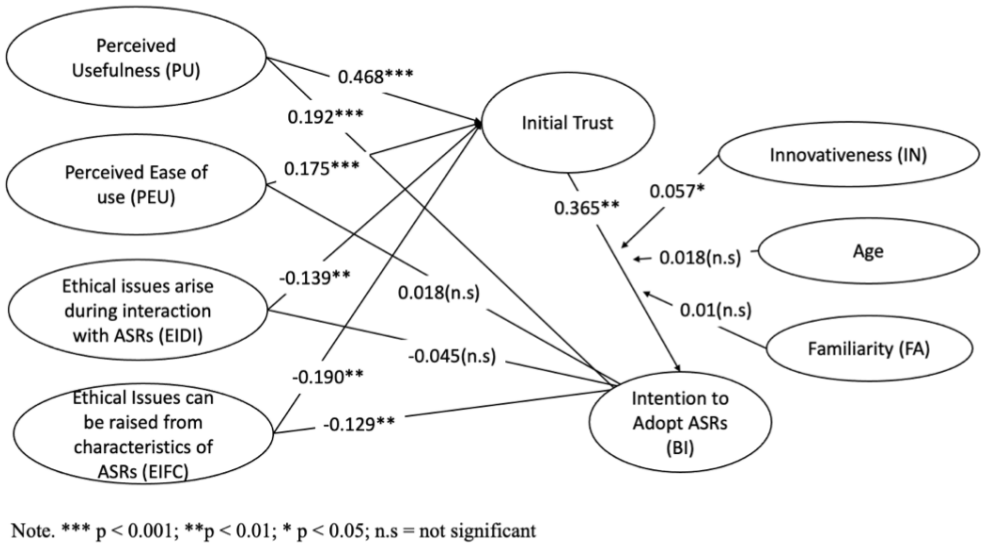

Figure 3 SEM results

8.2.6 Mediating Effects

Mediation analysis was conducted to assess the mediating role of initial trust, where significance is determined through a 95% confidence interval for the indirect effect (Preacher & Hayes, 2008). The assumption of mediating impact is the significant indirect effect. The results demonstrated that all indirect effects were significant, meaning the mediating effects existed. Based on the results in the structural model, the direct effects of PEU and EIDI were not significant, while the direct impacts of PU and EIFC were significant. Given the insignificant direct effects, the effects of PEU ($\beta = 0.064$, $t = 2.401$, $p = 0.016 < 0.05$) and EIDI ($\beta = -0.051$, $t = 2.027$, $p = 0.043 < 0.05$) on behavioral intention were fully mediated by initial trust. Initial trust could completely explain the relationship between PEU and EIDI, and BI. Thus, H6b and H6c were supported. Because of the significant direct effects, the initial trust plays partially mediating roles in the relationship between PU ($\beta = 0.171$, $t = 2.946$, $p = 0.003 < 0.01$) and EIFC ($\beta = -0.069$, $t = 2.403$, $p =$

0.016 < 0.05) and behavioral intention. Hence, H6a and H6d were supported. The direct effects of both PU and EIFC had the same direction as indirect effects, regarded as complementary mediation. In other words, PU and EIFC could affect behavioral intention, amplified by the indirect effect of initial trust.

Table 2

Mediation Analysis Results

Path	Indirect Effect				Results	Supported
	β	T	Confidence Intervals (2.5%)	(97.5%)		
H6a (PU → IT → BI)	0.171	2.946**	0.019	0.123	Partial	Yes
H6b (PEU → IT → BI)	0.064	2.401*	0.064	0.291	Full	Yes
H6c (EIDI → IT → BI)	-0.051	2.027*	-0.132	-0.021	Full	Yes
H6d (EIFC→ IT → BI)	-0.069	2.403*	-0.107	-0.009	Partial	Yes

Note. *** $p < 0.001$; **$p < 0.01$; * $p < 0.05$.

8.2.7 Moderating Effects

The moderating effects of age, familiarity, and innovativeness were examined in the model. The results revealed that there is no significant moderating influence of age (β = 0.018, t = 0.689, p = 0.491 >0.05) and familiarity (β = 0.010, t = 0.250, p = 0.803 >0.05). Thus, H7a and H7b were rejected. However, the moderator of innovativeness was found to have a positive moderating effect on the relationship between initial trust and behavioral intention (β = 0.057, t = 2.049, p = 0.041 < 0.05). This implied that the positive impact of initial trust on behavioral intention increased as consumers had higher innovativeness. Thus, H7c was supported.

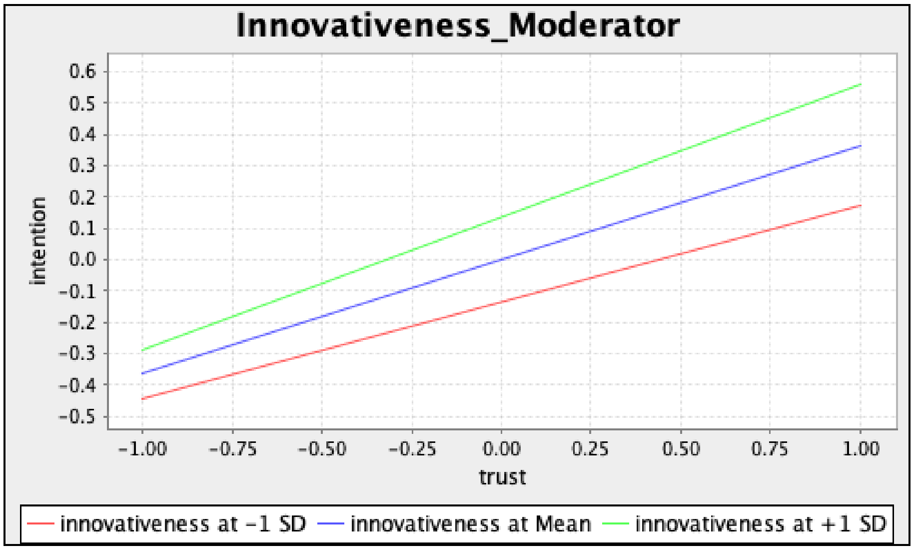

Figure 4 Moderating Effect of Innovativeness

CHAPTER 9

DISCUSSION

Study two established the model based on the Technology Acceptance Model and Initial Trust Model to mainly examine research questions 1) how consumers' perceived ethical issues affect the intention to adopt ASRs and 2) how initial trust mediates the relationship between consumers' perceived ethical issues and the intention to adopt ASRs. The model tested the relationships among the variables of consumers' perceived ethical issues that arise during interaction with ASRs (EIDI), consumers' perceived ethical issues that can be raised from the characteristics of ASRs (EIFC), perceived usefulness (PU), perceived ease of use (PEU), initial trust (IT), behavioral intention (BI), and moderators of age, familiarity (FA), and innovativeness (IN). The results achieve the goal of this study and present significant insights.

Firstly, the results reveal that two dimensions of consumers' perceived ethical issues (i.e., EIDI and EIFC) can negatively affect initial trust, while PU and PEU can positively affect IT. Previous studies have examined the impact of PU and PEU on initial trust (Oliveira et al., 2014; Zhang et al., 2020). The impact of ethical concerns on trust has been investigated regarding different technologies (Gao et al., 2015; Hwang & Choe, 2019). Hence, this study is in line with the results of previous studies and examines in the context of ASRs in hospitality. Additionally, most research adopted the trust concept and tested its impacts, but this study employs the initial trust because consumers lack experience. The results provide empirical evidence to present significant impacts on initial trust. Thus, the findings contribute to the literature and raise attention to the impact on IT. Even if many studies have adopted the concept of trust regarding different technologies, employing IT in terms of emerging intelligent technologies is essential due to lacking experience. Therefore, the results can provide empirical evidence to support further studies about the impact of IT.

Secondly, the findings present that EIDI and PEU have no impact on BI, whereas EIFC and PU significantly impact BI. IT can significantly affect BI. The direction of effects of EIDI and EIFC are negative, while other directions of impacts are positive. These significant results align with previous studies (Etemad-Sajadi et al., 2022; Oliveira et al., 2014; Silic & Ruf, 2018) and confirm the relationship in the Technology Acceptance Model. Specifically, previous studies have tested that consumers' ethical concerns can negatively affect BI in different contexts, for example, using ridesharing and service robots (Nadeem et al., 2021; Etemad-Sajadi et al., 2022). The results further present the impact of two dimensions of consumers' perceived ethical issues on BI, but EIDI has no effect on the intention to adopt ASRs. It can be inferred that even if consumers consider these ethical issues insignificant during service interactions, this does not lead to adoption behaviors. The possible reason is that consumers may not identify these ethical issues due to lacking direct experience with ASRs. Another possible reason is that the ethical issues of various ASRs may vary in different situations, so consumers may not imagine certain situations. Moreover, previous studies have tested that PU and PE can affect the intention to adopt new technologies (Mostafa & Kasamani, 2022; Zhang et al., 2020). The results present that the impact of PU is aligned with previous studies, which confirms the Technology Acceptance Model. However, the impact of PEU is not significant. It is not surprising that the same non-significant result has been found in previous studies. For example, the effect of perceived ease of use on the acceptance of digital voice assistants is not significant (Fernandes & Oliveira, 2021). Intelligent technologies may become easy to use without learning efforts, but PEU is not an important reason to convince consumers to use these new technologies. Hence, there should be other variables that consumers pay more attention to. Lastly, IT has been tested to affect technology adoption (Li et al., 2008; Oliveira et al., 2014). Recent research has examined that trust can positively affect acceptance of AI-based technologies, like chatbots and digital voice assistants (Fernandes & Oliveira, 2021; Pillai & Sivathanu, 2020). Thus, the results confirm and extend the impact regarding the initial stage of trust building in the context of ASRs adoption.

Thirdly, the results uncover that IT plays a mediating role between EIDI, EIFC, PU, and PEU and BI. Simply, all indirect effects of IT are significant. Previous studies have tested the mediating effect of IT (Pappas, 2016; Gao & Waechter, 2017). Going beyond the mediating effect of trust between privacy concerns and BI in the context of online information sharing (Ioannou et al., 2021), this study identifies the mediating effects of BI between two dimensions of consumers' perceived ethical issues and BI. For EIDI and PEU, IT has a full mediating effect. This suggests that EIDI and PEU are effective because they drive consumers to initially trust ASRs services and then increase the intention to adopt ASRs in hospitality. For EIFC and PU, IT can partially influence the relationship. The effect on the relationship can be strengthened by the fact that EIFC and PU can drive initial trust building, which in turn leads to the intention of ASRs adoption. Recent studies about intelligent technologies regard trust as an independent variable to affect BI (Fernandes & Oliveira, 2021; Pillai & Sivathanu, 2020). This study highlights the importance of initial trust as a mediating variable to reduce consumers' ethical concerns and facilitate ASRs adoption behaviors.

Lastly, for the moderators, the findings reveal that age and FA have no moderating impact, which generates different results compare with previous studies. For FA, as consumers rarely have experience with ASRs, the level of familiarity with ASRs is still low. The mean of three measurements of FA is lower than 2. The survey results present that most participants have never or just once searched for information about ASRs in hospitality. Thus, it is necessary to reexamine the impact of FA when more people are familiar with ASRs. Additionally, previous studies have tested that the young generations are more likely to adopt new technologies than older people (Arfi et al., 2021; Hoff& Bashir, 2015). The results uncover the non-significant effect, which is consistent with the findings in study one. The sample profiles confirm this result. As intelligent technology is complex, people need a professional background and knowledge to understand the principle and algorithms. Thus, regarding ASRs, age plays a minor role in trusting in acceptance of ASRs service in hospitality. However, IN as a personality has a significant moderating effect on the relationship between IT and BI. In other words, the impact of initial trust on behavioral intention can be strengthened when consumers have a high level of innovativeness. The moderating effect of innovativeness highlights the importance of understanding individual differences in willingness and ability to adopt new technologies. This result is consistent with previous studies (San Martin & Herrero, 2012; Zhu et al., 2022) and the qualitative findings that curiosity is the main reason to motivate consumers to adopt ASRs. Therefore, these results present new insights and explain the individual difference in ASRs adoption.

For practical implications, this study contributes to the hospitality managers and general service industry in several ways. Firstly, it uncovers the negative significant impact of consumers' ethical perceptions on initial trust, which raises attention to the ethical concerns of managers. The results confirm that initial trust plays a critical mediating role in reducing ethical concerns and facilitating the intention of adoption. Since consumers without experience have those ethical concerns, promoting ASRs services in hospitality is challenging. Thus, managers should implement strategic practices to build consumers' initial trust. For example, managers should disclose transparency about the purpose, capabilities, and limitations of the service robots; clearly communicate how they are designed to respect privacy, handle data, and prioritize safety; and provide detailed information on the technology's decision-making processes and algorithms. Managers also should ensure that service robots undergo rigorous testing and certification processes to guarantee their safety and reliability; regular maintenance and updates should be conducted to address any issues or vulnerabilities promptly; and provide transparency regarding safety protocols and measures taken to mitigate risks. The hotels and restaurants should showcase a commitment to social responsibility by actively addressing ethical concerns and demonstrating accountability and engaging in open dialogues with consumers, addressing their concerns, and actively incorporating their feedback into the design and deployment of service robots. The service industry should establish clear guidelines and regulations for using service robots in hospitality, collaborate with relevant stakeholders (e.g., legal experts, ethicists, and consumer advocacy groups) to develop industry standards and best practices, and publicly communicate adherence to these guidelines to build trust. The industry also should allow consumers to opt-in to interact with service robots rather than imposing their presence and provide alternative options for those who prefer human assistance, ensuring a customer-centric approach that respects individual preferences. By implementing these strategies, the managers can work towards building consumers' initial trust in service robots while actively addressing the ethical issues associated with their deployment in the hospitality or entire service industry.

Moreover, EIFC significantly influences BI, while EIDI does not affect BI. Thus, the ethics of EIFC is significant in the current stage of AI development. Many ethical issues of EIFC have received broad attention from different stakeholders, such as privacy, responsibility, and transparency. Thus, it is essential to pay attention to the EIDI, even if there is no significant impact of EIDI on BI. In the current stage, consumers may not realize the ethical issues of service robots during service interaction. Several reasons are followed. Even if consumers are aware of service robots, they may have a limited understanding of the underlying technology and its potential ethical challenges. They may not be familiar with concepts such as data privacy, algorithmic bias, or the impact of automation on employment. Then, with more advanced technologies applied in the service industry, there is a general tendency to trust new technology, assuming that it operates objectively and without bias. Consumers may not question the ethical aspects of service robots, assuming that they are designed to prioritize efficiency, convenience, and customer satisfaction. Consumers may also place trust in hospitality using service robots, assuming that these entities have considered and addressed any ethical concerns. They may rely on the reputation of the service provider without delving into the ethical dimensions of the technology. Thus, addressing these challenges requires increased awareness and education about the ethical issues of service robots. It is important to foster transparency, engage in public discourse, and provide accessible information to consumers. By promoting discussions around the ethical implications of service robots, consumers can make more informed decisions and actively participate in shaping the responsible and ethical use of these technologies.

Lastly, the results show that age and familiarity have no moderating impact, but innovativeness has a significant moderating impact. It indicates that personality is an important moderator. Different from previous studies, age and familiarity are not significant in the context of ASRs. The reasons are below. Age can influence an individual's values and ethical perspectives, but it does not necessarily dictate their sensitivity to ethical concerns. People of all ages can exhibit varying levels of ethical sensitivity and concern. Factors such as personal values, education, and life experiences can play a more significant role in shaping ethical sensitivity than age alone. While age can be a relevant factor in understanding consumers' perspectives and behaviors, it should not be the sole determinant when considering the impact of ethical concerns on trust and the adoption of service robots in hospitality. On the other hand, even if individuals are familiar with service robots, their perception of ethical issues can vary. Some individuals may not consider or prioritize ethical concerns, viewing robots as mere tools or gadgets. Familiarity alone does not guarantee a deeper understanding or sensitivity to ethical implications. Ethical concerns and their impact on initial trust and use of service robots can be influenced by personal values, cultural background, education, and other factors beyond familiarity with the emerging technology. While familiarity can have some influence on the impact of ethical concerns, it is not the sole determinant. Other factors, such as awareness, ethical sensitivity, and personal values, may play important roles in shaping individuals' trust and use of service robots in hospitality in the presence of ethical concerns. Therefore, innovativeness can moderate the impact of ethical concerns on initial trust and the use of service robots in hospitality. Innovativeness is often linked to future-oriented thinking and a focus on progress and advancement. More innovative individuals may prioritize the long-term benefits and potential positive impact of service robots over immediate ethical concerns. They may be more willing to support and use innovative technologies, even while acknowledging and considering ethical concerns.

Therefore, hospitality managers should plan how to maintain service quality and reduce potential risks when consumers adopt ASRs. For example, pilot tests of ASRs are necessary to mitigate potential risks. Effective marketing strategies on social media are vital to increasing the exposure and publicity of ASRs in hospitality. The managers can create compelling and engaging content that showcases the benefits, features, and unique aspects of ASRs in hospitality. This can include videos, images, testimonials, and success stories sharing real-life examples and anecdotes and demonstrating how ASRs have improved guests' satisfaction, streamlined operations, or enhanced the overall hospitality experience. Also, managers can encourage consumers, guests, and employees to share their experiences with ASRs on social media and promote hashtags and contests that encourage users to create and share content related to ASRs in hospitality. The hospitality industry should collaborate with other businesses (i.e., hotels, restaurants, and hospitality organizations) to jointly promote ASRs in the industry, co-create content, host webinars or panel discussions, or participate in industry events together, and leveraging industry partnerships can expand the reach and impact of your social media marketing efforts. As long as consumers identify the advantages of ASRs and regulations or measures to protect their rights, the acceptance and usage of ASRs in the hospitality or even service industry can be increased.

CHAPTER 10

CONCLUSION

10.1 Summary

This dissertation aimed to 1) explore consumers' ethical perceptions toward ASRs adoption in hospitality, 2) investigate how consumers' ethical concerns affect ASRs adoption in hospitality in post-pandemic, and 3) identify how initial trust mediate consumers' ethical concerns and adoption of ASRs in hospitality. To adequately address the research questions, an exploratory sequential mixed methods approach was applied, separated into two studies.

Study one focused on the first research question and empirically explored consumers' ethical perceptions of ASRs in hospitality through methodological triangulation. The findings emerge eight themes of consumers' perceived ethical issues of ASRs, including privacy, security, transparency, fairness, safety, socialization, autonomy, and responsibility. Each theme could be correspondently explained from two perspectives: ethical issues that arise during interaction with ASRs (e.g., ubiquitous surveillance, data excessiveness, unknown risks, full disclosure, inaccessibility, dehumanization, selection of services, service recovery) and ethical issues that can be raised from characteristics of ASRs (e.g., privacy infringement, malicious use, malfunctions, untrust, bias, job replacement, inflexibility, self-solved solutions). Therefore, a total of 16 specific ethical issues of ASRs have been recognized from consumers' perspectives.

Study two focused on the last two questions. This study first developed the measurements of consumers' perceived ethical issues based on the qualitative themes in study one. Then the hypothesized model was built based on the Technology Acceptance

Model and Initial Trust Model. Two rounds of online surveys were employed to collect the data. The measurements of consumers' perceived ethical issues were finalized through exploratory and confirmatory factor analysis. The variable of consumers' perceived ethical issues that arise during interaction with ASRs (EIDI) contains four constructs: personal privacy (6 items), disclosure (5 items), dehumanization (5 items), and service failure (6 items), and the variable of consumers' perceived ethical issues that can be raised from characteristics of ASRs (EIFC) consists of five constructs: informational security (6 items), untrustworthiness (5 items), bias (3 items), job replacement (3 items), and inflexibility (6 items). Partial least squares structural equation modeling was adopted to analyze the relationships in the model. The results demonstrate that EIDI negatively affects initial trust but has no impact on behavioral intention; EIFC negatively influences both initial trust and behavioral intention; perceived usefulness positively affects both initial trust and behavioral intention; perceived ease of use has a positive impact on initial trust but has no effect on behavioral intention; initial trust significantly influences the behavioral intention and plays a mediating role between antecedents and outcomes; age and familiarity have no moderating impact but innovativeness significant moderate the relationship between initial trust and behavioral intention. These findings provide essential theoretical contributions and managerial implications for the hospitality and tourism industry.

10..2 Implications to Ethics Literature

This dissertation contributes to the literature on ethics studies in the fields of business and information and communications technology (ICT). This dissertation conceptualizes the concept of consumers' ethical perceptions regarding ASRs adoption in hospitality. This concept is mainly examined in marketing literature targeting consumers' ethical perceptions toward employees' actions and firms' strategies (Brunk, 2012). Then, this concept is adopted in the area of information communications and technology, focusing on the users' ethical concerns about the outcomes of using technologies (Nadeem et al., 2021). However, as ASRs become increasingly autonomous and intelligent, consumers can simultaneously treat ASRs as human-like servers and technologies. Thus, they can generate various ethical concerns from different aspects. This dissertation extends the concept of consumers' ethical perceptions related to innovative ASRs services in the hospitality industry, defined as the consumers' subjective beliefs of the righteousness/wrongness of ASRs' behaviors related to specific services in hospitality. This dissertation further proposes to measure the consumers' ethical perceptions of ASRs by identifying the consumers' perceived ethical issues toward ASRs in hospitality via both qualitative and quantitative ways. The concept of consumers' ethical perceptions is context-related, so this study provides conceptual and statistical aspects to understand this important concept in terms of ASRs adoption in hospitality. Thus, the conceptualization of consumers' ethical perceptions of ASRs can extend the ethics studies in the literature on business and information and communications technology.

Moreover, this dissertation extends ethics studies about certain AI applications in the service industry. The previous literature largely neglected the perspectives of consumers' ethical concerns regarding ASRs in hospitality. Regarding consumers' perceived ethical issues toward ASRs, the existing ethics studies have primarily targeted the ethical issues of AI and robotics (Siau & Wang, 2020; Wirtz et al., 2018). The results demonstrate two dimensions of consumers' perceived ethical issues when applying ASRs in the service industry. As AI and robotics are the core of ASRs, the ethical issues of AI and robotics are regarded as ethical issues raised from the characteristics of ASRs. Another dimension is ethical issues that arise during service interaction, which is emphasized in this dissertation. Since only a few review papers theoretically point out the importance of the ethics of AI applications in services (Chi et al., 2020; Siau & Wang, 2020), this study contributes to the literature about ethical issues that arise during service interaction with empirical evidence, which should be received more attention from both scholars and practitioners.

Additionally, this dissertation provides a profound understanding of multidimensional constructs of consumers' perceived ethical issues toward ASRs in hospitality. Little empirical research in previous studies exists about the specific ethical issues of ASRs in hospitality. Extant studies targeted dominant ethical issues raised from features of service robots, such as information security and personal privacy (Tussyadiah et al., 2020; Tussyadiah & Miller, 2019). From the aspect of service interaction, review papers have mentioned some underlying ethical challenges of ASRs, such as dehumanization, responsibility, and fairness (Chi et al., 2020; Wirtz et al., 2018). The findings from study one uncover eight specific ethical issues from two dimensions of consumers' perceived ethical issues under a qualitative approach. In study two, these ethical issues are tested and formed into new constructs of two dimensions of consumers' perceived ethical issues. Thus, this dissertation presents that consumers' perceived ethical issues can be considered as second-order constructs. Each construct is an essential aspect of consumers' ethical perceptions of ASRs. Therefore, to the knowledge of the authors, this study is the first to investigate consumers' ethical perceptions as second-order constructs in the context of

ASRs adoption in hospitality and provide empirical evidence through both qualitative and quantitative methods.

Lastly, this dissertation proposes measurements of two dimensions of consumers' perceived ethical issues toward ASRs in hospitality. The measurements were developed from qualitative findings in study one. Using exploratory and confirmatory factor analysis, the measurements were finalized via two separate datasets. The current study is the first to propose measurements of consumers' ethical perceptions in the context of ASRs adoption in hospitality. These results can fill the gaps about lacking measurements of consumers' perceived ethical issues toward service robots and provide a theoretical basis to examine consumers' perceived ethical issues toward various intelligent technologies in the border service contexts.

10..3 Implications to ICT Literature

This dissertation contributes to information and communications technology (ICT) literature in several ways. Firstly, the Technology Acceptance Model (TAM) is confirmed to be used in intelligent technology adoption by adding consumers' perceived ethical issues. TAM has been employed in examining emergent technology adoption (de Kervenoael et al., 2020; Pillai & Sivatthanu, 2020). Even if one construct in TAM (perceived ease of use) has no significant impact on behavioral intention, other constructs and relationships in TAM are confirmed. Thus, TAM is still robust to building a theoretical basis to examine technology adoption, particularly emergent intelligent technologies. This dissertation further extends TAM by adding consumers' perceived ethical issues and initial trust to emphasize the significance of ethics and trust in the context of ASRs adoption in hospitality.

With more intelligent technologies emerging, the roles of ethics and initial trust become increasingly crucial in affecting adoption behaviors. Therefore, we must pay closer attention to consumers' ethical perceptions and initial trust in adopting intelligent technology.

Secondly, this dissertation advances the ICT literature by emphasizing the impact of consumers' ethical concerns and initial trust on behavioral intention. Because increasing chances exist for consumers to adopt ASRs in hospitality, how consumers' ethical concerns toward ASRs affect initial trust and adoption intention becomes urgent to examine. The results explain the importance of consumers' perceived ethical issues on initial trust and behavioral intention. Thus, the current findings contribute to the ICT literature by examining the impact of ethical issues of ASRs on behavioral intention. Particularly, this dissertation investigates the different impacts of two dimensions of consumers' perceived ethical issues on initial trust and behavioral intention. Therefore, the impact of ethical issues arising during service interactions needs further investigation.

In addition, this dissertation contributes to the literature by unveiling the theoretical connections by testing the mediating role of initial trust in the context of ASRs adoption. Ethics has become an increasingly crucial topic in intelligent technology. Consumers without experience and knowledge can barely trust these innovations. This research differentiates initial trust from the concept of trust in adopting ASRs for consumers without experience. The results reveal that initial trust based on three constructs is appropriate to employ in the context of ASRs and identify its important mediating impact in reducing consumers' ethical concerns and facilitating adoption behaviors. Thus, this study enhances the literature on initial trust and stresses the importance of the initial stage of trust to build an impressive image of ASRs and facilitate the behavioral intention of using ASRs in hospitality.

Lastly, this study contributes literature by identifying the moderating impact of innovativeness. Previous studies mainly focus on the moderators of demographics regarding new technologies. However, the results of this study show that age has no impact as a moderator, which is different from previous studies. Instead, this study emphasizes innovativeness as one type of personality that can significantly enhance people's intention to adopt ASRs. Therefore, this study contributes to the literature on the moderating impact of personality on intelligent technology adoption.

10..4 Implications for Tourism and Hospitality Industry

As frontline service industries, tourism and hospitality industries have widely employed ASRs, especially during the pandemic. However, consumers' perceived ethical issues have not been solved. Thus, this dissertation provides significant implications for the tourism and hospitality industries. These implications are relevant not only to the tourism and hospitality industries but also to the broader service industries.

Firstly, this dissertation highlights the importance of identifying and solving current consumers' ethical concerns about ASRs that significantly affect initial trust and behavioral intention. The results present specific consumers' perceived ethical issues in particular situations, so managers in the tourism and hospitality industries should pay more attention to these ethical issues. Even if the purpose of using ASRs to serve is to gain more benefits, like efficiency and convenience, the underlying ethical issues can directly affect consumers' acceptance and willingness to use these innovations. Especially when AI advances quickly, new ethical issues may appear, strengthening the resistance to adoption. Therefore, effective measurements must be implemented to reduce consumers' perceived ethical issues toward adopting ASRs. For example, organizations in tourism and hospitality should conduct a risk assessment before implementing ASRs to ensure that they do not pose any safety risks to consumers. Organizations also should be transparent about ASRs services, like how ASRs work, what tasks ASRs perform, and how ASRs are programmed, which can help alleviate their concerns. They can control consumers' interactions with ASRs, allow users to opt-in or opt-out of using the robots and enable them to customize their preferences and levels of engagement, and foster a sense of autonomy and respect for individual choices. The industry needs to establish mechanisms for collecting and incorporating consumer feedback to address ongoing ethical concerns, actively seek input from consumers, engage in dialogue, and iterate on the technology based on user experiences and preferences. Therefore, ASRs have different types and perform various tasks, so managers must thoughtfully consider the specific ethical issues in particular situations, especially during service interactions, to prevent underlying ethical risks. By recognizing and proactively addressing consumers' ethical concerns regarding ASRs, organizations in hospitality can establish a foundation of trust and positively influence consumer perceptions, initial trust, and behavioral intentions towards the ASRs. These actions can help drive widespread acceptance and adoption of ASRs in hospitality.

Secondly, this dissertation suggests that managers in the tourism and hospitality industry and policymakers must realize the importance of building initial trust. The findings explain the mediating role of initial trust in reducing consumers' ethical concerns and driving adoption behaviors regarding ASRs in hospitality. In other words, consumers with high initial trust in ASRs are more likely to use them in hospitality, even if ethical concerns exist. If consumers have trust in the ASRs, they are more likely to be open to interacting with service robots in various hospitality settings. Trust creates a positive perception, reduces skepticism, and increases the likelihood of consumers embracing and utilizing the robots. By building trust in the ASRs, managers and policymakers can help guests feel comfortable and confident in their interactions. This can lead to improved efficiency, personalized services, and enhanced convenience, ultimately resulting in a positive guest experience. Therefore, managers in tourism and hospitality and policymakers should find ways to build consumers' initial trust in ASRs. For the brand reputation of hospitality, the establishments that are seen as trustworthy and responsible in their deployment of robots are more likely to attract and retain customers. Positive word-of-mouth, online reviews, and recommendations can strengthen the brand reputation and lead to increased business opportunities. Especially policymakers who are crucial roles in creating a supportive environment for the use of service robots should develop ethical guidelines first to guide the use of service robots in the service industry and help to ensure that organizations using these robots operate in a socially responsible and ethical manner, such as safety in human-robot interaction and consumer data protection. Recognizing the importance of building initial trust can guide policymakers in developing regulations, standards, and guidelines that ensure ethical and responsible deployment of the technology. This support fosters confidence among businesses and consumers alike. By acknowledging and prioritizing the importance of building initial trust in service robots, managers in the tourism and hospitality industry and policymakers can facilitate the successful integration of these ASRs. This, in turn, leads to enhanced guest experiences, improved industry competitiveness, and the realization of the potential benefits that service robots offer.

Lastly, this dissertation proposes that managers in the tourism and hospitality industry should consider personality as an important factor in encouraging potential early adopters to use intelligent technologies in tourism and hospitality. Managers can target these individuals as potential early adopters and develop strategies that appeal to their innovative mindset. As the results show that personal innovativeness has a significant moderating effect, organizations can tailor their marketing strategies to appeal to different personality types and increase adoption. For example, they can highlight the innovative features of ASRs in advertisements and design more attractive features to appeal to individuals with a high level of innovativeness to initiate and experience the ASRs service. Personality includes several aspects. Personality traits related to technology readiness, such as technological optimism, self-efficacy, and comfort with technology, impact individuals' willingness to use intelligent technologies. Those with higher technology readiness are more likely to adopt and use intelligent technologies in the tourism and hospitality industry. Managers also can identify and target individuals with these traits to encourage their early adoption of the technology. Personality traits also influence individuals' perception of risks associated with adopting new intelligent technologies. Some individuals may be more risk-averse and cautious, while others may be more inclined to take risks. Managers need to understand these personality differences and develop strategies to alleviate concerns and provide assurances, addressing potential risks associated with the adoption of intelligent technologies. By considering personality as an important factor, managers can better understand potential early adopters and develop targeted strategies to encourage their use of intelligent technologies in tourism and hospitality. Personalized approaches, addressing risk perceptions, leveraging technology readiness, and harnessing the influence of key individuals can help drive adoption and ensure the successful integration of intelligent technologies in the service industry.

10.5 Limitations

This dissertation has limitations despite the contributions it makes. Firstly, the results only consider ethical concerns in the general context of ASRs in hospitality. Different ASRs' characteristics and service functions may generate various ethical issues. Thus, more considerations in certain situations are needed. Secondly, this dissertation only examines the impact of two dimensions of consumers' perceived ethical issues toward ASRs on initial trust and behavioral intention. There is lacking investigation on the effects of specific constructs. Lastly, in terms of moderators, this dissertation only examines the impact from personal dimensions. Hence, the extension of the effects of other moderators on the different relationships may increase valuable results.

10.6 Suggestions for Future Study

This dissertation makes valuable suggestions for future studies. Firstly, future studies can thoroughly consider multiple types of ASRs in specific ethical scenarios to identify particular consumers' perceived ethical issues. For example, various ASRs have their own unknown risks, for instance, the contamination of food delivery by robots and the deception of chatbots. Secondly, future studies can investigate how specific constructs of consumers' ethical concerns affects initial trust and behavioral intention. Lastly, future studies can extend the studies to testing more moderators from different dimensions, such as consumers with/without IT background and social norms, and more relationships, like the moderating impact on the relationship between perceived ease of use and perceived usefulness.

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APPENDIX A

STUDIES ABOUT ETHICAL ISSUES OF SERVICE ROBOTS

Studies About Ethical Issues of Service Robots

Source	Context	Ethical Issues	Type
Lin et al., 2011	General service robot	Safety and errors, law and ethics, social impact	Theoretical
Royakkers & van Est, 2015	Home robot, care robot, care robot, police robot, military robot	Technological issues, social robotization, the appearance of robots, autonomy, dehumanization, responsibility	Theoretical
Körtner, 2016	Socially assistive robots for senior adults	Deception, dignity, isolation, data protection, privacy and safety	Theoretical
Vandemeulebroucke et al., 2017	Aged care service robot	Dehumanization, safety, autonomy	Theoretical
Wirtz et al., 2018	General service robot	Micro level for consumers: privacy and security; dehumanization and social deprivation. Meso level for organizations: winner-take-it-all markets; investment, innovation and liability regimes. Macro level for society: employment; inequality within and across societies.	Theoretical
Cain et al., 2019	General service robot in hospitality	Labor protection, lability issues, laws, protection of personal information and privacy, inequality	Theoretical
Belk, 2020	Service industry	Ubiquitous surveillance, social engineering, military robots, sex robots, and transhumanism	Theoretical
Chi et al., 2020	AI devices in service delivery	Perceived identity threat, network security and information privacy, employment disruption, transparency, fairness, ai failure	Theoretical
Lu et al., 2020	General service robot	privacy and security, dehumanization and social deprivation, appearance, corporate digital responsibility, unemployment	Theoretical
Boada et al., 2021	Social assistive robotics	Well-being: privacy/data control, deception, autonomy, loss of human contact, safety, dignity, emotional attachment, unauthentic intersubjectivity, objectification, freedom, identify, recognition. Care: legitimacy of the introduction of robots, quality of practice, trust, role disruption. Justice: distributive justice, politics of robotic technology, social equality, responsibility, robots'	Literature review

		decision-making, ecological sustainability.	
Etemad-Sajadi et al., 2022	General human robot interaction (Pepper)	Social cues, trust and safety, responsibility, privacy and data protection, (job replacement and autonomy are not significant)	Empirical (SEM)

APPENDIX B

INTERVIEW PROTOCOL

Interview protocol of semi-structured interviews (Phase One)

This research is going to investigate consumers' ethical perceptions of service robots in hospitality. The interview is confidential and used for this research only. Do you have any questions before the interview? If not, please introduce yourself and review the descriptions of different service robots in the hospitality industry.

General questions:

1: What problems do you perceive when it comes to using service robots in the hospitality industry (referring more specifically to hotels and/or restaurants)?

Have experience with service robots	No experience with service robots
2: Can you describe your experience with service robots in a hotel and/or restaurant?	2: If you were to go to a hotel or a restaurant with a service robot, what experience might you perceive?
3. Would you use a service robot in a hotel and/or restaurant setting again? Why or why not?	3. How likely would you want to use a service robot in a hotel and/or restaurant setting? Why or why not?

4: What underlying ethical issues of these service robots concern you?

Additional comments:

Do you have anything else you would like to say about this service robot based on your experience, interests, or concerns? Any additional comments for this interview?

Interview protocol of focus groups (Phase Two)

Thank you for participating in the focus group discussion. This study is going to investigate consumers' ethical perceptions of service robots in the hospitality industry (focus group 1 about the delivery robot, focus group 2 about the robot bartender, and focus group 3 about the chatbot). The whole process is voluntary and confidential. The focus group will last around one hour. The data is only used for this research. Recording the conversation is necessary to capture the answers accurately. The results of the study may be used in the paper without releasing your name. If you would like to participate, please feel free to answer the questions during the focus group.

General questions:

1. What are your feelings about using this service robot?
2. What potential problems about this service robot concern you?
3. What ethical issues do you perceive when using the service robot in a hotel or restaurant setting?
4. How likely would you want to use this service robot in a hotel or restaurant setting?
5. What other risks or challenges are you worried about?

Additional comments:

Do you have anything else you would like to say about this service robot based on your experience, interests, or concerns? Any additional comments for this interview?

Interview protocol of on-site interviews (Phase Three)

Thank you for participating in the individual discussion. This study is going to investigate consumers' ethical perceptions of service robots in the hospitality industry (the delivery robot in Renaissance Hotel, the robot bartender in Planet Hollywood Hotel, and the chatbot in Cosmopolitan Hotel). The whole process is voluntary and confidential. The data is only used for this research. Recording the conversation is necessary to capture the answers accurately. The results of the study may be used in the paper without releasing your name. If you would like to participate, please feel free to answer the questions during the interview.

General questions:

1. What are your feelings about using this service robot?
2. What problems about this service robot concern you?
3. How likely would you want to use this service robot in a hotel or restaurant setting again?
4. What potential ethical issues are you worried about?

Additional comments:

Do you have anything else you would like to say about this service robot based on your experience, interests, or concerns? Any additional comments for this interview?

APPENDIX C

CONSENT FORM

Consent form of semi-structured interviews (Phase One)

I am a graduate student, Boyu Lin, under the direction of Dr. Woojin Lee in the School of Community Resources & Development at Arizona State University. I am conducting a research study investigating consumers' ethical perceptions of service robots in hospitality.

I am inviting your participation, which will involve different service robots in the hospitality industry. You have the right not to answer any questions and stop participation at any time. The process of interview will last around 30 minutes.

Your participation in this study is voluntary. If you choose not to participate or to withdraw from the study at any time, there will be no penalty. There are no foreseeable risks or discomforts to your participation.

Your responses will be anonymous. Only researchers can access that data. The results of this study may be used in publications, but your name will not be used. The data will be not shared with others. The managing process will be safe. The data will be confidential and destroyed after related research is finished. A $15 gift card will be given to each person at the end of the interview.

I would like to audio record this interview. The interview will not be recorded without your permission. Please let me know if you do not want the interview to be recorded; you also can change your mind after the interview starts; just let me know.

If you have any questions concerning the research study, please contact the research team: Boyu Lin (blin26@asu.edu) or principal investigator Dr. Woojin Lee (Woojin.Lee.1@asu.edu). If you have any questions about your rights as a subject/participant in this research, or if you feel you have been placed at risk, you can contact the Chair of the Human Subjects Institutional Review Board, through the ASU Office of Research Integrity and Assurance, at (480) 965-6788. Please let me know if you wish to be part of the study.

By signing below, you agree to be part of the study.

Name:

Signature: Date:

Consent form of focus groups (Phase Two)

I am a graduate student, Boyu Lin, under the direction of Dr. Woojin Lee in the School of Community Resources & Development at Arizona State University. I am conducting a research study investigating consumers' ethical perceptions of service robots in hospitality.

I am inviting your participation, which will involve one of these groups (focus group 1 about the delivery robots, focus group 2 about the robot bartenders, and focus group 3 about the chatbots). You have the right not to answer any questions and stop participation at any time. The process of the focus group will last around one hour.

Your participation in this study is voluntary. If you choose not to participate or to withdraw from the study at any time, there will be no penalty. There are no foreseeable risks or discomforts to your participation.

Due to the nature of focus groups, complete confidentiality cannot be guaranteed due to the participation of others in the discussion. In research publications, however, your responses will be anonymized. The data will be destroyed after finishing this study. Only researchers can access that data. The results of this study may be used in publications, but your name will not be used. The data will not be shared with others. The managing process will be safe. The data will be destroyed after related research is finished. A $15 gift card will be given to each person at the end of the focus group.

I would like to video record this focus group. The focus group will not be recorded without your permission. Please let me know if you do not want the focus group to be recorded; you also can change your mind after the focus group starts; just let me know.

If you have any questions concerning the research study, please contact the research team: Boyu Lin (blin26@asu.edu) or principal investigator Dr. Woojin Lee (Woojin.Lee.1@asu.edu). If you have any questions about your rights as a subject/participant in this research, or if you feel you have been placed at risk, you can contact the Chair of the Human Subjects Institutional Review Board, through the ASU Office of Research Integrity and Assurance, at (480) 965-6788. Please let me know if you wish to be part of the study.

By signing below, you agree to be part of the study.

Name:

Signature: Date:

Consent form of on-site interviews (Phase Three)

I am a graduate student, Boyu Lin, under the direction of Dr. Woojin Lee in the School of Community Resources & Development at Arizona State University. I am conducting a research study investigating consumers' ethical perceptions of service robots in hospitality.

I am inviting your participation, which will involve one of these on-site interviews (interview 1 about the delivery robot at Renaissance Hotel; interview 2 about the robot bartender at Planet Hollywood Hotel; interview 3 about the chatbot at Cosmopolitan Hotel). You have the right not to answer any questions and stop participation at any time. The process of the interview will last around 15-20 minutes.

Your participation in this study is voluntary. If you choose not to participate or to withdraw from the study at any time, there will be no penalty. There are no foreseeable risks or discomforts to your participation.

Your responses will be anonymous. Only researchers can access that data. The results of this study may be used in publications, but your name will not be used. The data will not be shared with others. The managing process will be safe. The data will be confidential and destroyed after related research is finished. A $15 gift card will be given to each person at the end of the interview.

I would like to audio record this interview. The interview will not be recorded without your permission. Please let me know if you do not want the interview to be recorded; you also can change your mind after the interview starts; just let me know.

If you have any questions concerning the research study, please contact the research team: Boyu Lin (blin26@asu.edu) or principal investigator Dr. Woojin Lee (Woojin.Lee.1@asu.edu). If you have any questions about your rights as a subject/participant in this research, or if you feel you have been placed at risk, you can contact the Chair of the Human Subjects Institutional Review Board, through the ASU Office of Research Integrity and Assurance, at (480) 965-6788. Please let me know if you wish to be part of the study.

By signing below, you agree to be part of the study.

Name:

Signature: Date:

APPENDIX D

IRB APPROVALS

IRB for Study One

ASU Knowledge Enterprise Development

EXEMPTION GRANTED

Woojin Lee
WATTS: Community Resources and Development, School of
602/496-1228
Woojin.Lee.1@asu.edu

Dear Woojin Lee:

On 4/29/2022 the ASU IRB reviewed the following protocol:

Type of Review:	Initial Study
Title:	Consumers' Ethical Perceptions of Autonomous Service Robots in Hospitality
Investigator:	Woojin Lee
IRB ID:	STUDY00015668
Funding:	None
Grant Title:	None
Grant ID:	None
Documents Reviewed:	• focus grouop protocol (Phase 2).pdf, Category: Recruitment Materials; • Interview protocol (Phase 1).pdf, Category: Recruitment Materials; • IRB Social Behavioral 2022_Boyu Lin.docx, Category: IRB Protocol; • on-site interview protocol (Phase 3).pdf, Category: Recruitment Materials; • Short Consent for focus group__Boyu Lin.pdf, Category: Consent Form; • Short Consent for Individual interview__Boyu Lin.pdf, Category: Consent Form; • Short Consent for on-site individual interviews__Boyu Lin.pdf, Category: Consent Form; • site permission, Category: Other;

The IRB determined that the protocol is considered exempt pursuant to Federal Regulations 45CFR46 (2) Tests, surveys, interviews, or observation on 4/12/2022.

In conducting this protocol you are required to follow the requirements listed in the INVESTIGATOR MANUAL (HRP-103).

If any changes are made to the study, the IRB must be notified at research.integrity@asu.edu to determine if additional reviews/approvals are required. Changes may include but not limited to revisions to data collection, survey and/or interview questions, and vulnerable populations, etc.

REMINDER - - Effective January 12, 2022, in-person interactions with human subjects require adherence to all current policies for ASU faculty, staff, students and visitors. Up-to-date information regarding ASU's COVID-19 Management Strategy can be found here. IRB approval is related to the research activity involving human subjects, all other protocols related to COVID-19 management including face coverings, health checks, facility access, etc. are governed by current ASU policy.

Sincerely,

IRB Administrator

IRB for Study Two

ASU Knowledge Enterprise Development

EXEMPTION GRANTED

Woojin Lee
WATTS-CRD: Community Resources and Development, School of
602/496-1228
Woojin.Lee.1@asu.edu

Dear Woojin Lee:

On 9/20/2022 the ASU IRB reviewed the following protocol:

Type of Review:	Initial Study
Title:	Mixed Study on Autonomous Service Robots (ASRs) adoption in Hospitality from Ethical Perspective
Investigator:	Woojin Lee
IRB ID:	STUDY00016436
Funding:	None
Grant Title:	None
Grant ID:	None
Documents Reviewed:	• cover page for survey.pdf, Category: Consent Form; • IRB Social Behavioral 2022_Boyu Lin.docx, Category: IRB Protocol; • Point by point response.docx, Category: IRB Protocol; • Questionnaire_ASR.pdf, Category: Measures (Survey questions/Interview questions /interview guides/focus group questions); • Questionnaires.pdf, Category: Measures (Survey questions/Interview questions /interview guides/focus group questions);

The IRB determined that the protocol is considered exempt pursuant to Federal Regulations 45CFR46 (2)(i) Tests, surveys, interviews, or observation (non-identifiable), (2)(ii) Tests, surveys, interviews, or observation (low risk) on 9/12/2022.

In conducting this protocol you are required to follow the requirements listed in the INVESTIGATOR MANUAL (HRP-103).

If any changes are made to the study, the IRB must be notified at research.integrity@asu.edu to determine if additional reviews/approvals are required. Changes may include but not limited to revisions to data collection, survey and/or interview questions, and vulnerable populations, etc.

REMINDER - - Effective January 12, 2022, in-person interactions with human subjects require adherence to all current policies for ASU faculty, staff, students and visitors. Up-to-date information regarding ASU's COVID-19 Management Strategy can be found here. IRB approval is related to the research activity involving human subjects, all other protocols related to COVID-19 management including face coverings, health checks, facility access, etc. are governed by current ASU policy.

Sincerely,

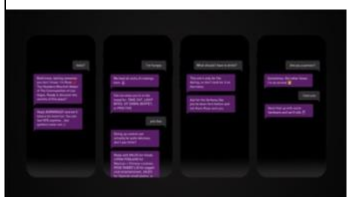
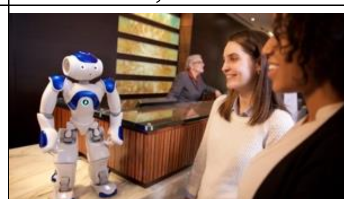
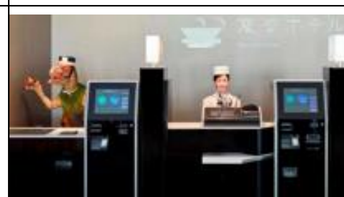
IRB Administrator

cc: Boyu Lin

APPENDIX E

ROLES OF ASRS IN HOSPITALITY

Different Roles of Autonomous Service Robots in Hospitality

Type	Example	Description
Robot Ambassador (High Interactive)	Mandarin Oriental Hospitality, “Pepper”	 Greet guests in different languages, answer hospitality-related questions, give directions, provide quick check-in/out service, make recommendations about attractions, and make reservations for events and restaurants in the hospitality.
Chatbot (High Interactive)	The Cosmopolitan of Las Vegas, “Rose”	 Deliver consumer service to guests via text message, make reservations about events and restaurants in the hospitality, provide recommendations about attractions, and ask for room service.
Robot Concierge (High Interactive)	Hilton Hospitality, “Connie”	 Interact with guests and respond to their questions on topics, such as nearby attractions, places to eat, and hospitality information.
Front Desk Robots (High Interactive)	Henn-na Hospitality	 Provide hospitality-related information and check-in/out services with facial recognition.
Room Voice Assistant (High Interactive)	Henn-na Hospitality	 Provide information for guests and help to control the digital devices like TV and lights,
Delivery Robot (Low Interactive)	Vdara Hospitality, “Fetch”	 Deliver snacks, towels, and other products and make a phone call to announce its arrival. Navigate around the

		hospitality with guests using elevators, and communicate with guests through its face-shaped touchscreen.
Robot Bartender (Low Interactive)	Planet Hollywood, “Tipsy Robot”	 Consumers input personal information, customize their drinks, and pay successfully. Then, the robot bartender can make a cocktail within 90 seconds.
Luggage Porter Robot (Low Interactive)	Sheraton Los-Angeles San Gabriel Hospitality, “Tugs”	 Welcome guests at the reception and take luggage up to the guests’ rooms, using internal GPS to find the way.
Security Robot (Low Interactive)	Pechanga Resort & Casino, “Buddy”	 Continuously capture 360-degree, high-definition videos of its surroundings, auto-detect license plates of vehicles and dangerous weapons, and utilize thermal imaging to gauge fire risks.
Robot housekeeping (Low Interactive)	Westin Houston Medical Center hospitality	 Clean the floor and disinfect the air, rooms, and common areas by implementing a germ-zapping UV light.
Cooking Robot (Low Interactive)	Zume Pizza	 Make the main foods, sides, and salads following the programming protocol.

Note. Adopted from Alderton (2018), Arkoff (2019), Glusac (2020), Newsdesk (2017), Revfine.com, Social Tables (2020), and TipsyRobot.com (2021).

APPENDIX F

DEMOGRAPHICS OF INTERVIEWEES

Demographics of Interviewees

No.	Gender	Age	Ethnicity	Occupation	Experience with ASRs	Willingness to Use ASRs	Group
P1	M	30	Asian	Enterprise Staff	Yes	Likely	SI
P2	M	35	Asian	Enterprise Staff	Yes	Likely	SI
P3	F	20	White	Undergraduate Student	No	Likely	SI
P4	F	35	Asian	Graduate Student	No	Likely	SI
P5	F	59	White	Self-employment	No	Hesitate	SI
P6	F	27	Asian	Graduate Student	Yes	Likely	SI
P7	F	22	African American	Undergraduate Student	No	Likely	SI
P8	F	21	White	Undergraduate Student	No	Hesitate	SI
P9	M	34	Asian	Enterprise Staff	Yes	Likely	SI
P10	F	24	White	Graduate Student	No	Likely	SI
P11	F	33	Latino	Graduate Student	Yes	Hesitate	SI
P12	M	35	Latino	Musician	No	Likely	SI
P13	F	23	Asian	Graduate Student	Yes	Hesitate	SI
P14	M	45	White	Enterprise Staff	No	Hesitate	SI
P15	M	50	Asian	Graduate Student	No	Likely	SI
P16	F	27	White	Doctor	No	Likely	SI
P17	M	22	Asian	Undergraduate Student	Yes	Likely	SI
P18	F	60	White	Teacher	No	Hesitant	FG1
P19	M	41	White	Engineer	No	Likely	FG1
P20	F	33	Asian	Enterprise Staff	No	Likely	FG1

P21	F	31	Asian	Graduate Student	No	Hesitant	FG1
P22	M	28	White	Graduate Student	No	Hesitant	FG1
P23	F	25	Asian	Enterprise Staff	No	Hesitant	FG1
P24	M	22	Asian	Undergraduate Student	No	Likely	FG1
P25	F	60	White	Professor	No	Likely	FG2
P26	M	50	Asian	Educator	No	Likely	FG2
P27	F	55	Asian	Engineer	No	Likely	FG2
P28	M	45	White	Program Evaluator	No	Likely	FG2
P29	M	48	Latino	Enterprise Staff	No	Likely	FG2
P30	M	30	White	Graduate Student	No	Likely	FG2
P31	F	28	Asian	Graduate Student	No	Hesitant	FG2
P32	M	27	White	Engineer	No	Hesitant	FG2
P33	M	32	White	Graduate Student	No	Likely	FG3
P34	F	30	Latino	Graduate Student	No	Likely	FG3
P35	M	60	Asian	Engineer	No	Likely	FG3
P36	F	56	Asian	Engineer	No	Hesitant	FG3
P37	M	48	Asian	Teacher	No	Likely	FG3
P38	M	35	Asian	Graduate Student	No	Hesitant	FG3
P39	M	24	White	Undergraduate Student	No	Hesitant	FG3
P40	M	31	Latino	Enterprise Staff	Yes	Likely	OI1
P41	F	28	White	Enterprise Staff	Yes	Likely	OI1
P42	M	37	White	Airline Steward	Yes	Likely	OI1
P43	F	30	African American	Enterprise Staff	Yes	Likely	OI1
P44	F	45	White	Enterprise Staff	Yes	Neutral	OI1

P45	M	32	White	Enterprise Staff	Yes	Neutral	OI1
P46	F	25	Asian	Enterprise Staff	Yes	Likely	OI2
P47	M	38	White	Engineer	Yes	Hesitant	OI2
P48	M	42	White	Teacher	Yes	Hesitant	OI2
P49	F	28	White	Enterprise Staff	Yes	Likely	OI2
P50	F	24	Asian	Student	Yes	Hesitant	OI2
P51	M	50	White	Enterprise Staff	Yes	Hesitant	OI2
P52	F	27	White	Enterprise Staff	Yes	Likely	OI3
P53	M	33	White	Enterprise Staff	Yes	Likely	OI3
P54	M	39	Latino	Enterprise Staff	Yes	Likely	OI3
P55	F	29	Asian	Enterprise Staff	Yes	Hesitant	OI3
P56	F	43	White	Enterprise Staff	Yes	Likely	OI3
P57	M	28	Asian	Enterprise Staff	Yes	Likely	OI3

Note. SI = Semi-structure interview; FG = Focus group, OI = On-site interview.

APPENDIX G

THEMES OF CONSUMERS' ETHICAL PERCEPTIONS

Themes of Consumers’ Ethical Perceptions of ASRs in Hospitality

	Ethical issues arise during interaction with ASRs	Ethical issues can be raised from characteristics of ASRs
Privacy	Ubiquitous Surveillance	Privacy Infringement
	The robots with cameras make me uncomfortable. I will be concerned about what behaviors and conversations are recorded. (P17)	Robots may have more and more data. Is there a corresponding protection measure to prevent information leakage? (P2)
Security	Data Excessiveness	Malicious Use
	The service robots in hotels sometimes collect too much information from me. I have to input a lot for processing, but I don’t know how these data to be used, so I don’t feel secure. (P6)	It is critical to figure out where hotels store my information and videos. It is very easy for companies to sell it to third parties. (P8)
Safety	Unknown Risks	Malfunctions
	Cross-contamination of food delivery. If somebody is allergic to peanuts, do hotels have to get cleaned robots between users, especially lots of people are touching it? (P16)	I guess it becomes more frustrating for guests if robots stop working or give the wrong information. (P3)
Transparency	Full Disclosure	Untrust
	The hotels have to clearly disclose the details of robot services. It is critical to know whether human service is available simultaneously. (P13)	It will be great to present an introduction about how robots’ function and the rationale for the recommendation. Guests have the right to know these, even if some might not be interested. (P1)
Fairness	Inaccessibility	Bias
	How do service robots treat the disabled groups? There should be special considerations for these groups of people. (P13)	The hotels need to make sure that the robots are not going to become racists over time. It seems like the program is designed by the people, so those people should not have bias. I would worry that robots would then give us inaccurate or prejudiced results. (P10)
Socialization	Dehumanization	Job Replacement
	A person can pick up your emotional response and sort of address the specific needs, but a	I feel like these robots may replace some human jobs. In Japan, they develop robots because of the small

	robot might not pick up that and come across as insensitive when people are dealing particularly hard issues. (P15)	number of populations, but so many people need jobs in Mexico. I am worried about these robots to replace human in the future. (P9)
Autonomy	Selection of Services	Inflexibility
	The hotels should provide the options served by robots or humans. I would argue if I was assigned to robot services. I would be disappointed if only robots serve me. (P13)	I am worried about the special requests for services. If my requests are outside the scope of the pre-designed program, the robots may not solve the problems and waste my time in the end. (P33)
Responsibility	Service Recovery	Self-Solved Solutions
	The delivery robots might get stuck when delivering food to guest rooms. If happened, can hotels solve the situation quickly and efficiently? (P17)	What if robots have errors and malfunctions, I don't know what will happen. Can they be resolved by themselves? (P16)

APPENDIX H

STUDIES ABOUT SERVICE ROBOT ADOPTION

Studies about Service Robot Adoption in Tourism and Hospitality (Consumers' Perspectives) (2019-2022)

Authors	Journal	Theory	Variables
Cain et al., 2019	Journal of Hospitality and Tourism Technology	Technology acceptance model (TAM), service robot acceptance model (SRAM)	Social elements (perceived humanness, perceived social interactivity, perceived social presence); Functional elements (perceived usefulness, perceived ease of use, subjective social norms); Relational elements (trust, rapport).
Lu et al, 2019	International journal of hospitality management	Service robot integration willingness (SRIW) scale	Performance efficacy, intrinsic motivation, anthropomorphism, facilitating conditions, emotions. Willingness to use service robots
Melián-González et al., 2021	Current issues in tourism	UTAUT 2	Performance expectancy, effort expectancy, social influence, hedonic motivations, habit, perceived innovativeness, inconvenience, anthropomorphism automation.
Go et al., 2020	Tourism view	Interactive technology acceptance model (ITAM)	Technology characteristics (type of AI robot, machine learning applications), individual characteristics (self-efficacy, social norm), perceived interactivity, perceived usefulness, perceived enjoyment.
Jang & Lee, 2020	Sustainability	Value-based adoption model	Anthropomorphism, animacy, likeability, intelligence, safety, perceived benefits, perceived risks, perceived value, satisfaction.
de Kervenoael et al., 2020	Tourism management	Technology acceptance model (TAM)	Perceived usefulness, perceived ease of use, service assurance, personal engagement, tangible, empathy, information sharing, perceived value, intention to use social robot

Lin et al., 2020	Journal of hospitality marketing & management	Artificial intelligent device use acceptance theory (AIDUA)	Social influence, hedonic motivation, anthropomorphism performance expectancy, effort expectancy, positive emotion. Willingness to use of AI devices, objective to use of AI devices
Pillai & Sivathanu, 2020	International Journal of Contemporary Hospitality Management	Technology acceptance model (TAM)	Perceived usefulness, perceived ease of use, technological anxiety, perceived trust, anthropomorphism, perceived intelligence, adoption intention of AI powered chatbots for travel planning, Stickiness to traditional human travel agents, actual usage of AI powered chatbots for travel planning
Shin & Jeong, 2020	International Journal of Contemporary Hospitality Management	Uncanny valley theory	Morphology of robot concierges, level of interactivity, level of hospitality service. Attitude toward robot concierges, adoption intention.
Zhong et al., 2020	Industrial Management & Data Systems	Technology acceptance model (TAM) Value-based acceptance model Theory of planned behavior	Perceived usefulness, perceived ease of use, sentimental value, self-efficacy. Attitude, perceived value, perceived behavioral control
Abou-Shouk et al., 2021	Journal of Hospitality and Tourism Technology	Technology acceptance model (TAM)	General attitude toward technology, appropriateness of robots to tourism jobs, perceived enjoyment of using robots, category of technology adopter, interest in using robots in tourism, perceived usefulness, perceived ease of using robots, attitude towards robot's usage

Lee et al., 2021	Tourism management perspectives	-	Functional aspect (Performance expectancy, facilitating conditions, perceived importance). Emotional aspect (innovativeness, social presence, hedonic motivation).
Lin & Mattila, 2021	International journal of hospitality management	Technology acceptance model (TAM), visual cue theory, value-attitude-behavior theory, self-service technology theory, congruency theory, consumption theory	Perceived privacy, functional benefits, novelty value, appearance of service robots, attitude toward service robots, anticipated overall hospitality experience, acceptance of service robots.
Chi et al., 2022	Journal of travel research	AIDUA model	Social influence, hedonic motivation, anthropomorphism, performance expectancy, effort expectancy, emotion, willingness to use AI devices, objection of using AI devices
Goel et al., 2022	Tourism review	-	Antecedents: Individual factors, service quality factors, technical & performance factors, social & cultural factors, infrastructure factors Mediator: attitude, trust formation, intention to use Moderator: product knowledge, device type, robot type, task type, customer type, tourism type, purpose of visit, demographic moderator Outcome: usage behavior, recommendation behavior
Kim et al, 2022	Tourism management	Social exchange theory	Human-robot interaction attributes (perceived intelligence, perceived social presence, perceived social interactivity), relational states (Rapport, trust), psychological state (uniqueness neglect) Acceptance of service robots (usage intentions)

			Sociodemographic control variables (age education, ethnicity, gender, income) Internal/external control variables (subjective norm, sense of uniqueness)
Liu et al., 2022	Annals of tourism research	-	Service context (Hedonic-dominant, Utilitarian-dominant), Perception of robot appearance (warm vs. competent), trust, intention to use

APPENDIX I

QUESTIONNAIRE

This survey is about your perceptions of service robot adoption in hotels. You will be asked to answer several questions about ethical issues, perceived usefulness, perceived ease of use, initial trust, and behavioral intention regarding service robots in hotels. The survey should take less than 30 minutes to complete. There are no foreseeable risks or discomforts to your participation. The survey responses will be grouped and analyzed for statistical purposes only. The results of this study may be used in reports, presentations, or publications, but your name will not be used. The current study will not be shared with others for future research or other uses. Your participation is voluntary. You may quit the survey at any time by closing your browser. To respect your desire to quit the study, we will delete all of your data. If you have any questions about this study, please get in touch with the researcher at (blin26@asu.edu).

In this study, you will be asked to answer several questions about hotel service robots; two examples are shown below:

1) Delivery Robot ("Fetch" in Vdara Hotel) can deliver snacks, towels, and other products and make a phone call to announce its arrival; navigate around the hotel with guests using elevators and communicate with guests through its face-shaped touchscreen.

2) Chatbot ("Rose" in Cosmopolitan of Las Vegas) can deliver consumer service to guests via text message, make reservations about events and restaurants in the hotel, provide recommendations about attractions, and ask for room service.

Six sections are listed here: 1) ethical issues that arise during the service interactions with service robots, 2) ethical issues can be raised by the characteristics of service robots, 3) perceived usefulness and perceived ease of use regarding service robots, 4) initial trust in service robots, 5) intention to use service robots in hotels in the future, and 6) demographics.

To be eligible for this survey, please answer the following screen questions.

If you are older than 18 years old and have no experience with service robots in hotels in last one year, you are eligible to conduct the survey. Otherwise, please quit the browser and stop!

Are you older than 18 years old? ☐YES ☐NO

Do you have experience with service robots in hotels in last one year? ☐YES ☐NO

Part one: (24 questions)
Please indicate how much you agree or disagree with the following ethical issues which arise during YOUR interaction with service robots in hotels:

	strongly disagree	somewhat disagree	neither agree or disagree	somewhat agree	strongly agree
I will be uncomfortable when using service robots with cameras	1	2	3	4	5
I am concerned that service robots with cameras will be used without prior notification	1	2	3	4	5
I am concerned that using service robots will record my behaviors and conversations	1	2	3	4	5
I am concerned that using service robots will ask for too much personal information that is irrelevant to the services	1	2	3	4	5
I am concerned that service robots will repeatedly request my information during hotel services	1	2	3	4	5
I am concerned that service robots will lose control and cause accidents during hotel services	1	2	3	4	5
I am concerned that service robots will produce unpredictable risks during hotel services	1	2	3	4	5
I am concerned that hotel staff will not clearly explain how to use service robots	1	2	3	4	5
I am concerned that hotels will not disclose functions service robots can perform	1	2	3	4	5
I am concerned that robot and human services will not be available simultaneously	1	2	3	4	5
I am concerned that service robots will not recognize my accents or dialects	1	2	3	4	5
I will be confused about how to use service robots for the first time	1	2	3	4	5

I am concerned that service robots will not offer appropriate care to minorities, like disabled groups	1	2	3	4	5
I am concerned that service robots will only perform basic hotel services	1	2	3	4	5
I am concerned that service robots will make hotel services less warm and welcoming	1	2	3	4	5
I am concerned that service robots will not recognize my emotions and feelings	1	2	3	4	5
I am concerned that services provided by robots will lack intimacy	1	2	3	4	5
I am concerned that service robots will not meet my demands for social interaction	1	2	3	4	5
I am concerned that services will be provided by robots without my consent	1	2	3	4	5
I am concerned that I will not have the right to choose between robot or human services	1	2	3	4	5
I will be disappointed if I am served only by robots in hotels	1	2	3	4	5
I will not know what to do if service robots provide the wrong services	1	2	3	4	5
I am concerned that hotels will not provide immediate supports when service robots stop working	1	2	3	4	5
I am concerned that there will be no way to connect with a real person when service robots serve me	1	2	3	4	5

Part two: (25 questions)
Please indicate how much you agree or disagree with the following ethical issues which can be raised by the characteristics of service robots in hotels:

	strongly disagree	somewhat disagree	neither agree or disagree	somewhat agree	strongly agree
Service robots' systems can be easily hacked	1	2	3	4	5

Service robots can automatically store information without my permission	1	2	3	4	5
Service robots lack protective measures to prevent the disclosure of my personal information	1	2	3	4	5
Service robots cannot prevent unauthorized access by hackers who may exploit my personal information for illegal purposes	1	2	3	4	5
Service robots cannot prevent hotels from selling my information without permission	1	2	3	4	5
Service robots cannot prevent hotels from leveraging my information for promotions	1	2	3	4	5
Service robots cannot provide the correct services for what I request	1	2	3	4	5
Service robots repeat certain steps and waste time when technical issues happen	1	2	3	4	5
Service robots can misinterpret my requests for services	1	2	3	4	5
Service robots can be easily broken	1	2	3	4	5
Service robots cannot be trusted as they are not human	1	2	3	4	5
Service robots' functions cannot be understandable and transparent	1	2	3	4	5
Service robots with high intelligence have the potential to pose a threat to humans	1	2	3	4	5
Service robots can be designed by people with a bias	1	2	3	4	5
Service robots can have a bias to produce prejudiced results	1	2	3	4	5
Service robots can have discriminatory appearances, such as being designed to resemble a female	1	2	3	4	5
Service robots can replace human jobs and impact the labor market	1	2	3	4	5
Service robots can affect the income of numerous individuals	1	2	3	4	5

Service robots can increase competition for job opportunities	1	2	3	4	5
Service robots cannot deal with emergency situations	1	2	3	4	5
Service robots cannot provide personalized services	1	2	3	4	5
Service robots can offer only limited service options	1	2	3	4	5
Service robots cannot respond appropriately in various service contexts	1	2	3	4	5
Service robots lack the ability to detect potential system errors	1	2	3	4	5
Service robots are unable to autonomously resolve system errors	1	2	3	4	5

Part Three: (8 questions)
Please indicate how much you agree or disagree with the following statements about your perceptions of the usefulness and ease of use of service robots in hotels:

	strongly disagree	somewhat disagree	neither agree or disagree	somewhat agree	strongly agree
Service robots will be useful in enhancing experience in hotels	1	2	3	4	5
Service robots will improve the efficiency of services	1	2	3	4	5
Service robots will provide more consistent services than humans	1	2	3	4	5
Service robots will provide accurate services with fewer human errors	1	2	3	4	5

	strongly disagree	somewhat disagree	neither agree or disagree	somewhat agree	strongly agree
It will be easy to become skillful at using service robots	1	2	3	4	5
Learning to use service robots will be easy for me	1	2	3	4	5
I will find service robots simple to use	1	2	3	4	5

Interacting with service robots will be straightforward and understandable	1	2	3	4	5

Part Four: (12 questions)
Please indicate how much you agree or disagree with the following your perceptions of initial trust in service robots in hotels:

	strongly disagree	somewhat disagree	neither agree or disagree	somewhat agree	strongly agree
I will trust service robots because of the hotel's reputation	1	2	3	4	5
I will trust service robots because the hotel has a well-known brand name	1	2	3	4	5
I will trust service robots because the hotels can provide high-quality services	1	2	3	4	5
I will trust service robots because the hotels are reliable	1	2	3	4	5
I believe that service robots will be effective at what they are designed to do	1	2	3	4	5
I think service robots will provide the services I need	1	2	3	4	5
I will trust service robots until they give me a reason not to	1	2	3	4	5
When using service robots for the first time, I tend to give them the benefit of the doubt	1	2	3	4	5
In general, service robots will be robust and safe	1	2	3	4	5
I feel confident that technological advances will make it safe to use service robots	1	2	3	4	5
I feel confident that regulations, laws, and social norms will make it safe to use service robots	1	2	3	4	5
I feel okay using service robots because they will be backed by hotel protections	1	2	3	4	5

Part Five: (8 questions)

Please indicate how much you agree or disagree with the following statements about perceptions of your innovativeness and familiarity about service robots in hotels:

	strongly disagree	somewhat disagree	neither agree or disagree	somewhat agree	strongly agree
In general, I like to try out new information technology	1	2	3	4	5
Among my peers, I am usually the first to try out new information technology	1	2	3	4	5
If I hear about a new information technology, I look for ways to experiment with it	1	2	3	4	5
I like to experiment with new information technologies	1	2	3	4	5

	strongly disagree	somewhat disagree	neither agree or disagree	somewhat agree	strongly agree
I have heard of service robots before	1	2	3	4	5
I consider myself familiar with service robots	1	2	3	4	5
I am more familiar with service robots compared to the average person	1	2	3	4	5
I dedicate time to gather information about service robots	1	2	3	4	5

Part Six: (3 questions)
Please indicate how much you agree or disagree with the following statements about your intention to use service robots in hotels:

	strongly disagree	somewhat disagree	neither agree or disagree	somewhat agree	strongly agree
I intend to use service robots when they are available in hotels	1	2	3	4	5

I am likely to use hotel service robots in the near future	1	2	3	4	5
I plan to visit the hotels that offer service robots	1	2	3	4	5

1. What is your age?
   ☐Below 20 ☐20 to 29 ☐30 to 39
   ☐40 to 49 ☐50 to 59 ☐over 60

2. What is your gender?
   ☐ Female ☐ Male ☐ Non-binary / third gender ☐ Prefer not to say

3. What is your ethnicity? (Multiple choices)
   ☐ White ☐ African American ☐ Asian ☐ Hispanic or Latino
   ☐ Native American ☐ Other (Please specify) ________________

4. What is the highest level of education you have achieved?
   ☐ Less than high school ☐ High school ☐ Some college
   ☐ Bachelor's degree ☐ Master’s degree ☐ Doctoral degree

5. Do you have a technology-related or engineering background?
   ☐ Yes ☐ No

6. What is your current occupation?
   ☐ Full-time employment ☐ Part-time employment
   ☐ Student ☐ Unemployed ☐ Other (Please specify) ________________

7. What is your level of annual income?
   ☐ $25,000 or less ☐ $25,001 – $50,000 ☐ $50,001 – $75,000
   ☐ $75,001 – $100,000 ☐ $100,001 – $125,000 ☐ Above $125,001

8. How many times do you actively gather information about service robots in hotels (e.g., watching videos and reading online articles)?
   ☐ Never ☐ Once ☐ Twice
   ☐ 3 times ☐ 4 times ☐ 5 times, or more

9. What types of robots do you prefer to use in hotels?
   ☐ Cooking Robots ☐ Delivery Robots
   ☐ Front-desk Robots ☐ Chatbots
   ☐ Never ☐ Other (Please specify) ________________

10. What kind of trips do you prefer to use service robots in hotels?
    ☐ Leisure ☐ Business trips or conferences
    ☐ Both ☐ Never

APPENDIX J

DEMOGRAPHICS OF PRE-TEST SURVEY

Demographic Profile of Pre-test Survey

Characteristics	Frequency	%
Gender		
Male	35	22.9
Female	116	75.8
Non-binary / third gender	1	0.7
Prefer not to say	1	0.7
Age		
Below 20	20	13.1
20-29	109	71.2
30-39	13	8.5
40-49	8	5.2
50-59	2	1.3
Over 60	1	0.7
Ethnicity (Multiple)		
White	93	60.8
African American	10	6.5
Asian	23	15
Hispanic or Latino	40	26.1
Native American	1	0.7
Others	8	5.2
Education		
Less than high school	1	0.7
High school	17	11.1
Some college	126	82.4
Bachelor degree	6	3.9
Master degree	2	1.3
Doctoral degree	1	0.7
Occupation		
Full-time employment	39	25.2

Part-time employment	46	30.1
Student	62	40.5
Unemployed	4	2.6
Other	2	1.3
Annual Income (USD)		
$25000 or less	94	61.4
$25001 – $50000	38	24.8
$50001 – $75000	14	9.2
$75001 – $100000	3	2.0
$100001 – $125000	4	2.6
Preferences of ASRs (Multiple)		
Robot Bartender	29	19.0
Chatbots	27	17.6
Delivery Robots	89	58.2
Never	48	31.4
Trip purposes of using ASRs		
Vacations	29	19.0
Business or conferences	20	13.1
Both	50	32.7
Never	54	35.3

APPENDIX K

DEMOGRAPHICS OF MAIN SURVEY

Demographic Profile of Main Survey

Characteristics	Frequency	%
Gender		
Male	191	37.9
Female	309	61.3
Non-binary / third gender	2	0.4
Prefer not to say	2	0.4
Age		
18-29	64	12.7
30-39	181	35.9
40-49	114	22.6
50-59	94	18.7
Over 60	51	10.1
Ethnicity (Multiple)		
White	471	93.5
African American	2	0.4
Asian	20	4.0
Hispanic or Latino	2	0.4
Native American	0	0
Others	13	2.6
Education		
Less than high school	4	0.8
High school	78	15.5
Some college	117	23.2
Bachelor degree	212	42.1
Master degree	79	15.7
Doctoral degree	14	2.8
Tech Background		
Yes	76	15.1
No	428	84.9

Occupation		
Full-time employment	293	58.1
Part-time employment	101	20.0
Student	11	2.2
Unemployed	42	8.3
Other	57	11.3
Annual Income (USD)		
$25000 or less	174	34.5
$25001 – $50000	205	40.7
$50001 – $75000	84	16.7
$75001 – $100000	24	4.8
$100001 – $125000	11	2.2
Above $125001	6	1.2
Times of gathering information about ASRs		
Never	442	87.7
Once	35	6.9
Twice	23	4.6
3 or 4 times	0	0
5 time or more	4	0.8
Preferences of ASRs (Multiple)		
Cooking Robots	20	4.0
Delivery Robots	140	27.8
Front-desk Robots	67	13.3
Chatbots	86	17.1
Never	300	59.5
Others	15	3.0
Trip purposes of using ASRs		
Vacations	139	27.6
Business or conferences	8	1.6
Both	84	16.7
Never	273	54.2

APPENDIX L

RESULTS OF EFA IN MAIN SURVEY

Results of Exploratory Factor Analysis in Main Survey

Ethical Issues that Arise during Interaction with ASRs (EIDI)

Variable	Items	Factor 1	Factor 2	Factor 3	Factor 4
Personal Privacy	Ubiquitous Surveillance_1	.749			
	Ubiquitous Surveillance_2	.795			
	Ubiquitous Surveillance_3	.818			
	Data Excessiveness_1	.734			
	Data Excessiveness_2	.640			
	Selection of Services_1	.536			
Disclosure	Unknown Risks_1		.682		
	Unknown Risks_2		.654		
	Full Disclosure_1		.653		
	Full Disclosure _2		.554		
	Inaccessibility_1		.597		
Dehumani-zation	Inaccessibility_4			.566	
	Dehumanization_1			.725	
	Dehumanization _2			.723	
	Dehumanization _3			.801	
	Dehumanization _4			.762	
Service Failure	Inaccessibility_2				.571
	Full Disclosure _3				.590
	Selection of Services_2				.590
	Service Recovery_1				.670
	Service Recovery _2				.695
	Service Recovery _3				.733

Ethical Issues that can be Raised from Characteristics of (EIFC)

Variable	Items	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5
Informational Security	Privacy Infringement_1	.574				
	Privacy Infringement_2	.712				
	Privacy Infringement_3	.725				
	Malicious Use_1	.710				
	Malicious Use_2	.760				
	Malicious Use_3	.741				
Untrustworth-iness	Malfunctions_1		.614			
	Untrust_1		.583			
	Untrust_2		.703			
	Untrust_3		.704			
	Untrust_4		.672			
Bias	Bias_1			.836		
	Bias_2			.813		
	Bias_3			.779		
Job Replacement	Job Replacement_1				.801	
	Job Replacement_2				.765	
	Job Replacement_3				.723	
Inflexibility	Inflexbility_1					.759
	Inflexbility_2					.671
	Inflexbility_3					.676
	Self-solved Solutions_1					.678
	Self-solved Solutions_2					.684
	Self-solved Solutions_3					.703

APPENDIX M

RESULTS OF CFA IN LOWER-ORDER MODEL

Results of Confirmatory Factor Analysis in Lower-Order Model

Measurements	Mean	SD	FL
Personal Privacy AVE = 0.662, CR = 0.922, Cronbach's α = 0.898			
I will be uncomfortable when using service robots with cameras	3.431	1.153	0.772
I am concerned that service robots with cameras will be used without prior notification	3.653	1.071	0.850
I am concerned that using service robots will record my behaviors and conversations	3.742	1.081	0.840
I am concerned that using service robots will ask for too much personal information that is irrelevant to the services	3.258	1.124	0.844
I am concerned that service robots will repeatedly request my information during hotel services	3.155	1.153	0.789
I am concerned that services will be provided by robots without my consent	3.228	1.188	0.784
Disclosure AVE = 0.580, CR = 0.872, Cronbach's α = 0.818			
I am concerned that service robots will lose control and cause accidents during hotel services	2.694	1.143	0.713
I am concerned that service robots will produce unpredictable risks during hotel services	2.757	1.138	0.747
I am concerned that hotel staff will not clearly explain how to use service robots	3.123	1.132	0.851
I am concerned that hotels will not disclose functions service robots can perform	3.188	1.105	0.853
I am concerned that service robots will not recognize my accents or dialects	3.05	1.306	0.617
Dehumanization AVE = 0.663, CR = 0.907, Cronbach's α = 0.871			
I am concerned that service robots will only perform basic hotel services	3.042	1.104	0.638
I am concerned that service robots will make hotel services less warm and welcoming	3.72	1.197	0.845
I am concerned that service robots will not recognize my emotions and feelings	3.488	1.236	0.834
I am concerned that services provided by robots will lack intimacy	3.349	1.235	0.878
I am concerned that service robots will not meet my demands for social interaction	3.169	1.293	0.851
Service Failure AVE = 0.602, CR = 0.900, Cronbach's α = 0.866			
I will be confused about how to use service robots for the first time	3.595	1.087	0.582

I am concerned that robot and human services will not be available simultaneously	3.575	1.115	0.793
I am concerned that I will not have the right to choose between robot or human services	3.712	1.147	0.835
I will not know what to do if service robots provide the wrong services	3.813	1.036	0.732
I am concerned that hotels will not provide immediate supports when service robots stop working	3.792	1.063	0.818
I am concerned that there will be no way to connect with a real person when service robots serve me	3.871	1.115	0.862
Informational Security AVE = 0.623, CR = 0.908 , Cronbach's α = 0.879			
Service robots' systems can be easily hacked	3.54	0.931	0.721
Service robots can automatically store information without my permission	3.829	0.971	0.793
Service robots lack protective measures to prevent the disclosure of my personal information	3.556	1	0.838
Service robots cannot prevent unauthorized access by hackers who may exploit my personal information for illegal purposes	3.7	0.97	0.833
Service robots cannot prevent hotels from selling my information without permission	3.585	1.08	0.768
Service robots cannot prevent hotels from leveraging my information for promotions	3.694	1.024	0.777
Untrustworthiness AVE = 0.584, CR = 0.874, Cronbach's α = 0.819			
Service robots cannot provide the correct services for what I request	3.133	0.998	0.735
Service robots can be easily broken	3.595	0.923	0.630
Service robots cannot be trusted as they are not human	2.903	1.16	0.861
Service robots' functions cannot be understandable and transparent	3.042	1.065	0.854
Service robots with high intelligence have the potential to pose a threat to humans	2.812	1.221	0.717
Bias AVE = 0.725, CR = 0.886, Cronbach's α = 0.814			
Service robots can be designed by people with a bias	3.802	0.994	0.921
Service robots can have a bias to produce prejudiced results	3.526	1.08	0.914
Service robots can have discriminatory appearances, such as being designed to resemble a female	3.27	1.159	0.702

Job Replacement AVE = 0.674, CR = 0.858, Cronbach's α = 0.767			
Service robots can replace human jobs and impact the labor market	4.206	0.894	0.880
Service robots can affect the income of numerous individuals	4.079	0.922	0.927
Service robots can increase competition for job opportunities	3.849	1.064	0.624
Inflexibility AVE = 0.584, CR = 0.894, Cronbach's α = 0.857			
Service robots cannot deal with emergency situations	4.111	0.978	0.703
Service robots cannot provide personalized services	3.573	1.108	0.760
Service robots can offer only limited service options	3.978	0.883	0.723
Service robots cannot respond appropriately in various service contexts	3.831	0.853	0.794
Service robots lack the ability to detect potential system errors	3.544	0.993	0.804
Service robots are unable to autonomously resolve system errors	3.621	0.943	0.796

Note: SD = standard deviation, FL = factor loading, CR = composite reliability, AVE = average variance extracted, Cronbach's α = Cronbach's alpha

Assessment of Discriminant Validity of Lower-Order Model

Heterotrait-monotrait ratio

	DH	DC	IS	JR	PEU	PU	PP	SF	BS	UT	FRR	IF	BI	PT	SA
DH															
DC	0.743														
IS	0.538	0.639													
JR	0.409	0.419	0.516												
PEU	0.429	0.534	0.327	0.227											
PU	0.515	0.53	0.45	0.268	0.61										
PP	0.657	0.752	0.719	0.437	0.467	0.556									
SF	0.74	0.792	0.622	0.587	0.528	0.521	0.734								
BS	0.317	0.427	0.485	0.407	0.156	0.183	0.409	0.363							
UT	0.751	0.83	0.741	0.491	0.581	0.607	0.729	0.782	0.385						
FR	0.417	0.579	0.497	0.284	0.507	0.682	0.585	0.444	0.261	0.599					
IF	0.666	0.593	0.599	0.515	0.403	0.516	0.581	0.758	0.297	0.735	0.464				
BI	0.522	0.549	0.514	0.379	0.582	0.744	0.611	0.566	0.328	0.615	0.703	0.514			
PT	0.515	0.633	0.507	0.301	0.62	0.787	0.639	0.518	0.282	0.692	0.802	0.499	0.797		
SA	0.498	0.624	0.578	0.286	0.617	0.757	0.661	0.503	0.362	0.672	0.796	0.476	0.758	0.899	

Note: PU = perceived usefulness, PEU = perceived ease of use, BI = behavioral intention,

PP = personal privacy, DH = dehumanization, DC = disclosure, JR = job replacement,

IS = informational security, SF = service failure, BS = bias, UT = untrustworthiness, IF = inflexibility

FR = firm reputation, PT = propensity to trust, SA = Structural Assurance

Fornell-Larcker criteria

	DH	DC	IS	JR	PEU	PU	PP	SF	BS	UT	FRR	IF	BI	PT	SA
DH	0.814														
DC	0.626	0.761													
IS	0.481	0.554	0.789												
JR	0.356	0.34	0.439	0.821											
PEU	-0.398	-0.468	-0.302	-0.21	0.909										
PU	-0.47	-0.472	-0.408	-0.251	0.557	0.856									
PP	0.587	0.656	0.641	0.386	-0.43	-0.505	0.814								
SF	0.66	0.656	0.558	0.511	-0.464	-0.469	0.659	0.776							
BS	0.275	0.368	0.424	0.321	-0.142	-0.172	0.366	0.309	0.851						
UT	0.646	0.692	0.635	0.403	-0.518	-0.528	0.632	0.663	0.326	0.765					
FR	-0.391	-0.531	-0.462	-0.267	0.484	0.641	-0.546	-0.422	-0.245	-0.536	0.953				
IF	0.58	0.507	0.529	0.442	-0.368	-0.455	0.514	0.664	0.259	0.624	-0.427	0.764			
BI	-0.48	-0.492	-0.46	-0.334	0.535	0.679	-0.549	-0.507	-0.289	-0.539	0.658	-0.451	0.897		
PT	-0.469	-0.56	-0.455	-0.282	0.572	0.713	-0.577	-0.472	-0.257	-0.604	0.75	-0.445	0.722	0.879	
SA	-0.457	-0.557	-0.523	-0.27	0.574	0.691	-0.602	-0.461	-0.332	-0.592	0.752	-0.428	0.693	0.821	0.898

Note: PU = perceived usefulness, PEU = perceived ease of use, BI = behavioral intention,

PP = personal privacy, DH = dehumanization, DC = disclosure, JR = job replacement,

IS = informational security, SF = service failure, BS = bias, UT = untrustworthiness, IF = inflexibility

FR = firm reputation, PT = propensity to trust, SA = Structural Assurance

APPENDIX N

RESULTS OF CFA IN HIGHER-ORDER MODEL

Results of Confirmatory Factor Analysis in Higher-Order Model

Constructs	FL	AVE	CR	Cronbach's α
EIDI		0.730	0.915	0.877
Personal privacy	0.862			
Disclosure	0.864			
Dehumanization	0.827			
Service failure	0.864			
EIFC		0.567	0.860	0.797
Informational security	0.834			
Untrustworthiness	0.856			
Bias	0.557			
Job replacement	0.649			
Inflexibility	0.792			
Perceived usefulness		0.732	0.916	0.880
Perceived usefulness _1	0.881			
Perceived usefulness _2	0.898			
Perceived usefulness _3	0.814			
Perceived usefulness _4	0.828			
Perceived ease of use		0.826	0.950	0.930
Perceived ease of use _1	0.872			
Perceived ease of use _2	0.921			
Perceived ease of use _3	0.932			
Perceived ease of use _4	0.910			
Initial trust		0.849	0.944	0.911
Firm reputation	0.898			
Propensity to trust	0.933			
Structural assurance	0.933			
Behavioral intention		0.805	0.925	0.880
Behavioral intention_1	0.908			

Behavioral intention _2	0.899			
Behavioral intention _3	0.884			

Note: SD = standard deviation, FL = factor loading, CR = composite reliability,

AVE = average variance extracted, Cronbach's α = Cronbach's alpha,

EIDI = consumers' perceived ethical issues that arise during interaction with ASRs,

EIFC = consumers' perceived ethical issues that can be raised from characteristics of ASRs,

Assessment of Discriminant Validity of Higher-Order Model

Heterotrait-monotrait ratio

	BI	EIDI	EIFC	IT	PEU	PU
BI						
EIDI	0.667					
EIFC	0.661	0.845				
IT	0.826	0.715	0.7			
PEU	0.582	0.567	0.478	0.638		
PU	0.744	0.627	0.571	0.814	0.61	

Fornell-Larcker criteria

	BI	EIDI	EIFC	IT	PEU	PU
BI	0.897					
EIDI	-0.593	0.854				
EIFC	-0.571	0.813	0.746			
IT	0.75	-0.646	-0.622	0.922		
PEU	0.535	-0.515	-0.443	0.591	0.909	
PU	0.68	-0.562	-0.517	0.741	0.558	0.856

Note: PU = perceived usefulness, PEU = perceived ease of use,

EIDI = consumers' perceived ethical issues that arise during interaction with ASRs,

EIFC = consumers' perceived ethical issues that can be raised from characteristics of ASRs,

IT = Initial trust, BI = behavioral intention

APPENDIX O

RESULTS OF SEM IN SECOND-ORDER MODEL

Results of Structural Equation Modelling in Second-Order Model

Hypotheses	β	T	P	Supported
Direct Effects				
H1a PU → IT	0.468	8.477***	0.000	YES
H1b PU → BI	0.192	4.321***	0.000	YES
H2a PEU → IT	0.175	4.267***	0.000	YES
H2b PEU → BI	0.018	0.464	0.643	NO
H3a EIDI → IT	-0.139	2.740**	0.006	YES
H3b EIDI → BI	-0.045	0.866	0.386	NO
H4a EIFC → IT	-0.190	3.824***	0.000	YES
H4a EIFC → BI	-0.129	2.637**	0.008	YES
H5 IT → BI	0.365	3.130**	0.002	YES
Indirect Effects				
H6a PU → IT → BI	0.171	2.924**	0.003	YES
H6b PEU → IT → BI	0.064	2.351*	0.019	YES
H6a EIDI → IT → BI	-0.051	2.053*	0.040	YES
H6b EIFC → IT → BI	-0.069	2.404*	0.016	YES
Interaction Effects				
H7a IT*age → BI	0.018	0.687	0.492	NO
H7b IT*FA → BI	0.010	0.248	0.804	NO
H7c IT*IN → BI	0.057	2.055*	0.040	YES

Note. *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.