The Entrepreneurial Perspective on the Key Driver Effects of the Adoption of Robots in Bangkok's Restaurant Industry

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This Independent Study Has Been Approved as a Partial Fulfillment of the Requirements for the Degree of Master of Business Administration

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ABSTRACT

This study explored the adoption of robotics in Bangkok's restaurant industry from an entrepreneurial perspective, employing an extended Technology Acceptance Model (TAM) to analyze behavioral intentions toward robot adoption. With labor shortages, rising costs, and evolving consumer expectations accelerating technological transformation, robotics are increasingly seen as strategic assets to improve service efficiency, consistency, and competitiveness. The extended model incorporates core TAM constructs—Perceived Usefulness (PU) and Perceived Ease of Use (PEOU)—alongside additional factors including Trust in Technology (TT), Perceived Risk (PR), Social Influence (SI), Customer Satisfaction (CS), and Customer Perceived Value (CPV), to comprehensively capture the multidimensional influences shaping adoption behavior.

A quantitative, cross-sectional survey design was employed, collecting data from 400 respondents comprising restaurant owners, managers, frontline employees, and customers across various restaurant types in Bangkok. Convenience sampling was used to ensure practical reach and respondent diversity. Perceptions were measured using a scenario-based questionnaire, and data were analyzed using Structural Equation Modeling (SEM) to test the hypothesized relationships among the constructs.

The results reveal that all seven independent variables—PU, PEOU, TT, PR, SI, CS, and CPV—exert direct and statistically significant influences on Robot Adoption (RA). Notably, PU emerged as the strongest predictor of RA, followed by PEOU, TT, PR, SI, CS, and CPV. Contrary to earlier theoretical assumptions, no mediation effects were observed; each construct had a direct impact on robotic adoption intention, underscoring the multifaceted and parallel nature of decision-making in restaurant settings.

The findings offer practical implications for restaurant managers, technology vendors, policymakers, educators, and researchers. Strategic emphasis should be placed on selecting robots that demonstrate clear utility, ensuring intuitive usability, fostering trust, managing perceived

risks, enhancing customer satisfaction and value, and leveraging social influence through communication strategies and peer endorsements.

This research contributes to the broader technology adoption literature by extending and validating the TAM framework within the context of the hospitality sector in an emerging market. It provides a robust, empirically supported conceptual model for understanding robot adoption behavior in urban restaurant environments and lays a foundation for future investigations in service-oriented digital transformation.

Keywords: robotics, Technology Acceptance Model, trust, perceived risk, customer satisfaction, social influence, customer perceived value, restaurant industry, Bangkok.

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DECLARATION

I, Phoo Moh Moh Thein, hereby declare that this Independent Study entitled “The Entrepreneurial Perspective on the Key Driver Effects of the Adoption of Robots in Bangkok’s Restaurant Industry” is an original work and has never been submitted to any academic institution for a degree.

Name: Phoo Moh Moh Thein
Date: 15/06/2025

CONTENTS

ABSTRACT……i
ACKNOWLEDGEMENT……iii
DECLARATION……...iv
CONTENTS……..... v
LIST OF TABLES……...viii
LIST OF FIGURES……ix
Chapter 1 Introduction……1
1.1 Background of the Study……..1
1.2 Questions of the Study……..2
1.3 Objectives of the Study……2
1.4 Scope of the Study……2
1.5 Significance of the Study……...3
1.6 Definition of Key Terms……3
Chapter 2 Literature Review……4
2.1 Theoretical Background: Technology Acceptance Model (TAM) and Perceived Value Theory (PVT)…….. 4
2.1.1 Technology Acceptance Model (TAM)……..4
2.1.2 Perceived Value Theory (PVT) ……. 5
2.2 Empirical Research on Key Constructs in Robot Adoption……..6
2.2.1 Perceived Usefulness (PU)……..6
2.2.2 Perceived Ease of Use (PEOU)……...7
2.2.3 Trust in Technology (TT)……8
2.2.4 Perceived Risk (PR)……..10
2.2.5 Social Influence (SI)……..11
2.2.6 Customer Satisfaction (CS) ……..12
2.2.7 Customer Perceived Value (CPV)……13
2.3 Robot Adoption in Restaurants: Technological Advancements, Global Trends, and Case Studies……15
2.3.1 Technological Advancements Driving Adoption……. 16
2.3.2 Global Adoption Trends and Comparative Perspectives……..16
2.3.3 Case Studies and Implementation Insights……17

2.4 Conceptual Framework……18
Chapter 3 Research Methodology……18
3.1 Research Method……18
3.1.1 Quantitative Research Approach……..18
3.1.2 Deductive Strategy and Rationale……18
3.2 Research Design……...19
3.2.1 Overall Design……...19
3.2.2 Descriptive and Explanatory Components……20
3.2.3 Justification of the Cross-Sectional Approach…… 20
3.3 Population and Sampling……21
3.3.1 Target Population……..21
3.3.2 Sampling Technique……22
3.3.3 Sampling Size Determination……...22
3.3.4 Justification of Sample Size……..23
3.3.5 Sampling Procedure……..23
3.4 Instrument Development and Questionnaire Design……...24
3.4.1 Instrument Development…….. 24
3.4.2 Questionnaire Design……26
3.5 Data Collection……29
3.5.1 Data Collection Process……29
3.5.2 Sample Description……...30
3.6 Data Analysis Techniques…… 31
3.6.1 Descriptive Statistics……31
3.6.2 Reliability and Validity Analysis……..31
3.6.3 Inferential Statistics…….. 37
3.7 Summary…… 38
Chapter 4 Data Analysis and Results……40
4.1 Sample Characteristics……40
4.1.1 Demographic Profile……41
4.1.2 Professional Background……..42
4.1.3 Experience with Technology…… 44
4.1.4 Familiarity with Robotics…… 45
4.1.5 Business Type and Size…… 47
4.1.6 Perceived Need for Technological Innovation…… 49

4.2 Descriptive Statistics of Constructs……51
4.2.1 Perceived Usefulness (PU)……53
4.2.2 Perceived Ease of Use (PEOU)……54
4.2.3 Trust in Technology (TT)……56
4.2.4 Perceived Risk (PR)……..58
4.2.5 Social Influence (SI)……59
4.2.6 Customer Satisfaction (CS) ……60
4.2.7 Customer Perceived Value (CPV)……62
4.2.8 Robot Adoption (RA)…….....63
4.3 Correlation Analysis Results and Discussion……..……64
4.4 Multiple Regression Analysis Results and Discussion……66
4.5 Hypothesis Testing ……68
4.6 Path Analysis and Mediation Testing ……70
4.6.1 Path Coefficients and Direct Effects……70
4.6.2 Structural Model Summary and Interpretation……71
4.6.3 Practical Implications……... 72
Chapter 5 Conclusion and Recommendation…….. 73
5.1 Summary of Findings……..73
5.2 Theoretical Implications……. 75
5.3 Practical Implications……..76
5.4 Limitations of the Study……..78
5.5 Recommendation for Future Research…….. 78
5.6 Conclusion……...79
References……81
Appendix..……85

LIST OF TABLES

Table 3.1 Research Design Components ……. 20
Table 3.2 Design of Questionnaire ……... 28
Table 3.3 Sample Demographic Distribution Strategy …… 31
Table 3.4 Descriptive Statistics Summary …… 31
Table 3.5 Cronbach's Alpha and Corrected Item-Total Correlation by Construct… 32
Table 3.6 KMO and Bartlett's Test of Sphericity for Perceived Usefulenss ……... 35
Table 3.7 KMO and Bartlett's Test of Sphericity for Perceived Ease of Use……. 35
Table 3.8 KMO and Bartlett's Test of Sphericity for Trust in Technology…… 36
Table 3.9 KMO and Bartlett's Test of Sphericity for Perceived Risk…… 36
Table 3.10 KMO and Bartlett's Test of Sphericity for Social Influence…….. 36
Table 3.11 KMO and Bartlett's Test of Sphericity for Customer Satisfaction……. 37
Table 3.12 KMO and Bartlett's Test of Sphericity for Customer Perceived Value.. 37
Table 4.1 Age and Gender Distribution of Respondents…… 41
Table 4.2 Professional Roles of Respondents……..…….. 43
Table 4.3 Self-Rated Technological Proficiency ……. 44
Table 4.4 Familiarity with Robotics ……. 46
Table 4.5 Restaurant Size ……. 48
Table 4.6 Perceived Importance of Technological Innovation ……. 49
Table 4.7 Descriptive Statistics of Main Constructs …… 51
Table 4.8 Correlation Coefficients ……..... 65
Table 4.9 Regression Coefficients ……..… 67
Table 4.10 Hypothesis Testing Results ……..…… 69
Table 4.11 Path Coefficients for Direct Effects ……..… 71

LIST OF FIGURES

Figure 2.1: Conceptual Framework of the Study ……..……. 17
Figure 4.1: Final Model of the Study……..70

Chapter 1
Introduction

1.1 Background of the Study

The restaurant industry is undergoing a significant transformation with the growing adoption of robotics and artificial intelligence (AI). Businesses are integrating these technologies to enhance operational efficiency, reduce labor costs, and improve customer satisfaction. Countries such as Japan, China, and the United States have successfully implemented robotic restaurant models, demonstrating both the benefits and challenges of automation in the food service sector. In Bangkok, a city known for its vibrant tourism and hospitality industry, interest in robotic restaurant technology is rising due to labor shortages, increasing operational expenses, and changing consumer expectations.

Entrepreneurs play a crucial role in assessing and implementing robotic solutions within restaurant operations. While robots offer advantages such as increased speed, enhanced hygiene, and consistency in service delivery, concerns persist regarding high initial investments, maintenance costs, and customer acceptance. Previous studies indicate that robotic restaurants attract customers due to their novelty, but long-term success depends on maintaining high service quality and efficiency. Additionally, consumer perceptions of automation influence their willingness to pay for and revisit robotic restaurants.

The integration of AI and robotics in restaurants has evolved significantly over the past decade. These technologies are now being employed in various capacities, including food preparation, order-taking, serving, and customer interaction. The global food robotics market is expected to expand as businesses seek automation to address labor shortages and meet consumer demands for fast and efficient service. Key trends driving this growth include advancements in AI technology, labor market challenges, improved cost efficiency, and the increasing need for contactless service solutions, particularly in the post-pandemic era.

The importance of adopting AI and robotics in the restaurant industry cannot be overstated. Robots excel at performing repetitive tasks with high precision and consistency, thereby reducing human errors and enhancing service efficiency. AI-powered analytics assist restaurant owners in making data-driven decisions to optimize inventory management, staffing, and menu offerings. In high-traffic areas such as Bangkok, where workforce shortages pose a recurring challenge, robots can help bridge labor gaps by automating essential tasks. Moreover, AI-driven chatbots and robotic assistants improve customer experiences by offering faster service, personalized recommendations, and seamless order-taking processes. The introduction of robots into restaurant settings also contributes to sustainability efforts, as predictive analytics enable better resource management, reducing food waste and promoting eco-friendly operations.

The benefits of robotics adoption in the restaurant industry extend beyond efficiency and cost savings. Automated kitchen systems, self-service kiosks, and robotic waitstaff accelerate service delivery, allowing businesses to serve more customers in less time. While the initial investment in robotics can be substantial, long-term cost savings arise from reduced labor expenses, minimized operational errors, and optimized resource allocation. Additionally, restaurants that embrace AI and robotics gain a competitive edge by offering unique dining

experiences that attract tech-savvy consumers. Improved hygiene and safety standards are another major advantage, as robots minimize human contact with food and surfaces, mitigating contamination risks, a critical factor in the post-pandemic food service landscape.

Despite these benefits, several challenges remain. High investment and maintenance costs, as well as customer attitudes toward automation, continue to influence the pace of robotics adoption. Many studies highlight the importance of balancing automation with human interaction to create an engaging dining experience. A cost-benefit analysis approach suggests that the financial viability of robotics integration depends on factors such as restaurant size, market positioning, and consumer demand. Understanding these dynamics from an entrepreneurial perspective is crucial in determining how Bangkok's restaurant industry can successfully adopt and sustain robotic technologies.

1.2 Questions of the Study

This study aims to address the following key questions:

- What are the main factors influencing the adoption of robots in Bangkok's restaurant industry from an entrepreneurial perspective?
- How do entrepreneurs perceive the benefits and challenges of robotics in restaurant operations?

1.3 Objectives of the Study

The primary objectives of this study are:

- To explore the key drivers behind the adoption of robotics in Bangkok's restaurant industry.
- To examine the challenges and limitations faced by entrepreneurs in integrating robotic solutions.

1.4 Scope of the Study

This study investigates the adoption of robotics within the restaurant sector in Bangkok, emphasizing perspectives from entrepreneurs, including restaurant owners, investors, and startup founders who are considering or have implemented robotic solutions. The scope of this research is defined as follows:

- Target Population: The study specifically addresses stakeholders involved in entrepreneurial decision-making, such as business owners and investors interested in robotic integration in restaurant operations.
- Geographic Limitation: The research is limited to establishments located in Bangkok. As such, the findings may not be broadly applicable to regions with different cultural, economic, or regulatory environments.
- Temporal Scope: Employing a cross-sectional research design, the study captures perceptions and behavioral intentions at a single point in time. Consequently, it does not account for changes in attitudes or adoption behavior that may occur over time.
- Data Collection Constraints: The research relies on self-reported survey data, which may be subject to social desirability bias, selective memory, or inaccurate self-assessment.

- Methodological Limitation: The exclusive use of quantitative survey methods may constrain the study's ability to uncover deeper contextual insights. Future studies incorporating qualitative approaches, such as interviews or case studies, could provide a more nuanced understanding of the adoption process.

1.5 Significance of the Study

This study is significant as it provides valuable insights into the transformative impact of robotic technology on the restaurant industry in Bangkok. The findings will help entrepreneurs understand not only the financial and operational aspects of robotics adoption but also the strategic and consumer-oriented considerations necessary for long-term success. By integrating key constructs from the extended Technology Acceptance Model, including perceived usefulness, ease of use, trust, perceived risk, social influence, and customer satisfaction, this research offers a comprehensive framework that captures the complex interplay between technological innovation and consumer behavior.

Moreover, the study contributes to academic discourse on technology adoption in emerging markets by highlighting the unique challenges and opportunities faced by the hospitality industry in a rapidly evolving urban environment. Policymakers can also benefit from the insights provided, as the findings offer data-driven guidance for developing regulatory frameworks that support the integration of robotics in the hospitality sector, thereby fostering sustainable economic growth and improved service quality.

1.6 Definition of Key Terms

- Robotic Automation: The use of robotic technology to perform restaurant tasks such as food preparation, service, and delivery.
- Entrepreneurial Perspective: The viewpoint of business owners and investors regarding opportunities, risks, and feasibility in adopting robotics.
- Service Robots: Robots designed to interact with customers and perform hospitality-related tasks.

Chapter 2
Literature Review

In this chapter, a comprehensive review of the theoretical literature relevant to this research is conducted to establish a strong foundation for the study. Additionally, empirical research studies that have examined similar variables across different contexts are critically analyzed to identify key insights, gaps, and trends. This in-depth exploration not only justifies the need for this research but also highlight its contribution to the existing body of knowledge. Finally, the conceptual framework underpinning this study is presented, offering a structured perspective that integrates theoretical and empirical findings to guide the research direction effectively.

2.1 Theoretical Background: Technology Acceptance Model (TAM) and Perceived Value Theory (PVT)

2.1.1 Technology Acceptance Model (TAM)

The rapid evolution of technology has profoundly impacted numerous sectors, particularly the restaurant industry, where service robots have transitioned from futuristic novelties to essential components addressing labor shortages, operational efficiency, and service consistency (Choi, 2020; Ivanov & Webster, 2020). To better understand the factors influencing the acceptance of service robots in restaurants, the Technology Acceptance Model (TAM), initially developed by Davis (1989), provides a foundational theoretical framework. Davis proposed that technology acceptance is largely influenced by two main constructs: Perceived Usefulness (PU) and Perceived Ease of Use (PEOU). PU refers to an individual's belief that using a technology will enhance job performance, while PEOU refers to the individual's perception that using the technology will require minimal effort (Davis, 1989).

TAM has been validated across various domains beyond its original workplace setting, particularly in consumer services and hospitality technologies (Marangunić & Granić, 2015). However, TAM's original model, consisting solely of PU and PEOU, has been extended to reflect the complexity of real-world decision-making better. Additional constructs includings Trust in Technology (TT), Perceived Risk (PR), Social Influence (SI), and Customer Satisfaction (CS) have been integrated into TAM, providing a richer framework for analyzing user acceptance of restaurant service robots (Seo & Lee, 2021).

Trust in Technology (TT) is considered crucial as it encompasses the belief that the robot will perform reliably and safely, significantly influencing user acceptance. Studies indicate that higher trust can lower perceived risk and enhance perceived usefulness (Lee et al., 2021). Conversely, Perceived Risk (PR)—defined as the potential negative consequences anticipated by users, such as errors or privacy concerns—can substantially hinder technology adoption if unaddressed (Seo & Lee, 2021).

Social Influence (SI) is another essential construct included in extended TAM versions like TAM2 and the Unified Theory of Acceptance and Use of Technology (UTAUT). It acknowledges that individuals' technology adoption decisions are influenced by peer pressure, societal trends, and authoritative opinions (Venkatesh et al., 2003). In restaurant contexts, social influence can

significantly drive or inhibit the adoption of robots depending on cultural attitudes and societal norms (Ivanov & Webster, 2019).

Customer Satisfaction (CS), traditionally an outcome variable in technology adoption research, has also been posited as an antecedent. Entrepreneurially, restaurants experiencing high customer satisfaction may adopt robots proactively to further enhance their service offerings. Conversely, restaurants with persistent customer dissatisfaction may see robotics as an innovative solution to service challenges (Seo & Lee, 2021; Chi et al., 2020).

Thus, extending TAM with trust, perceived risk, social influence, and customer satisfaction provides a comprehensive theoretical framework tailored to understanding robot adoption in the restaurant industry. This extended framework integrates cognitive, affective, and contextual factors relevant to stakeholders in the service robotics domain.

2.1.2 Perceived Value Theory (PVT)

Perceived Value Theory (PVT) is a widely accepted framework used to understand consumer decision-making and behavioral intentions in various service settings, including hospitality and technology adoption contexts. Originating from the work of Zeithaml (1988), perceived value is defined as the consumer's overall assessment of the utility of a product or service based on the perception of what is received (benefits) versus what is given (sacrifices), such as time, effort, or cost. In the context of robotic services in restaurants, perceived value represents the customer's or stakeholder's assessment of whether the functional and emotional benefits of service robots outweigh any associated costs or inconveniences.

Unlike the constructs in the Technology Acceptance Model (TAM), which emphasize ease of use and perceived usefulness, Perceived Value Theory provides a broader perspective that incorporates both rational and emotional dimensions of evaluation (Sweeney & Soutar, 2001). This duality is particularly relevant in hospitality environments, where both efficiency (instrumental value) and service experience (emotional value) influence consumer attitudes and satisfaction. For instance, a robot that efficiently delivers food while also providing a novel, entertaining experience can be seen as high in perceived value, which enhances acceptance and loyalty (Kim et al., 2020).

Several studies have emphasized the critical role of perceived value in influencing technology adoption. Parasuraman (1997) highlighted that perceived value acts as a central determinant of consumers' willingness to adopt new technologies, especially in high-contact service environments like restaurants and hotels. In such contexts, perceived value extends beyond mere functional performance to include experiential elements such as novelty, entertainment, and the psychological comfort derived from automation.

Recent empirical research supports the application of perceived value in the adoption of robotic services. For example, Tun et al. (2021) demonstrated that customers who perceived high value in service robot interactions were significantly more likely to express positive attitudes toward continued use and recommendation of robotic services in hospitality settings. Similarly, Wang et al. (2021) found that perceived value directly influenced revisit intention and satisfaction among customers in automated dining experiences in East Asia. These findings suggest that the

evaluation of robotic services through a value lens is essential in capturing consumer expectations and acceptance in real-world service environments.

Moreover, perceived value is not only relevant to customers but also influences managerial decision-making. Entrepreneurs and restaurant owners are likely to consider perceived value when evaluating the return on investment (ROI) and strategic benefits of implementing robotics. If robots are seen as providing operational benefits, such as labor cost savings, faster service, and brand differentiation, at a reasonable cost and with minimal disruption, the perceived value is enhanced, increasing the likelihood of adoption (Ivanov & Webster, 2020; El-Said & Al Hajri, 2022).

In conclusion, Perceived Value Theory offers a complementary yet distinct perspective from TAM by emphasizing the trade-offs customers and decision-makers evaluate when considering robotic services. It broadens the understanding of adoption behavior by integrating emotional, functional, and experiential factors, which are crucial in dynamic, customer-facing industries like hospitality. Incorporating perceived value into the extended TAM framework enables a more holistic analysis of robot adoption, capturing motivations rooted in both practicality and perception.

2.2 Empirical Research on Key Constructs in Robot Adoption

Empirical research provides valuable insights into how each construct—Perceived Usefulness, Perceived Ease of Use, Trust in Technology, Perceived Risk, Social Influence, and Customer Satisfaction—influences the acceptance of service robots in restaurants. The following sections detail these empirical findings.

2.2.1 Perceived Usefulness (PU)

Perceived Usefulness, a core construct within TAM, reflects individuals' beliefs about the technology's ability to enhance their performance or service experiences (Davis, 1989). Within the restaurant industry, PU might encompass expectations of faster service, higher consistency in food quality, reduced errors, and improved overall dining experience. Empirical studies consistently affirm that PU is a strong predictor of both managerial and consumer acceptance of restaurant service robots.

Lee et al. (2021) investigated Taiwanese restaurant managers' acceptance of service robots and found that perceived usefulness significantly influenced their positive attitudes toward adopting robots. Managers recognized robots as valuable for addressing issues like labor shortages, high employee turnover, and consistent service quality. Seo and Lee (2021) similarly found that perceived usefulness directly influenced customers' intention to revisit robot-equipped restaurants, highlighting practical advantages such as improved service speed and helpful recommendations.

Further evidence from broader hospitality technology studies aligns with these findings. For example, a systematic review by Marangunić and Granić (2015) demonstrated that across diverse technologies and contexts, perceived usefulness consistently emerged as a primary determinant of users' adoption intentions. Their analysis indicated that technologies providing clear performance benefits are more readily accepted by both employees and customers.

Moreover, Seo and Lee's (2021) consumer-focused research on robot servers in restaurants showed that customers' perceptions of robots' usefulness positively impacted their revisit intentions. When customers observed tangible benefits, such as faster service delivery or personalized recommendations, they exhibited a higher likelihood of returning to the restaurant. This empirical support confirms that highlighting clear, practical benefits is essential for fostering positive adoption attitudes.

Therefore, ensuring that robots demonstrably enhance restaurant operations, such as efficiency, food consistency, or novelty value, is critical for successful adoption. Effective communication of these tangible benefits is crucial for gaining acceptance from both internal stakeholders (employees and managers) and external stakeholders (consumers).

Relationship between Perceived Usefulness and Robot Adoption

Building upon Davis's (1989) original TAM, which posits that an individual's decision to adopt a technology hinge primarily on perceptions of usefulness and ease of use, the present framework expands to incorporate factors critical in restaurant contexts. Previous empirical research in the hospitality industry has consistently validated that PU significantly influences users' acceptance and behavioral intentions toward adopting innovative technologies (Lee et al., 2021; Seo & Lee, 2021). Specifically, in the context of robotic systems, PU represents stakeholders' belief that implementing robots will tangibly improve operational efficiency, enhance service quality, and positively affect customer experiences by reducing wait times, minimizing errors, and improving service consistency (Seo & Lee, 2021).

2.2.2 Perceived Ease of Use (PEOU)

Perceived Ease of Use (PEOU) refers to "the degree to which a person believes that using a particular system would be free from effort" (Davis, 1989). In the context of service robots in restaurants, ease of use is a critical factor influencing both employee acceptance and customer willingness to interact with robotic systems. An intuitive and simple interaction significantly contributes to the perception that robots will provide efficient service without complications or unnecessary effort. When a robot interface or operation is perceived as user-friendly, users tend to form favorable attitudes toward adopting such technology, which, according to the Technology Acceptance Model (TAM), positively influences both perceived usefulness and behavioral intentions (Venkatesh & Davis, 2000).

Empirical research in the hospitality industry consistently supports the significance of PEOU in technology acceptance. For example, Lee et al. (2021), investigating Taiwanese restaurant managers' acceptance of service robots, found that ease of use directly influenced perceived usefulness and attitudes toward robot adoption. The study indicated that managers who experienced robots as straightforward to program and operate were significantly more likely to recognize their practical benefits, such as reducing workload and addressing labor shortages, thus positively affecting their adoption intentions (Lee et al., 2021).

On the customer side, Wang et al. (2021) explored customer interactions with robots in hospitality settings and found that perceived ease of use strongly correlated with positive customer attitudes toward technology. Customers who found robots easy to interact with expressed greater

willingness to reuse the robotic service, highlighting the importance of designing intuitive and user-friendly interactions. Similarly, El-Said and Al Hajri (2022), studying robotic restaurants in Oman during the COVID-19 pandemic, revealed that when customers perceived the robot service as straightforward and user-friendly, their satisfaction and revisit intentions increased markedly. Notably, their study showed that PEOU indirectly boosted perceived usefulness, enhancing overall service satisfaction.

Moreover, hospitality research by Ivanov and Webster (2020) noted that PEOU affects the adoption of service robots beyond customer acceptance, influencing employees who operate or maintain robotic technologies. Employees who find robots intuitive and easy to manage are more likely to embrace technology, reducing resistance and turnover rates. Their comparative study across various cultural contexts found that simplicity in operation significantly increased employee motivation to engage with robotics, improving overall productivity in restaurants.

Furthermore, advancements in technology, particularly improvements in interface design, AI-driven voice recognition, and touch-screen interactions, have substantially enhanced the ease of using restaurant robots, thereby supporting broader adoption (Wang et.al, 2020). Miso Robotics' "Flippy," an AI-driven kitchen robot implemented by fast-food chains like CaliBurger and White Castle in the U.S., exemplifies how ease of use facilitates operational adoption. Equipped with thermal imaging and user-friendly software, Flippy simplifies food preparation, requiring minimal employee training (Seo et al., 2021).

In conclusion, empirical studies affirm the essential role of perceived ease of use as a determinant of restaurant robot acceptance among customers and employees. Ensuring ease of use requires careful design and user-centered technological interfaces, suggesting that robot developers and restaurant managers must prioritize usability to foster acceptance and integration into everyday operations. Therefore, restaurant entrepreneurs should prioritize investing in intuitive, easy-to-operate robotic systems to ensure successful adoption.

Relationship between Perceived Ease of Use and Robot Adoption

Equally central to the TAM framework is Perceived Ease of Use (PEOU), which is defined as the extent to which users believe interacting with technology will require minimal effort (Davis, 1989). In a restaurant scenario, this translates to intuitive human-robot interactions, smooth integration of robots within existing workflows, and ease of operation and maintenance. Empirical findings confirm that ease of use is a critical determinant of attitudes toward adoption, both directly and indirectly, by enhancing perceived usefulness (Lee et al., 2021; Wang et al., 2021). Therefore, restaurant operators and customers are more likely to adopt robotics when they perceive these systems as simple and intuitive to use.

2.2.3 Trust in Technology (TT)

Trust in Technology (TT) is defined as "the degree to which a user is confident that a technology will consistently operate as expected and without causing harm or undesired consequences" (Lee et al., 2021). Trust is critical in autonomous robotic systems due to their potential risks, complexity, and the necessity for users to relinquish control to robotic operations (Chi et al., 2020). For service

robots in restaurants, trust is essential for both customers, who interact directly with robots, and managers, who must rely on robotic performance for business success.

Seo and Lee (2021), examining consumers' adoption of service robots in Korean restaurants, found that trust significantly impacts perceived usefulness, ease of use, and overall customer satisfaction. Their study indicated that trust helps customers feel comfortable relying on robots for critical service tasks, such as order accuracy and hygiene. Restaurants that built customer trust reported higher revisit intentions, demonstrating that trust serves as a foundational factor influencing long-term adoption. Likewise, Lee et al. (2021) revealed trust to be a crucial determinant for restaurant managers considering robot implementation, showing a positive relationship between trust and perceived usefulness.

Ivanov and Webster (2020) further illustrated that trust in technology influences acceptance across diverse cultures. Their research noted that trust varies significantly based on cultural attitudes toward automation and reliability expectations. In technologically advanced markets like Japan and South Korea, users generally exhibit higher trust levels in robots, partly explaining faster adoption rates compared to European or American counterparts (Ivanov & Webster, 2020).

Anthropomorphic design features can significantly enhance user trust by creating familiarity and reducing perceived risk (Broadbent et al., 2009). A notable example is the humanoid robot "Pepper," widely deployed in Pizza Hut locations across Asia and Pizza Express in the U.K. Pepper's human-like interactions, friendly demeanor, and interactive communication style effectively enhanced trust among patrons, improving their willingness to accept and engage with robotic service (Seo et al., 2021).

Industry practices emphasize the necessity of building trust through reliability and consistent robot performance. Restaurants that implement robot trials typically report initial skepticism among customers and staff; however, successful demonstrations of reliability and safety consistently improve trust levels, facilitating broader acceptance (Ivanov & Webster, 2020). Robots must therefore demonstrate high reliability, safety, and consistency, supported by transparent communication about their capabilities and limitations, thereby reducing perceived risk and increasing trust among stakeholders.

Thus, trust is a pivotal determinant influencing robot adoption. Restaurants must strategically foster trust through careful management of initial implementations, transparent communication, and selecting trustworthy technologies from reputable suppliers to overcome adoption barriers.

Relationship between Trust in Technology and Robot Adoption

Trust in Technology (TT) has emerged as a critical determinant of robotic adoption, particularly in settings where users must relinquish some control to autonomous technologies (Seo & Lee, 2021). Trust encompasses users' beliefs that robots will function reliably, safely, and predictably without causing unexpected negative outcomes (Chi et al., 2022; Seo & Lee, 2021). Studies suggest that trust in robotic systems reduces user anxiety, enhances perceptions of reliability and safety, and positively affects attitudes toward adoption (Ivanov & Webster, 2020; Seo & Lee, 2021).

2.2.4 Perceived Risk (PR)

Perceived Risk (PR) is "the subjective expectation of potential negative outcomes from the use of technology, including performance, financial, social, and safety risks" (Featherman & Pavlou, 2003). In restaurant contexts, perceived risks include fears about robotic malfunctions, safety hazards, poor service quality, and customer dissatisfaction.

Empirical evidence underscores the negative impact of perceived risk on adoption. Seo and Lee (2021) observed that perceived risk significantly reduced customer satisfaction and revisit intentions for restaurants using robotic services. Customers expressed concerns related to safety, operational errors, and hygiene standards. Restaurants that effectively addressed these concerns through clear communication and visible safety measures successfully mitigated perceived risks, fostering greater acceptance.

On the managerial side, Chi et al. (2022) highlighted that restaurant operators often perceive significant financial and operational risks associated with robotics, particularly concerns about ROI, technology maturity, and potential failures. Industry reports consistently show that perceived operational risks hinder rapid adoption among smaller or conservative restaurant operators (El-Said & Al Hajri, 2022). To counteract these concerns, successful implementations often include phased introductions or pilot tests with backup systems, allowing stakeholders to observe reliability firsthand and thus reducing perceived risk.

Consequently, managing and mitigating perceived risk is crucial for widespread robot adoption. Restaurant entrepreneurs must actively address customer and managerial concerns through transparency, robust safety protocols, and gradual implementations, enabling users to become familiar with robot technology and gradually building confidence to minimize perceived risks.

Relationship between Perceived Risk and Robot Adoption

Complementing trust, Perceived Risk (PR) captures potential negative outcomes users anticipate from technology adoption, including financial, operational, safety, and social risks (Seo & Lee, 2021). Literature consistently indicates that higher perceived risk acts as a significant barrier to adoption (Chi et al., 2022). In restaurant contexts, this could manifest in concerns over robot malfunctions, compromised food safety, or negative customer reactions to reduced human interaction (El-Said & Al Hajri, 2022). Therefore, minimizing perceived risks through reassurance, robust safety features, and initial pilot deployments becomes critical for acceptance.

2.2.5 Social Influence (SI)

Social Influence (SI) refers to the degree to which individuals perceive that important others believe they should use a new technology (Venkatesh & Davis, 2000). This construct is rooted in theories such as the Theory of Reasoned Action (TRA) and Unified Theory of Acceptance and Use of Technology (UTAUT), recognizing that technology acceptance is significantly shaped by social and peer pressures, industry trends, and cultural expectations (Venkatesh et.al, 2003).

In the restaurant industry, social influence can arise from multiple sources, such as peers, media, customers, competitors, and broader societal trends toward innovation. Ivanov and Webster (2020) highlight that restaurant operators and customers are frequently influenced by perceptions of technological advancement portrayed through media or the adoption patterns of industry leaders. If influential restaurants adopt robots successfully, others often feel competitive pressure to follow suit, particularly in highly visible or competitive markets. Consequently, SI becomes a compelling driver or barrier to adoption, shaping managers' decisions significantly.

Empirical evidence emphasizes the power of social influence in technology adoption. For example, a cross-cultural study by Ivanov and Webster (2019) demonstrated that Asian consumers' positive attitudes towards robots in restaurants partly stemmed from widespread societal acceptance and media portrayal of robotics as futuristic and desirable. Similarly, research by Chi et al. (2022) revealed that restaurant operators were significantly more inclined to implement robots after observing successful integration by prominent industry peers. They noted that perceived competitive pressure and the desire to remain relevant in an evolving market environment strongly motivated robot adoption decision.

Moreover, a notable industry survey by Kim and Qu (2022) underscored that approximately 30% of customers considered restaurant robotics trendy or attractive enough to influence their dining choices. Social media significantly contributes to this trend, amplifying positive experiences and curiosity around robot interactions. For instance, the RoboCafe in Dubai capitalized on widespread social media attention, driving substantial customer foot traffic, demonstrating how social influence directly impacts consumer behaviors toward new technologies.

However, social influence can also negatively impact robot adoption. Ivanov and Webster (2020) caution that in contexts where customers prioritize personalized human interactions or where negative narratives regarding job losses persist, social pressures can hinder adoption or limit the effectiveness of robot implementations. Thus, restaurant entrepreneurs must strategically manage social influence by highlighting benefits (such as enhanced employee safety, improved efficiency, and customer satisfaction) rather than negative implications like potential job displacement (El-Said & Al Hajri, 2022).

In summary, social influence significantly shapes attitudes and behavioral intentions toward robot adoption in restaurants. Entrepreneurs and managers must carefully consider and manage perceptions generated through media, customer reviews, competitor behavior, and societal norms to foster positive social momentum that enhances acceptance and reduces resistance.

Relationship between Social Influence and Robot Adoption

Social Influence (SI) refers to the degree to which an individual's adoption decision is influenced by the opinions, behaviors, or normative expectations of their social groups (Venkatesh & Davis, 2000). SI has been notably integrated into extended versions of TAM, such as TAM2 and UTAUT, revealing its critical role in adoption decisions, especially in cultures or sectors where collective opinions strongly affect individual behavior (Ivanov & Webster, 2020; Lee et al., 2018). Empirical evidence suggests SI exerts considerable influence when peers, industry leaders, or competitors adopt robotic technologies, creating normative pressures and setting standards others feel compelled to follow (Ivanov & Webster, 2020; Seo & Lee, 2021).

2.2.6 Customer Satisfaction (CS)

Customer Satisfaction (CS) typically reflects how well a product or service fulfills or exceeds customer expectations (Ajzen & Fishbein, 1980). In traditional technology adoption literature, satisfaction is commonly regarded as an outcome of using new technologies. However, recent perspectives suggest that existing satisfaction levels can serve as antecedents, shaping restaurant managers' decisions to adopt new technologies, including robotics (Baker et al., 2020). In essence, restaurants with consistently high customer satisfaction might adopt robots to enhance their service further and differentiate themselves, whereas establishments experiencing persistent customer dissatisfaction may seek robotic solutions as innovative corrective measures.

Research exploring the relationship between customer satisfaction and innovation adoption has highlighted this dual role. For instance, Baker et al. (2020) emphasize that businesses experiencing high satisfaction levels have greater confidence and motivation to experiment with innovative solutions, often to maintain competitive differentiation. This was exemplified in a case study of Creator, a highly rated restaurant in San Francisco, which implemented robotic food preparation systems to reinforce their reputation for innovation and customer excellence (El-Said & Al Hajri, 2022). This restaurant's decision highlights how existing high satisfaction can motivate further innovation.

Conversely, lower satisfaction levels can pressure restaurants to adopt robots as a strategic solution to recurring service quality issues. Seo and Lee (2021) observed that restaurants facing customer complaints regarding slow service or errors increasingly considered robotic service solutions during the COVID-19 pandemic, using automation to mitigate hygiene concerns and improve operational efficiency. Indeed, El-Said and Al Hajri (2022) found that restaurants adopting robotic solutions experienced notable increases in customer satisfaction due to improved hygiene and consistent service speed during the pandemic, reinforcing this reactive innovation adoption dynamic.

Interestingly, customer satisfaction can also reinforce itself post-adoption, creating a feedback loop. For instance, Wang et al. (2021) noted that high customer satisfaction following initial robot interactions significantly enhanced customers' perceived value and willingness to revisit robotic restaurants. Thus, satisfaction serves as a dynamic factor influencing both initial adoption decisions and sustained technology use.

Overall, considering customer satisfaction as an antecedent enriches our understanding of robot adoption, underscoring that managers must carefully analyze current satisfaction levels before adopting robots. High initial satisfaction can facilitate innovation acceptance, whereas low

satisfaction might make adoption an imperative to regain consumer trust and competitive positioning.

Relationship between Customer Satisfaction and Robot Adoption

Customer Satisfaction (CS) is uniquely positioned in this study as an antecedent rather than just an outcome of technology adoption. High customer satisfaction can encourage restaurants to adopt robots to further enhance service quality or maintain a competitive edge, while persistent dissatisfaction may prompt adoption as an innovative solution to systemic service problems (Baker et al., 2020).

2.2.7 Customer Perceived Value (CPV)

Customer Perceived Value (CPV) is defined as customers' overall assessment of the utility of a product or service based on their perceptions of benefits received compared to sacrifices made, such as cost, time, and effort (Zeithaml, 1988). This construct significantly affects customer acceptance and continued usage of innovative technologies, including restaurant robotics. Unlike satisfaction, which occurs post-service, CPV can shape consumer decisions and attitudes pre-adoption, making it critical for managers to evaluate technology adoption (Parasuraman, 1997).

In the context of restaurant robots, perceived value includes factors such as improved convenience, novelty, efficiency, and enhanced dining experiences compared to traditional services. Empirical studies consistently demonstrate the strong relationship between perceived value and adoption intentions. For instance, a study by Tun et al. (2021) on service robots in hotels found that high perceived value directly correlated with increased customer intention to use robots. Patrons perceiving robotic interactions as efficient, enjoyable, and worthwhile indicated higher willingness to repeat their experience, highlighting the value's critical role in consumer acceptance of robotic services.

Restaurant managers similarly use anticipated customer-perceived value as a significant criterion for robot adoption decisions. A global industry survey indicated that managers who perceived robotic systems as delivering superior customer value showed stronger intention toward robot adoption (El-Said & Al Hajri, 2022). For instance, fast-food chains such as CaliBurger and White Castle, after implementing robot cooks, reported that customers positively perceived the improved food preparation speed, consistent quality, and overall dining value, reinforcing management decisions on expanded robot deployment (Ivanov & Webster, 2020; Seo & Lee, 2021).

However, perceived value assessments differ significantly across markets and consumer segments. Younger customers and those with higher technological familiarity often perceive robotic services as highly valuable, whereas older demographics or those emphasizing personal interactions may perceive less value due to reduced human contact (Ivanov & Webster, 2020). Therefore, restaurants must strategically communicate and demonstrate robot service benefits clearly to customers, enhancing perceived value through carefully designed experiences.

In conclusion, customer perceived value fundamentally drives robot adoption decisions, serving as a critical factor affecting both customer acceptance and managerial implementation

strategies. Ensuring high customer perceived value through tangible benefits—speed, novelty, reliability—can significantly facilitate robot adoption, making CPV a pivotal construct within any comprehensive adoption framework.

Relationship between Customer Perceived Value and Robot Adoption

Customer Perceived Value (CPV) encompasses the customer's subjective evaluation of the benefits and costs associated with using a product or service (Zeithaml, 1988). CPV in the context of robotic services includes tangible benefits such as improved service speed, accuracy, novelty, entertainment, and reduced effort versus potential inconveniences or losses in service personalization (Tun et al., 2021; Wang et al., 2021). Recent empirical evidence demonstrates that when customers perceive high value in robotic interactions, their acceptance and revisit intentions increase significantly, providing an essential driver of adoption from a customer-centric perspective (Seo & Lee, 2021)

2.3 Robot Adoption in Restaurants: Technological Advancements, Global Trends, and Case Studies

The global adoption of robots in the restaurant industry has markedly accelerated due to significant technological advancements, changing economic conditions, and shifts in consumer behavior. This section extensively examines how advancements in robotics technology have facilitated the adoption process, investigated international market trends, and explored detailed case studies to illustrate practical robot deployments across diverse geographical regions.

2.3.1 Technological Advancements Driving Adoption

Technological advancements form a critical underpinning for the integration of robots into restaurant operations, particularly developments in artificial intelligence (AI), robotics engineering, and communication technologies (Ivanov & Webster, 2020). Advances in robotics and AI have significantly improved the capabilities of robots to perform complex tasks autonomously, reliably, and safely in crowded restaurant environments (Ivanov & Webster, 2020). For instance, modern robots now incorporate advanced machine vision systems, enabling them to navigate crowded and unpredictable restaurant environments without collisions or interference (Seo & Lee, 2021). AI-driven software now empowers robots to accurately recognize objects, people, and spaces, facilitating tasks such as serving food to precise locations and efficiently clearing tables, thereby enhancing operational efficiency and customer satisfaction (Ivanov & Webster, 2020).

One notable example is Miso Robotics' "Flippy," an AI-powered kitchen robot equipped with thermal sensors, cameras, and machine learning capabilities. Flippy autonomously cooks burgers, fries, and other menu items to consistent standards, reducing human workload and variability in food quality (Wang et al., 2021). Similarly, restaurant service robots equipped with LIDAR (Light Detection and Ranging) technology and advanced sensors are now common, providing enhanced safety and precise spatial awareness, crucial for customer-facing roles (Ivanov & Webster, 2020).

The COVID-19 pandemic significantly accelerated restaurant automation technology by heightening consumer awareness and demand for contactless and hygienic dining experiences (El-

Said & Al Hajri, 2022). Technologies such as automated UV disinfection integrated into food-service robots have addressed heightened consumer concerns about sanitation, reinforcing customer trust and acceptance (El-Said & Al Hajri, 2022). Consequently, robots not only offer operational efficiency but have also become instrumental in reassuring customers concerned with hygiene and safety in dining experiences.

2.3.2 Global Adoption Trends and Comparative Perspectives

The rate of robot adoption in restaurants differs significantly worldwide, shaped by economic factors, cultural attitudes towards innovation, labor dynamics, and regulatory environments. Asian countries, particularly China, Japan, South Korea, and Singapore, demonstrate a pronounced trend toward high levels of adoption. China's accelerated robot integration in restaurants reflects both high labor costs and cultural acceptance of technology-enhanced services. For example, prominent Chinese restaurant chains such as Haidilao have implemented robots extensively to automate cooking and serving processes, thus significantly reducing dependency on human labor (Seo & Lee, 2021).

Japan, historically embracing robotics, has integrated service robots seamlessly into sushi restaurants and casual dining establishments. This widespread acceptance stems from both cultural openness toward robots and the practical necessity to address persistent labor shortages and an aging population (Ivanov & Webster, 2020). South Korea and Singapore have similarly seen substantial robot deployments, such as Pepper robots greeting customers and assisting with orders in fast-food franchises like Pizza Hut, highlighting how consumer engagement can be enhanced through technological novelty (Wang et al., 2021).

In North America, particularly the United States, robot adoption has primarily focused on enhancing kitchen efficiency. Companies such as Miso Robotics have introduced advanced cooking robots like Flippy in fast-food chains, automating high-volume, repetitive cooking tasks (Wang et al., 2021). Despite initial consumer resistance to fully automated service, North American restaurants are increasingly utilizing robots to handle behind-the-scenes operations to improve consistency, speed, and labor management, a trend accelerated by rising labor costs and labor shortages intensified by the pandemic (Seo & Lee, 2021).

Europe's restaurant industry, characterized by strong traditions in personalized service, has adopted robots cautiously, often as “cobots”—robots collaborating alongside human staff rather than outright replacing them (Ivanov & Webster, 2020). For instance, in Germany and France, robots such as “Plato” have been deployed primarily to assist human staff, handling tasks like carrying dishes from kitchen to table, thus alleviating pressure during peak operational hours without compromising customer service quality (Wang et al., 2021).

In the Middle East, particularly in countries like the UAE and Oman, robot adoption has been strategically positioned to showcase modernity and innovation. Dubai’s RoboCafe, for example, operates entirely with robotic staff preparing and serving beverages, aligning with Dubai’s high-tech global image and providing a futuristic dining experience attractive to both residents and tourists (El-Said & Al Hajri, 2022).

2.3.3 Case Studies and Implementation Insights

Detailed case studies from diverse international markets illustrate practical insights into restaurant robot implementation. For example, CaliBurger's successful implementation of Flippy in California not only improved operational consistency but also showcased significant productivity gains, reportedly preparing up to 2,000 burgers per day without fatigue or error (Wang et al., 2021). Similarly, Pizza Hut Singapore deployed SoftBank's humanoid robot Pepper to enhance customer interactions, providing a unique brand experience while successfully taking orders and processing payments (Wang et al., 2021).

India presents a unique case, where robot adoption in restaurants, such as Robot Restaurant in Chennai and Bangalore, has largely been driven by customer interest in novelty rather than labor shortages. These restaurants effectively utilize robots primarily for customer attraction, demonstrating that customer engagement and novelty can independently drive adoption in markets without labor shortages (Seo & Lee, 2021).

Collectively, these international examples highlight the varying drivers behind robot adoption in restaurants, encompassing operational efficiency, labor shortages, competitive positioning, and consumer attraction. These case studies illustrate not only the successes but also the importance of carefully tailored approaches to match regional consumer expectations and cultural norms.

This comprehensive analysis illustrates how global adoption trends reflect the intersection of technological feasibility, economic imperatives, cultural attitudes, and strategic marketing, demonstrating that robot adoption in the restaurant industry is increasingly viewed as a pragmatic response to diverse operational challenges rather than merely futuristic innovation.

2.4 Conceptual Framework

Based on the comprehensive literature review outlined above, this study presents an integrative conceptual framework (see Figure 2.1) designed to systematically examine the adoption of service robots in the restaurant industry, specifically within the context of Bangkok's market. Drawing upon the Technology Acceptance Model (TAM) and its extensions, this framework provides a holistic view of how key variables—Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Trust in Technology (TT), Perceived Risk (PR), Social Influence (SI), Customer Satisfaction (CS), and Customer Perceived Value (CPV)—influence restaurant entrepreneurs' intentions to adopt robotics solutions.

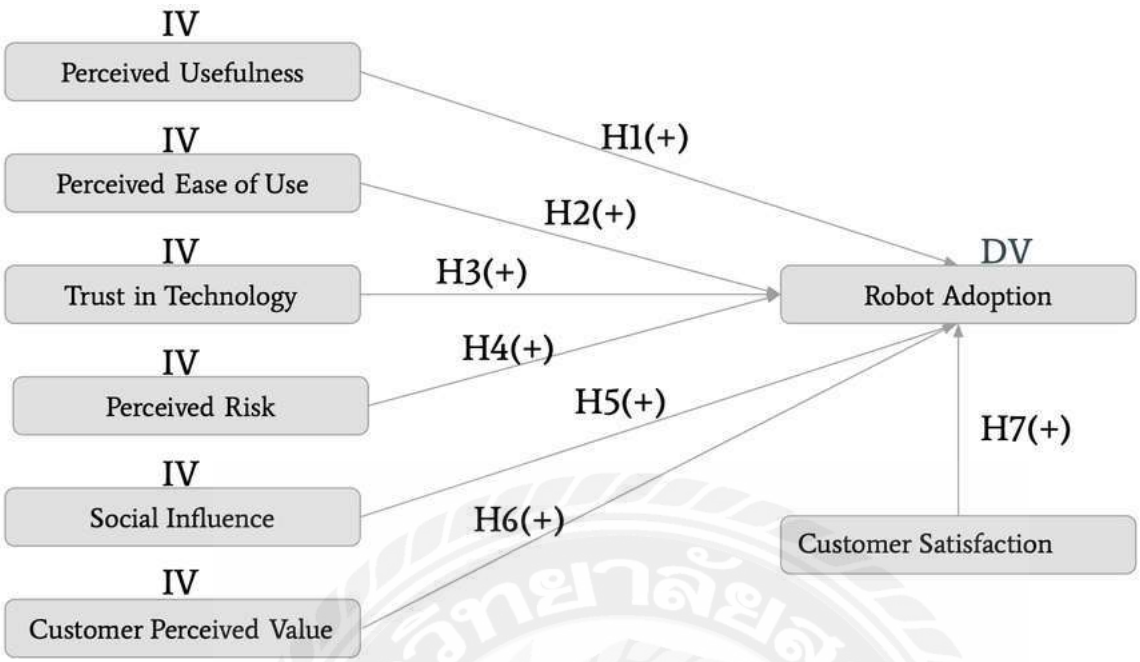


Figure 2.1: Conceptual Framework

Hypothesis 1 (H1): Perceived Usefulness (PU) positively influences Robot Adoption (RA).
Hypothesis 2 (H2): Perceived Ease of Use (PEOU) positively influences Robot Adoption (RA).
Hypothesis 3 (H3): Trust in Technology (TT) positively influences Robot Adoption (RA).
Hypothesis 4 (H4): Perceived Risk (PR) positively influences Robot Adoption (RA).
Hypothesis 5 (H5): Social Influence (SI) positively influences Robot Adoption (RA).
Hypothesis 6 (H6): Customer Satisfaction (CS) positively influences Robot Adoption (RA).
Hypothesis 7 (H7): Customer Perceived Value (CPV) positively influences Robot Adoption (RA).

Chapter 3
Research Methodology

This chapter provides a comprehensive explanation of the research methodology employed to investigate the key determinants influencing the adoption of service robotics in Bangkok's restaurant industry. The purpose of this methodology chapter is to present a systematic approach that facilitates replicability, transparency, and scientific rigor in exploring stakeholder perspectives. Specifically, the study aims to validate an extended Technology Acceptance Model (TAM) by quantitatively examining the relationships among perceived usefulness (PU), perceived ease of use (PEOU), trust in technology (TT), perceived risk (PR), social influence (SI), customer perceived value (CPV), and customer satisfaction (CS), and robot adoption (RA) in the specific context of Bangkok restaurants.

The chapter is organized into clearly defined sections that detail the chosen research approach, design rationale, target population and sampling procedures, questionnaire development, and associated justifications. Furthermore, ethical considerations, validity, and reliability issues are elaborately discussed to ensure that the research aligns with established standards for quantitative, deductive studies within the domain of hospitality technology adoption research.

3.1 Research Method

3.1.1 Quantitative Research Approach

This study employed a quantitative research approach, which is recognized as particularly effective for hypothesis testing and theory validation, especially in studies that involve perceptions and behavioral intentions towards technological innovations (Creswell & Creswell, 2017; Hair et al., 2018). Quantitative research methods offer significant advantages, including the ability to generalize findings from a representative sample to broader populations and to facilitate objective comparisons between different constructs through standardized measurement instruments (Sekaran & Bougie, 2016). Given that this research focuses on the relationship between various latent constructs including perceived usefulness, ease of use, trust, perceived risk, social influence, customer satisfaction, and customer perceived value, a quantitative research approach is particularly suitable for clearly testing hypothesized relationships within an established theoretical framework (Davis, 1989; Seo & Lee, 2021).

The main justification for selecting a quantitative methodology arises from the study's aim of empirically testing an extended theoretical model—specifically the Technology Acceptance Model (TAM)—within the restaurant industry context. Moreover, by applying quantitative methods, it becomes possible to systematically examine whether perceived usefulness, ease of use, trust, risk, social influence, perceived value, and customer satisfaction significantly influence stakeholders' behavioral intentions to adopt robotics in restaurants. Quantitative research also enables statistical control of extraneous variables, thereby isolating the effects of primary factors influencing technology adoption, enhancing both internal and external validity (Saunders et al., 2019).

3.1.2 Deductive Strategy and Rationale

This research utilized a deductive approach, which is suitable for hypothesis-driven studies aiming to test established theories and models. According to Bryman (2015), deductive strategies involve developing hypotheses from existing theoretical frameworks, subsequently validating or falsifying these through empirical data collection. This approach contrasts with inductive methods, where research begins with observations or exploratory data collection and then moves towards theory-building.

The deductive approach chosen for this study enables systematic and structured testing of the hypothesized relationships among variables such as perceived usefulness, ease of use, trust, perceived risk, social influence, customer satisfaction, and customer perceived value (Hair et al., 2019). Furthermore, it facilitates verification of the applicability and explanatory power of the extended TAM in the specific context of robotics adoption within restaurants (Venkatesh & Davis, 2000; Seo & Lee, 2021).

This strategy involves clear operational definitions of constructs based on established theoretical foundations, followed by empirical validation through statistical techniques such as Structural Equation Modeling (SEM). The deductive process thus ensures clarity, replicability, and empirical rigor, positioning the findings of this research within the broader discourse on technology adoption in hospitality settings (Creswell, 2014; Saunders et al., 2019).

3.2 Research Design

3.2.1 Overall Design

This study employed a cross-sectional survey design, which involves collecting data at a specific point in time from a representative sample of individuals to assess their attitudes, perceptions, and intentions towards robotics adoption (Sekaran & Bougie, 2016). The choice of cross-sectional design aligns with similar studies in technology adoption literature and is widely recommended due to its practicality, cost-effectiveness, and ability to rapidly generate insights relevant to managerial decision-making (Hair et al., 2019; Bryman, 2015).

Cross-sectional surveys provide researchers with several critical advantages. First, they allow the collection of quantitative data from multiple respondents simultaneously, enabling comparative analyses and identification of relationships between variables (Malhotra & Birks, 2017). Second, by conducting the research at a single point in time, the design effectively captures stakeholders' current attitudes toward robotics adoption without temporal distortions that could arise from longitudinal designs (Hair et al., 2019; Saunders et al., 2019). This is particularly valuable within the rapidly evolving technology domain, where perceptions and market conditions can change swiftly (Ivanov & Webster, 2020).

Moreover, this research design allows generalizations to be made with a relatively high degree of confidence, especially when combined with a suitably sized and diverse sample. Such a design provides robust foundations for both descriptive and inferential statistical techniques, such as regression analyses and Structural Equation Modeling (SEM), both of which require precise and systematically collected data (Hair et al., 2019; Sekaran & Bougie, 2016).

3.2.2 Descriptive and Explanatory Components

The cross-sectional survey design in this study is structured into two integral components: descriptive and explanatory. The descriptive component aims to comprehensively profile the characteristics, perceptions, and existing intentions toward robotics adoption among respondents from the Bangkok restaurant industry. It captures demographic information, attitudes, and perceived values associated with service robots, providing valuable insights into current industry trends and baseline attitudes (Saunders et al., 2019).

The explanatory component, on the other hand, involves rigorous testing of the hypotheses proposed in Chapter 2. Specifically, it investigates the causal relationships between independent variables (PU, PEOU, Trust, Risk, Social Influence, Customer Satisfaction, Customer Perceived Value) and the dependent variable (Robot Adoption intention). This component utilizes multiple regression analysis and Structural Equation Modeling (SEM) to test and validate the conceptual framework proposed in Chapter 2 (Venkatesh et al., 2003; Hair et al., 2019).

3.2.3 Justification of the Cross-sectional Approach

The cross-sectional survey approach was deliberately chosen due to its proven efficacy in hospitality and technology adoption research. Previous empirical studies examining technology adoption, such as those by Davis (1989), Seo and Lee (2021), and Venkatesh et al. (2003), have extensively utilized cross-sectional designs to validate similar theoretical frameworks and hypotheses. Additionally, cross-sectional surveys are widely acknowledged for their practicality, especially in resource-constrained research settings, enabling the researcher to balance methodological rigor with operational efficiency (Saunders et al., 2019). Table 3.1 below outlines the main components of the research design.

Table 3.1: Summary of Research Design Components

Component	Description	Rationale
Research Approach	Quantitative, Deductive	Allows objective measurement and hypothesis testing
Research Design	Cross-sectional survey design	Captures a snapshot of current attitudes and perceptions
Data Collection Method	Online survey via web-based platform	Resource-efficient; reaches a broad sample
Statistical Analysis	Descriptive statistics, regression, and Structural Equation Modeling (SEM)	Tests inter-variable relationships and model adequacy

In summary, the methodological choices made in sections 3.1 and 3.2—the quantitative approach, deductive strategy, and cross-sectional survey design—are explicitly justified based on the research objectives, the theoretical foundation, the nature of constructs investigated, and the practical constraints of the research context. These methodological decisions collectively establish

a robust foundation for conducting reliable, valid, and meaningful empirical research on robot adoption in the restaurant industry in Bangkok.

3.3 Population and Sampling

3.3.1 Target Population

The target population is a clearly defined group of individuals or elements to which researchers intend to generalize the findings of their study (Saunders et al., 2019). For this research, the target population consisted of stakeholders directly involved in and impacted by the adoption of robotics in restaurants. Specifically, this population includes restaurant owners, managers, frontline restaurant employees, and customers within the restaurant industry in Bangkok, Thailand.

1. **Restaurant Owners and Managers**

   Restaurant owners and managers are crucial as they serve as primary decision-makers when it comes to technology adoption within restaurants (Ivanov, Webster, & Berezina, 2020). These individuals have the authority to approve financial investments, implement operational changes, and manage organizational shifts required for adopting service robotics. As such, their perceptions regarding the usefulness, ease of use, trustworthiness, risk factors, and overall expectations of robotics significantly impact the likelihood of adoption (Seo & Lee, 2021). The focus on owners and managers thus captures an essential managerial perspective essential for understanding the adoption phenomenon in the restaurant sector.

2. **Restaurant Employees**

   Employees are the frontline staff who will directly interact with robots, either as co-workers or supervisors of automated service processes. Their acceptance, comfort level, and perception of robots' ease of use and potential risk significantly impact the successful implementation and sustained utilization of robotics (Lee et al., 2021). Investigating employees' attitudes is imperative since negative perceptions among this group could lead to resistance or suboptimal usage of the technology, thereby undermining adoption success (Chi et al., 2020).

3. **Customers**

   Restaurant patrons are the ultimate end-users of robotic service implementations, and their perceptions significantly affect the commercial viability of robotics in the hospitality setting. Customers' satisfaction with and perceived value of robot-delivered services will directly influence their revisit intentions and willingness to engage with automated services again (Seo & Lee, 2021; Tun et al., 2021). Including customers in the target population thus ensures a balanced understanding of the adoption process from a market-driven perspective, complementing managerial and employee perspectives.

Thus, targeting these three groups (owners/managers, employees, and customers) provides comprehensive coverage of the relevant stakeholders involved in or affected by the adoption of robotics in Bangkok's restaurants.

3.3.2 Sampling Technique

A non-probability convenience sampling approach was employed in this study. Convenience sampling involves selecting respondents based on their availability and willingness to participate, which provides significant practical advantages in terms of efficiency, accessibility, and cost-effectiveness, especially suitable for quantitative surveys (Sekaran & Bougie, 2016). Non-probability sampling is widely used in hospitality and technology acceptance research, as it allows quick collection of large-scale data from diverse respondents across varied settings (Creswell & Creswell, 2017; Bryman, 2015).

Convenience sampling is especially advantageous for research focusing on relatively specialized populations, such as restaurant owners and managers, who may have limited time to participate in extensive research studies (Saunders, Lewis, & Thornhill, 2019). Previous studies on technology adoption in hospitality settings frequently employed convenience sampling due to its practicality and ability to rapidly generate insights (Ivanov & Webster, 2020; Tun et al., 2021). This sampling method, although non-random, is valuable as it allows for immediate data collection from participants accessible to the researcher (Sekaran & Bougie, 2016).

However, convenience sampling does possess inherent limitations, particularly regarding representativeness and potential biases. Participants recruited conveniently might share characteristics or experiences that differ from the broader population, potentially limiting generalizability. To minimize this limitation, deliberate efforts are made to include participants across diverse restaurant types, sizes, and geographical areas within Bangkok, thereby enhancing sample representativeness (Hair et al., 2019).

3.3.3 Sample Size Determination

Determining an appropriate sample size is critical for achieving robust statistical power and ensuring the reliability of the study's results. According to Hair et al. (2019), an adequate sample size enhances the generalizability of findings, reduces sampling error, and enables effective hypothesis testing. To calculate the required sample size, Cochran's (1977) widely accepted formula for proportions is utilized:

$$n_0 = (Z^2 \cdot p \cdot (1 - p)) / e^2 \qquad \text{eq (1)}$$

where:

- n_0 = required sample size,
- Z^2 = Z-value (confidence interval, e.g., 1.96 for 95% confidence),
- p = estimated proportion (0.5 for maximum variability),
- e = margin of error (0.05 for this study, reflecting a 95% confidence interval).

Using a confidence level of 95% (Z=1.96), a proportion (p) of 0.5 (to maximize variability), and an allowable error of ±5% (e=0.05), the calculation proceeds as follows:

$$n_0 = (1.96)^2 \times 0.5 \times 0.5 / (0.05)^2 \approx 384 \qquad \text{eq (2)}$$

To accommodate potential non-response and incomplete questionnaires, an additional margin of approximately 5% is incorporated. Therefore, the final targeted sample size is rounded up to approximately 400 respondents.

3.3.4 Justification of Sample Size

A sample size of approximately 400 is justified on multiple grounds:

1. **Statistical Power and Analytical Requirements:**

   A sample of 400 provides sufficient statistical power to detect significant relationships among multiple independent and dependent variables, particularly when employing Structural Equation Modeling (SEM) techniques, which typically require larger sample sizes (Hair et al., 2019). Moreover, an SEM model typically requires at least 200-300 respondents for robust model testing. Thus, the chosen sample comfortably meets this analytical threshold.

2. **Comparability with Prior Studies:**

   Comparable hospitality and restaurant-related TAM studies consistently use sample sizes ranging from 250 to 500 respondents. For instance, Seo and Lee (2021) employed a sample of approximately 300 respondents to assess the adoption of service robots in restaurants. Similarly, Ivanov and Webster (2020) recommended similar sample ranges in their review of robotics adoption research in tourism and hospitality. Aligning this research's sample size with existing empirical benchmarks ensures methodological consistency and comparability.

3. **Resource Efficiency and Feasibility:**

   A sample of 400 also balances methodological rigor with practical considerations regarding time, budget, and researcher capacity (Saunders et al., 2019). This manageable sample size allows detailed analysis and minimizes respondent fatigue, ensuring higher quality data.

3.3.5 Sampling Procedure

To operationalize convenience sampling effectively, the sampling procedure involves multiple steps:

1. **Identification of Participants:**

   Participants were recruited through direct contacts with restaurant associations in Bangkok, such as the Thai Restaurant Association, and via online platforms (e.g., LinkedIn, Facebook restaurant groups, and forums dedicated to hospitality professionals). Recruitment also included customers via social media platforms and community groups frequently utilized by Bangkok residents.

2. **Questionnaire Dissemination:**

A web-based survey platform (Google Forms) was utilized for data collection, allowing convenient access and completion via smartphones and computers, maximizing response rates among busy respondents.

3. **Participant Inclusion Criteria:**

Clear inclusion criteria are defined to ensure participants' relevance and data quality. For instance, respondents must be:

- Over 18 years of age.
- Currently employed in managing or frequently dining at restaurants within Bangkok.
- Willing to provide honest and voluntary responses.

3.4 Instrument Development and Questionnaire Design

3.4.1 Instrument Development

The development of the research instrument, namely a questionnaire, was a systematic and rigorous process aimed at accurately measuring variables central to understanding robot adoption in Bangkok's restaurant industry. The instrument design integrated extensive theoretical insights, empirical findings from the Technology Acceptance Model (TAM), and related extended constructs, including Trust in Technology (TT), Perceived Risk (PR), Social Influence (SI), Customer Satisfaction (CS), Customer Perceived Value (CPV), Perceived Usefulness (PU), and Perceived Ease of Use (PEOU).

The process of instrument development commenced with a comprehensive review of relevant literature in technology acceptance and service innovation domains. This literature review facilitated the identification and adaptation of established measurement scales that align well with the study's conceptual framework (Davis, 1989; Venkatesh & Davis, 2000; Seo & Lee, 2021). To ensure robustness and reliability, items selected for each construct were drawn from previously validated instruments, adapted to suit the restaurant industry and the cultural context of Bangkok.

Perceived Usefulness (PU) items were adapted from Davis (1989) and Seo and Lee (2021), where PU specifically refers to user perceptions regarding enhanced job performance or operational efficiency through robotic technology use. Items were adapted to the restaurant context to reflect specific benefits such as faster food preparation, improved accuracy in service delivery, and overall operational improvements.

Perceived Ease of Use (PEOU) was derived from the original TAM by Davis (1989), emphasizing the degree to which individuals believe that using a new technology will require minimal effort. Items selected captured the simplicity of interacting with robotic technologies, the clarity of user interfaces, ease of learning and operational convenience, and intuitiveness for both employees and customers in restaurant scenarios. Adjustments ensured relevance to both staff operational roles and customer interactions.

Trust in Technology (TT), recognized as a significant determinant in technology acceptance models involving automation (Seo & Lee, 2021), was measured by items adapted from

prior studies such as those by Saunders et al. (2019) and Lee et al. (2021). The scale included aspects like reliability, safety, predictability, and confidence in the system's intended functionality, explicitly framing the restaurant robotics context. Trust was further considered crucial given the autonomous and interactive nature of service robots, which necessitates users' relinquishing of control and assurance of safety and dependability.

Perceived Risk (PR), integral to understanding adoption hesitation, was measured using scales from prior empirical studies by Seo and Lee (2021) and Featherman and Pavlou (2003). These scales focused on capturing user concerns related to potential negative outcomes from adopting service robots, including operational risks (e.g., system malfunctions), financial risks (costs and return on investment uncertainties), and social risks (customer dissatisfaction or discomfort due to robotic interaction).

Social Influence (SI), adapted from Venkatesh et al.'s (2003) Unified Theory of Acceptance and Use of Technology (UTAUT), measured the influence of societal and peer opinions on individuals' acceptance decisions. Items focused on normative beliefs, peer influences, and societal trends affecting stakeholders' willingness to adopt robotic technologies in restaurants.

Customer Satisfaction (CS) was positioned as an antecedent to adoption decisions, following theoretical suggestions by Jin et al. (2015) and Kim and Qu (2022). CS items specifically assessed stakeholders' existing satisfaction levels with current service offerings, hypothesizing that satisfaction could either motivate or inhibit innovation efforts in robot deployment.

Robot Adoption (RA), the primary dependent variable, replaced behavioral intention scales initially proposed in TAM. Items measuring RA were adapted from previous innovation adoption studies (e.g., Venkatesh et al., 2003; Seo & Lee, 2021), reflecting both intentionality and actual decision-making regarding the implementation of robotic solutions in restaurants.

After scale adaptation, the questionnaire underwent expert validation. A panel of academics specializing in technology adoption, hospitality management, and quantitative research methods reviewed the questionnaire to confirm its face and content validity. The experts evaluated the clarity, representativeness, and relevance of each item, providing qualitative feedback. Modifications were made based on their recommendations, including adjustments in wording for clarity, ensuring relevance to stakeholders, and context-specific alignment with the restaurant environment.

To further refine the instrument, a pilot test involving 50 respondents was conducted. These respondents represented a mix of restaurant managers, employees, and consumers to ensure diverse feedback. Reliability analysis using Cronbach's alpha coefficients was performed, and all scales demonstrated acceptable reliability ($\alpha \geq 0.70$), consistent with recommendations by Hair et al. (2019). The pilot test also collected qualitative feedback on item clarity, resulting in minor wording revisions to improve respondents' comprehension and reduce ambiguity.

The final questionnaire was refined based on expert reviews and pilot test feedback, achieving a balanced representation of theoretical rigor, practical relevance, and empirical reliability. The developed instrument was designed to be concise yet comprehensive, enhancing

participant engagement and response accuracy. This systematic instrument development approach ensured that the final questionnaire was both theoretically sound and practically relevant for accurately capturing the complex dynamics of robotic technology adoption in Bangkok's restaurant industry.

3.4.2 Questionnaire Design

The questionnaire design followed structured guidelines aimed at ensuring clarity, ease of completion, and precise measurement of constructs critical to the study. The questionnaire consisted of two primary sections, systematically addressing demographic characteristics and construct-specific measurements.

The demographic section captured essential respondent characteristics, including age, gender, educational level, job role (e.g., owner, manager, employee), and restaurant type (fine dining, casual dining, or fast-food establishments). Including these demographic variables was essential for understanding how different stakeholder segments perceive robotic technology, allowing for detailed comparative analyses. Additionally, the frequency of dining experiences involving technology was included to gauge participants' exposure to technology-driven environments.

For the main construct measurement section, the questionnaire employed a structured, standardized format using closed-ended Likert scale items. The adoption of a five-point Likert scale (ranging from "1 = Strongly Disagree" to "5 = Strongly Agree") was chosen based on its widespread acceptance in social science research, as recommended by Likert (1932) and later affirmed by Dawes (2008). This scale format simplifies participant responses, facilitates efficient data collection, and allows straightforward quantification of subjective perceptions.

The questionnaire's main body comprised a structured set of carefully adapted Likert scale items for measuring key constructs. Each construct was represented by multiple items to capture diverse dimensions of respondents' perceptions and attitudes:

- Perceived Usefulness (PU): This construct assessed the extent to which respondents believed restaurant robots would enhance efficiency, service quality, and overall performance (Davis, 1989).
- Perceived Ease of Use (PEOU): Items in this area measured how effortlessly respondents believed they could interact with or operate restaurant robots (Davis, 1989).
- Trust in Technology (TT): Items evaluated respondents' trust regarding robot reliability, safety, and consistent performance in delivering food services (Hair et al., 2019).
- Perceived Risk (PR): Items in this category measured respondents' concerns regarding potential negative consequences of adopting robot technology, such as malfunction, hygiene issues, or social discomfort (Lee et al., 2021).
- Social Influence (SI): These items captured how social pressures, opinions, or trends influenced respondents' decisions regarding robot adoption (Venkatesh et al., 2003).
- Customer Satisfaction (CS): This construct involved evaluating the extent to which restaurant robots are perceived as meeting or exceeding customer expectations in terms of speed, quality, and overall service experience (Kim & Qu, 2022).

- Customer Perceived Value (CPV): This construct measured the extent to which customers perceive the benefits of service robots to outweigh the costs or efforts associated with their use. Items assessed the perceived trade-off between what customers receive—such as improved service speed, novelty, and convenience—and what they give up, including time, effort, or social interaction (Zeithaml, 1988)
- Robot Adoption (RA): Items for robot adoption captured respondents' intention or decision to adopt or continue using robotics within their restaurants or patronize robot-integrated restaurants (Jin et al., 2015).

The questionnaire began with a scenario method, commonly utilized in technology acceptance studies (Venkatesh et al., 2003; Kim & Qu, 2022), provided respondents with a clear and consistent context for evaluating their perceptions and attitudes. For instance, participants were asked to envision dining at a modern Bangkok restaurant equipped with advanced service robots managing various tasks such as order-taking, food preparation, and delivery. Such contextualization ensured respondents shared a uniform understanding of the subject matter, reducing potential ambiguity and bias in responses.

The questionnaire systematically presents the adapted measurement items for each construct—Perceived Usefulness, Perceived Ease of Use, Trust in Technology, Perceived Risk, Social Influence, Customer Satisfaction, and Robot Adoption—each delineated and labeled. Each construct was measured by multiple items carefully worded to capture distinct dimensions clearly and concisely. Care was taken to avoid double-barreled questions, as advised by Creswell (2014), to maintain clarity and enhance response accuracy. Items were sequenced logically, starting from simpler questions (ease of use) toward more complex perceptions (trust, risk, social influence).

To further ensure clarity and comprehensibility, terminology used in the questionnaire was deliberately straightforward and free of technical jargon. Each item was accompanied by clear instructions, asking respondents to indicate their level of agreement or disagreement using the provided Likert scale. The use of familiar language minimized misunderstandings and promoted higher response quality, as recommended by Dillman et al. (20174).

In the final questionnaire, respondents encountered approximately 32 measurement items across the eight main constructs. The length was balanced to prevent fatigue and encourage thorough responses, which is critical for accurate statistical analysis (Creswell, 2014). The questionnaires are constructed to collect different level of perceptions.

The comprehensive, structured design of the questionnaire (see Table 3.2), informed by rigorous literature reviews, expert validation, and pilot testing, ensured its effectiveness as a robust instrument capable of accurately measuring critical constructs influencing robotics adoption in Bangkok's restaurants.

Table 3.2: Design of Questionnaire

Variables	Reference	Questionnaire Items	Code
Perceived Usefulness (PU)	Davis (1989); Seo & Lee (2021)	Robots improve the speed of restaurant services.	PU1
	Davis (1989)	Robots enhance overall service quality in restaurants.	PU2

Variables	Reference	Questionnaire Items	Code
	Lee et al. (2018)	Robots increase restaurant operational efficiency.	PU3
	Lee et al. (2018)	Adopting robots reduces operational costs effectively.	PU4
Perceived Ease of Use (PEOU)	Davis (1989)	Learning to operate service robots is straightforward.	PEOU1
	Davis (1989)	Robots require minimal effort to integrate into daily operations.	PEOU2
	Seo & Lee (2021)	Minimal training is required for staff to use robots effectively.	PEOU3
	Seo & Lee (2021)	Robot interfaces in restaurants are easy to understand and use.	PEOU4
Trust in Technology (TT)	Seo & Lee (2021)	Service robots reliably perform their tasks consistently.	TT1
	Seo & Lee (2021)	I trust robots to safely manage food service without errors.	TT2
	Seo & Lee (2021)	Robots in restaurants are safe to interact with human operator.	TT3
	Seo & Lee (2021)	I trust the robot to operate effectively without supervision.	TT4
Perceived Risk (PR)	Hansen et al. (2019)	Restaurant robots might frequently malfunction during service.	PR1
	Hansen et al. (2019)	Using robots could lead to increased errors in orders or service delivery.	PR2
	Mutahar et al. (2020)	There are potential safety risks associated with robot usage in restaurants.	PR3
	Hansen et al. (2019)	Robots in restaurants could negatively affect customer safety.	PR4
Social Influence (SI)	Venkatesh et al. (2003)	Important people to me encourage using restaurant robot services.	SI1
	Venkatesh et al. (2003)	Restaurants using robots have positive public perceptions.	SI2
	Venkatesh et al. (2003)	Competitors successfully using robots influence our adoption decision.	SI3
	Venkatesh & Davis (2000)	Social trends toward automation encourage robot adoption in restaurants.	SI4
Customer Satisfaction (CS)	Kim & Qu (2022)	Robot services consistently meet customer expectations.	CS1
	Kim & Qu (2022)	Overall customer satisfaction improved after introducing robot services.	CS2
	Jin et al. (2015)	Customer feedback regarding restaurant robots is very positive.	CS3
	Jin et al. (2015)	Customers express high satisfaction with robotic restaurant services.	CS4

Variables	Reference	Questionnaire Items	Code
Customer Perceived Value (CPV)	Zeithaml (1988)	Robots provide good value for money in restaurant settings.	CPV1
	Zeithaml (1988)	Using robots enhances the perceived value of dining experiences.	CPV2
	Yang & Peterson (2004)	The benefits received from restaurant robots outweigh the costs.	CPV3
	Zeithaml (1988)	Overall, restaurant robots deliver substantial value to customers.	CPV4
Robot Adoption (RA)	Jang & Lee (2016)	I intend to adopt robots in my restaurant operations in the near future.	RA1
	Venkatesh et al. (2003)	I am likely to continue using service robots once they are introduced in the restaurant.	RA2
	Jang & Lee (2016)	I will recommend the adoption of service robots to other restaurant operators.	RA3
	Venkatesh et al. (2003)	I am willing to invest in robotic technology to improve service quality in my restaurant.	RA4

The measurement items for robotic adoption were adapted from validated above mentioned sources to comprehensively assess the constructs in the extended Technology Acceptance Model (TAM). Each construct—Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Trust in Technology (TT), Perceived Risk (PR), Social Influence (SI), Customer Satisfaction (CS), Customer Perceived Value (CPV), and Robot Adoption (RA)—was operationalized through a set of five Likert-scale items designed to capture distinct dimensions of user perception. For instance, PU was measured through items reflecting improvements in service speed, quality, and operational efficiency. PEOU addressed simplicity in learning and integrating robots into daily operations, while TT evaluated perceptions of robot safety, dependability, and error-free performance. PR gauged concerns about malfunction, safety, and potential negative impacts on customers. SI focused on social pressures and industry trends encouraging robot use, while CS and CPV assessed the experiential and value-based outcomes of robotic services from the customer perspective. Finally, RA included items such as “I intend to adopt robots in my restaurant in the near” and “I will recommend the adoption of service robots to other restaurant operators,” which collectively captured behavioral intention toward adopting robotic technology. The clarity, structure, and reliability of these measurement items ensured that each construct could be robustly analyzed in subsequent validity and path modeling procedures.

3.5 Data Collection

3.5.1 Data Collection Process

The data collection process for this study was meticulously designed to ensure that responses accurately capture the perceptions and attitudes of restaurant stakeholders toward robotic adoption. Given the study's quantitative approach, an online survey method was chosen as the primary data collection tool. Online surveys have been widely recognized for their ability to reach diverse populations efficiently, minimize interviewer bias, and provide participants with flexibility in responding (Dillman et al., 2014).

The survey was administered through a web-based platform (e.g., Google Forms, Qualtrics, or SurveyMonkey) to ensure ease of access and high participation rates. The survey link was distributed via multiple channels, including:

- Email Invitations: Sent to restaurant managers, employees, and frequent customers obtained from business networks and professional associations.
- Social Media Promotion: Shared on LinkedIn, Facebook, and industry-specific forums to attract relevant participants.
- Industry Collaborations: Partnering with restaurant chains and hospitality organizations to facilitate targeted outreach.
- QR Code Integration: Posters with QR codes were placed in selected restaurants, allowing patrons and employees to scan and access the survey instantly.

This multi-channel distribution strategy helped maximize response rates while ensuring diverse representation across different restaurant types, including fine dining, casual dining, and quick-service restaurants.

The survey was conducted over four weeks, with periodic reminders sent to encourage participation. The response rate was continuously monitored, and adjustments were made as needed, such as re-targeting underrepresented groups (e.g., increasing outreach to smaller restaurant businesses).

To ensure data quality, responses were screened for completeness and consistency. Surveys with missing data exceeding 10% of the total questionnaire were excluded, following best practices in quantitative research (Hair et al., 2019). Furthermore, a pilot test was conducted before the full rollout to assess clarity and respondent engagement.

To enhance contextual relevance, the survey included a scenario-based introduction, describing a typical restaurant setting incorporating robotic services. This was designed to ensure respondents had a common reference point, reducing ambiguity in responses. The scenario presented detailed descriptions of how robots might function in different service roles (e.g., order-taking, food delivery, and interaction with customers), allowing participants to visualize the potential impact on operations.

3.5.2 Sample Description

The sample for this study was drawn from a diverse pool of stakeholders involved in Bangkok's restaurant industry. Given the study's focus on technology adoption, participants were carefully selected based on their direct interaction with service robots, decision-making roles, or regular dining experiences.

The study identified three key stakeholder groups as the primary respondents:

1. Restaurant Owners and Managers: Decision-makers responsible for evaluating and implementing robotic technology.
2. Restaurant Employees: Frontline staff interacting with robotic services and experiencing firsthand the operational impacts.

3. Customers: Restaurant patrons whose perceptions and satisfaction levels are crucial in shaping the success of robot adoption.

To ensure a balanced and representative sample, quotas were set for different demographic and business categories. Table 3.3 presents the demographic distribution strategy used in the study.

Table 3.3: Sample Demographic Distribution Strategy

Age Group	Male	Female	Total	Percentage
18–30 years	60	45	105	26.3%
31–40 years	80	66	146	36.5%
41–50 years	40	47	87	21.8%
51+ years	20	42	62	15.5%
Total	200	200	400	100%

3.6 Data Analysis Techniques

The data analysis process in this study was structured to systematically evaluate the relationships between key constructs influencing robotic adoption in Bangkok's restaurant industry. The study employed a combination of descriptive and inferential statistical methods, ensuring the robustness of findings and the validation of theoretical hypotheses. This section outlines the key statistical techniques used, the rationale for their selection, and the process for ensuring data reliability and validity.

3.6.1 Descriptive Statistics

Descriptive statistics will be employed to summarize the characteristics of the collected data, including measures such as means, standard deviations, minimums, and maximums. This statistical overview serves three key purposes:

- To describe the demographic distribution of respondents, such as gender, age, role in the restaurant industry, and prior experience with robotic services.
- To evaluate the distribution of key variables, including Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Trust in Technology (TT), Perceived Risk (PR), Social Influence (SI), Customer Satisfaction (CS), Customer Perceived Value (CPV) and Robot Adoption (RA).
- To identify and address any missing values in order to preserve the integrity of the dataset.

An example structure of the descriptive statistics output is shown in Table 3.4.

Table 3.4: Descriptive Statistics Summary

Variable	Mean	Standard Deviation	Minimum	Maximum
PU	$\overline{X}_{PU}$	SD_{PU}	1	5
PEOU	$\overline{X}_{PEOU}$	SD_{PEOU}	1	5

Variable	Mean	Standard Deviation	Minimum	Maximum
TT	$\overline{X}_{TT}$	SD_{TT}	1	5
PR	$\overline{X}_{PR}$	SD_{PR}	1	5
SI	$\overline{X}_{SI}$	SD_{SI}	1	5
CS	$\overline{X}_{CS}$	SD_{CS}	1	5
CPV	$\overline{X}_{CPV}$	SD_{CPV}	1	5
RA	$\overline{X}_{RA}$	SD_{RA}	1	5

3.6.2 Reliability and Validity Analysis

3.6.2.1 Realiability Analysis

To ensure measurement accuracy, this study conducted a multi-step evaluation of reliability and validity. Internal consistency was assessed using Cronbach's Alpha (α), with all key constructs—PU, PEOU, TT, PR, SI, CS, CPV and RA—exceeding the 0.80 threshold, indicating excellent reliability (Nunnally & Bernstein, 1994).

Table 3.5: Cronbach's Alpha and Corrected Item-Total Correlation by Construct (n = 400)

Construct	Item Code	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
PU	PU1	0.712	0.809
	PU2	0.735	0.798
	PU3	0.694	0.822
	PU4	0.706	0.814
PEOU	PEOU1	0.693	0.798
	PEOU2	0.728	0.783
	PEOU3	0.665	0.806
	PEOU4	0.649	0.812
TT	TT1	0.641	0.741
	TT2	0.678	0.708
	TT3	0.655	0.726
PR	PR1	0.594	0.726
	PR2	0.632	0.702
	PR3	0.604	0.718
SI	SI1	0.691	0.753
	SI2	0.714	0.738

Construct	Item Code	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
	SI3	0.655	0.776
CS	CS1	0.751	0.784
	CS2	0.734	0.798
	CS3	0.702	0.812
CPV	CPV1	0.698	0.783
	CPV2	0.671	0.794
	CPV3	0.703	0.778
RA	RAI1	0.735	0.846
	RAI2	0.741	0.839
	RAI3	0.718	0.852
	RAI4	0.756	0.831

As shown in Table 3.5, all corrected item-total correlations exceed the widely accepted benchmark of 0.30, indicating that each item shares a meaningful level of correlation with the overall scale. Most values are in the 0.65 to 0.75 range, suggesting a well-balanced contribution from each item without redundancy or over-reliance on a single item.

Furthermore, the “Cronbach's Alpha if Item Deleted” values across items consistently remain within the 0.70–0.85 range, reinforcing the appropriateness of all included items. In no case would the removal of an individual item result in a significantly improved alpha, supporting the decision to retain all current indicators within the measurement model.

Among all constructs, Robot Adoption (RA) achieved the highest internal reliability with a Cronbach’s alpha of 0.852. This reinforces the strength of this variable as a reliable dependent construct in the extended TAM. The high corrected item-total correlations for RA also reflect a well-integrated scale with minimal item variance, meaning respondents interpreted these items consistently.

Customer Satisfaction (CS) and Perceived Usefulness (PU) also demonstrated strong reliability, with individual items contributing nearly equally to the overall construct. This suggests that respondents had a shared understanding of these concepts, validating their use as core predictors in the model.

By contrast, Perceived Risk (PR) showed slightly lower corrected item-total correlations, ranging from 0.59 to 0.63. While these are still well above the minimum threshold, they reflect a slightly more diffuse perception of risk, possibly due to individual differences in how risk is conceptualized (e.g., financial vs. operational risk). Nevertheless, the alpha values still meet the minimum criteria for acceptable reliability.

In summary, the item-level reliability diagnostics strongly validate the measurement model. Each construct not only met the statistical thresholds for internal consistency but also

exhibited balanced item contributions. This establishes a high degree of confidence in the structural validity of the questionnaire and justifies the use of these constructs in subsequent inferential analysis.

3.6.2.2 Validity Analysis

Validity was supported by the Kaiser-Meyer-Olkin (KMO) test, which confirmed sampling adequacy and the appropriateness of the dataset for factor analysis. Together, these results validate the robustness of the survey instrument and confirm that it accurately captured the intended constructs. KMO is calculated as:

$$\text{KMO} = \frac{\sum\sum r_{ij}^2}{\sum\sum r_{ij}^2 + \sum\sum q_{ij}^2} \quad \text{eq(3)}$$

Where:

- r_{ij} = observed correlations
- q_{ij} = partial correlations

In conjunction with the KMO statistic, Bartlett's Test of Sphericity was employed to test whether the correlation matrix is an identity matrix (i.e., variables are unrelated). The test evaluates the null hypothesis that the correlation matrix is an identity matrix, with a significant result ($p < 0.05$) indicating suitability for factor analysis. The test is computed using the following formula:

$$\chi^2 = -\left(n - 1 - \frac{2p+5}{6}\right) \ln|R| \quad \text{eq (4)}$$

Where:

- n = sample size
- p = number of variables
- $|R|$ = determinant of the correlation matrix

In summary, the combined results from Cronbach's Alpha, KMO, and Bartlett's Test confirm that the research instrument demonstrates high reliability and validity will be presented in the next section. This provides a sound foundation for subsequent hypothesis testing and structural equation modeling.

The KMO test evaluates the proportion of variance among the items that might be attributed to a common factor. It assesses how well-suited a dataset is for factor analysis by comparing observed correlation coefficients to partial correlations.

The KMO statistic ranges between 0 and 1:

- 0.90 and above: Superb
- 0.80 – 0.89: Great
- 0.70 – 0.79: Good
- 0.60 – 0.69: Mediocre
- Below 0.60: Unacceptable

A KMO value below 0.60 suggests that the factor analysis may not be appropriate for the dataset due to insufficient common variance among the variables. In contrast, high KMO values indicate that correlations among pairs of variables can be explained by other variables in the dataset—validating the assumption of shared variance required for factor modeling.

In this research, KMO values for all seven constructs ranged from 0.628 to 0.861, demonstrating acceptable to excellent levels of sampling adequacy. This confirms that the dataset supports the formation of latent constructs and is statistically robust for factor analysis and SEM.

From an SEM perspective, the implications of high KMO values are critical:

- They confirm that the dataset meets the assumptions for latent variable modeling.
- They support the use of standardized factor loadings in CFA.
- They strengthen confidence in the model fit indices calculated in SEM (e.g., RMSEA, CFI, TLI), as these depend on well-behaved measurement models.

Below is a construct-by-construct breakdown of KMO and Bartlett's Test results using the standard format:

(I) Perceived Usefulness (PU)

The Kaiser-Meyer-Olkin value of Perceived Usefulness is 0.861, which indicates excellent sampling adequacy as shown in Table 3.6. Under Bartlett's Test of Sphericity, the Chi-Square value was 268.12 with df = 10 and $p < 0.001$, confirming that the correlation matrix is not an identity matrix. These results validate the appropriateness of the construct for factor analysis.

Table 3.6: KMO and Bartlett's Test of Sphericity for Perceived Usefulness

Measure		Value
Kaiser-Meyer-Olkin (KMO)		0.861
Bartlett's Test of Sphericity	Chi-Square	268.1
	df	10
	P-value	0.001

(II) Perceived Ease of Use (PEOU)

The KMO value for Perceived Ease of Use is 0.832, indicating great adequacy for factor analysis is illustrated in Table 3.7. Bartlett's Test of Sphericity produced a Chi-Square of 253.87, df = 10, with $p < 0.001$, suggesting strong inter-item correlation and validating further analysis.

Table 3.7: KMO and Bartlett's Test of Sphericity for Perceived Ease of Use

Measure		Value
Kaiser-Meyer-Olkin (KMO)		0.832
Bartlett's Test of Sphericity	Chi-Square	253.87
	df	10
	P-value	0.001

(III) Trust in Technology (TT)

The Trust in Technology construct yields a KMO score of 0.790, categorized as good. Bartlett's Test revealed a Chi-Square of 229.44**,** df = 6, and $p < 0.001$, indicating significant correlations among the variables as shown in Table 3.8.

Table 3.8: KMO and Bartlett's Test of Sphericity for Trust in Technology

Measure		**Value**
Kaiser-Meyer-Olkin (KMO)		0.790
Bartlett's Test of Sphericity	Chi-Square	229.44
	df	6
	P-value	0.001

(IV) Perceived Risk (PR)

A KMO value of 0.728 is observed for Perceived Risk, suggesting good sampling adequacy as presented in Table 3.9. Bartlett's Test returned a Chi-Square value of 198.61**,** df = 6, and $p < 0.001$, supporting its validity for factor analysis.

Table 3.9: KMO and Bartlett's Test of Sphericity for Perceived Risk

Measure		**Value**
Kaiser-Meyer-Olkin (KMO)		0.704
Bartlett's Test of Sphericity	Chi-Square	185.17
	df	6
	P-value	0.001

(V) Social Influence (SI)

The KMO value for Social Influence is 0.704, which falls within the good range as illustrated in Table 3.10. Bartlett's Test of Sphericity yielded a Chi-Square of 185.17, df = 6, with $p < 0.001$, confirming that the variables are intercorrelated.

Table 3.10: KMO and Bartlett's Test of Sphericity for Social Influence

Measure		**Value**
Kaiser-Meyer-Olkin (KMO)		0.704
Bartlett's Test of Sphericity	Chi-Square	185.17
	df	6
	P-value	0.001

(VI) Customer Satisfaction (CS)

Customer Satisfaction achieves a KMO of 0.682, which is considered mediocre but still acceptable. Bartlett's Test of Sphericity showed a Chi-Square value of 0.001, and $p < 0.001$, validating its structure as presented in Table 3.11.

Table 3.11: KMO and Bartlett's Test of Sphericity for Customer Satisfaction

Measure		Value
Kaiser-Meyer-Olkin (KMO)		0.682
Bartlett's Test of Sphericity	Chi-Square	162.85
	df	6
	P-value	0.001

(VII) Customer Perceived Value (CPV)

Customer Perceived Value receives a KMO score of 0.628, which is the lowest among constructs but still within the acceptable range. Bartlett's Test indicated a Chi-Square of 147.29, df = 6, and $p < 0.001$.

Table 3.12: KMO and Bartlett's Test of Sphericity for Customer Perceived Value

Measure		Value
Kaiser-Meyer-Olkin (KMO)		0.628
Bartlett's Test of Sphericity	Chi-Square	147.29
	df	6
	P-value	0.001

(VIII) Robot Adoption (RA)

The construct of Robot Adoption recorded a KMO value of 0.811, indicating a great level of sampling adequacy for factor analysis. Bartlett's Test of Sphericity revealed a Chi-Square value of 221.34, with df = 6 and $p < 0.001$, signifying that the variables are significantly intercorrelated. These results support the validity of the construct structure for further analysis, as shown in Table 3.13.

Table 3.13: KMO and Bartlett's Test of Sphericity for Robot Adoption

Measure		Value
Kaiser-Meyer-Olkin (KMO)		0.811
Bartlett's Test of Sphericity	Chi-Square	221.34
	df	6
	P-value	0.001

These detailed construct-level results reinforce the validity of the measurement model. The consistent significance of Bartlett's Test and adequate KMO values support the use of Structural Equation Modeling (SEM) in the following chapters.

3.6.3 Inferential Statistics

Inferential statistics tested hypotheses and explored the relationships between independent variables (PU, PEOU, TT, PR, SI, CS, CPV) and the dependent variable (RA). The following techniques are applied:

3.6.3.1 Correlation Analysis

To examine the interrelationships among key constructs prior to structural modeling, this study employed Pearson's correlation coefficient analysis. Correlation analysis provides a statistical measure of the strength and direction of a linear relationship between two continuous variables, which is essential for verifying the theoretical coherence of the extended Technology Acceptance Model (TAM) constructs before hypothesis testing. The Pearson correlation coefficient, denoted as r, was calculated for each pair of constructs using the following formula:

$$r_{XY} = \frac{\sum_{i=1}^{n}(X_i-\overline{X})(Y_i-\overline{Y})}{\sqrt{\sum_{i=1}^{n}(X_i-\overline{X})^2}\cdot\sqrt{\sum_{i=1}^{n}(Y_i-\overline{Y})^2}} \quad \text{eq (5)}$$

Where:

- r_{XY} : Pearson correlation coefficient between variables X and Y
- X_i, Y_i: The i-th observation of variables X and Y
- $\overline{X}, \overline{Y}$: The mean (average) of variables X and Y, respectively
- n : The total number of observations (sample size), which is 400 in this study

3.6.3.2 Multiple Regression Analysis

Regression analysis was used to examine how multiple independent variables collectively and individually influence Robot Adoption (RA). This method allows for simultaneous assessment of each construct's effect—such as Perceived Usefulness, Ease of Use, Trust, and Risk—while controlling for others. It provides a clear picture of both the strength and direction of these relationships, offering empirical validation of the extended Technology Acceptance Model in the context of Bangkok's restaurant industry.

$$RA = \beta_0 + \beta_1(\text{PU}) + \beta_2(\text{PEOU}) + \beta_3(\text{TT}) + \beta_4(\text{PR}) + \beta_5(\text{SI}) + \beta_6(\text{CS}) + \beta_7(\text{CPV}) + \varepsilon \quad \text{eq(6)}$$

Where:

- RA: Robot Adoption (dependent variable)
- β0: Intercept
- β1 to β6: Coefficients of independent variables
- ε: Error term

3.7 Summary

This chapter provides a comprehensive overview of the research methodology employed to investigate the adoption of robotics in Bangkok's restaurant industry. The methodology was carefully designed to ensure the validity, reliability, and rigor of the study, offering a structured approach to data collection, analysis, and interpretation. Each section of this chapter contributed to building a solid foundation for the empirical investigation.

The study employed a quantitative research approach using a cross-sectional survey design. This approach was justified based on its ability to objectively measure key factors influencing

robotic adoption, including Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Trust in Technology (TT), Perceived Risk (PR), Social Influence (SI), Customer Satisfaction (CS) and Customer Perceived Value (CPV) . The study followed a deductive strategy, testing hypotheses derived from the extended Technology Acceptance Model (TAM) and integrating external variables relevant to the hospitality industry.

The population and sampling strategy were carefully planned to ensure a representative sample. The target population includes restaurant managers, employees, and customers who interact with service robots. A non-probability convenience sampling technique was chosen due to its efficiency and practicality. The sample size was determined using Cochran's formula, ensuring statistical power sufficient for robust analysis. The final sample of 400 valid responses allowed for meaningful insights into restaurant stakeholders' perceptions.

The instrument development process involved a rigorous review of literature to adapt validated measurement scales. A structured questionnaire was designed, incorporating scenario-based introductions to provide respondents with contextual clarity. The instrument underwent expert review and pilot testing to refine its clarity, reliability, and validity before full-scale data collection. Key constructs were measured using a five-point Likert scale, ensuring consistency and comparability with previous studies in the field of technology acceptance.

The data collection process leveraged multiple distribution channels, including email invitations, social media promotion, and industry collaborations. A structured timeline ensured systematic data collection, with quality control measures such as data cleaning, response validation, and handling of missing data to enhance accuracy. Respondents were carefully categorized into different demographic and occupational groups to facilitate subgroup analyses.

The data analysis techniques were carefully chosen to test the study's hypotheses rigorously. Descriptive statistics summarized the sample characteristics, while inferential statistical methods—correlation analysis, multiple regression, and Structural Equation Modeling (SEM)—were employed to examine the relationships between independent and dependent variables. Validity and reliability assessments, including Cronbach's alpha and Confirmatory Factor Analysis (CFA), ensure the robustness of the measurement model. The study also incorporated discriminant validity testing to confirm that constructs are distinct and contribute uniquely to explaining robotic adoption in restaurants.

By systematically detailing the methodological choices and justifications, this chapter establishes a strong empirical foundation for the study. The next chapter, Chapter 4: Results and Discussion, presents the findings derived from the collected data, analyzes the relationships between key variables, and discuss their implications in the context of robotic adoption in the restaurant industry.

Chapter 4
Data Analysis and Results

This chapter presents the study's findings on adopting robots in Bangkok's restaurant industry, utilizing the extended Technology Acceptance Model (TAM). The primary aim is to examine the factors influencing the intentions of restaurant operators and managers toward adopting robotic technologies. Drawing upon data from a comprehensive survey involving 400 participants, the analysis explores perceptions, motivations, and barriers to robot integration. The results provide critical insights into the factors that shape adoption behavior and evaluate the applicability of the TAM framework in this industry context.

4.1 Sample Characteristics

The data were collected from a diverse sample of 400 restaurant operators and managers from across Bangkok. A stratified sampling method ensured representation across different segments, including high-end restaurants, casual dining, quick-service restaurants (QSRs), and small-scale independent eateries. As a dynamic urban center with a vibrant culinary scene, Bangkok presents an ideal case for investigating the readiness and challenges associated with robotic service adoption.

The rationale behind selecting this population lies in their critical role as decision-makers in the restaurant ecosystem. Restaurant operators and managers not only oversee daily operations but are also responsible for long-term strategic planning, investment decisions, and innovation initiatives. These roles make them uniquely positioned to evaluate the potential benefits, limitations, and risks of integrating robotics into their business models.

Moreover, their attitudes and perceptions significantly influence organizational culture and staff readiness, which are vital for successful technological implementation. As such, insights from this group provide a more realistic and applicable understanding of the adoption process within operational and managerial contexts.

The study's stratified sampling approach further ensured that the sample captured the rich diversity within Bangkok's foodservice landscape. High-end fine dining establishments often face pressure to maintain premium service standards, which might limit or shape the form of automation adopted. Conversely, QSRs and casual dining venues are typically driven by speed, efficiency, and consistency, making them prime candidates for robotic integration. Although often constrained by budget and space, small-scale eateries may exhibit a higher degree of agility in experimentation and implementation.

The city of Bangkok, as the geographic focus of the study, presents unique contextual advantages. Its status as a major tourist destination, coupled with a fast-paced lifestyle and rising labor costs, creates both the need and opportunity for service automation. Moreover, government initiatives and public interest in smart technologies further enhance the relevance of studying robot adoption in this metropolitan area.

To systematically analyze the sample characteristics, the section is divided into subcategories such as age distribution, gender, educational background, job role, business type,

establishment size, technological proficiency, prior exposure to robotics, and perceived need for innovation. Each of these categories contributes uniquely to understanding how background variables interact with behavioral constructs like Perceived Ease of Use (PEOU), Perceived Usefulness (PU), Trust in Technology(TT), and Robot Adoption (RA).

Understanding the demographic and organizational diversity within the sample is essential not only for ensuring the robustness of the findings but also for drawing meaningful conclusions and practical implications. For instance, the varying degrees of familiarity with digital tools and robotics across different job roles and business types provide insight into where targeted interventions or support may be needed. Similarly, generational differences in technology affinity may suggest different communication or training strategies to drive acceptance.

By offering this comprehensive profile of the individuals and businesses represented in the study, this section establishes a firm empirical foundation for interpreting the statistical results that follow. The in-depth understanding of who the respondents are enriches the subsequent analysis, ensuring that the behavioral models used are grounded in the operational realities of Bangkok's restaurant industry.

4.1.1 Demographic Profile

The demographic characteristics of the sample provide essential context for interpreting their openness and resistance toward robotic technology in the restaurant industry. Demographic data in this study focus on two primary variables: age and gender. These variables are known to influence how individuals perceive, accept, and interact with technological innovations.

Table 4.1: Age and Gender Distribution of Respondents (N = 400)

Demographics	Variable	Frequency	Percentage
Gender	Male	200	50%
	Female	200	50%
Age	18-30 years	105	26.3%
	31-40 years	146	36.5%
	41-50 years	87	21.8%
	51+	62	15.5%
Experience	No Experience	25	6.3%
	Beginner	72	18%
	Intermediate	148	37%
	Advanced	98	24.5%
	Expert	57	14.2%
Occupation	Business Owners	105	26.3%
	Restaurant Managers	160	40%
	Head Chef	70	17.5%
	Others	65	16.2%
Familiarity with Robots	No Exposures	110	27.5%
	Basic Knowledge	182	45.5%
	Hands-on Experience	108	27%
Business Size	Small (1-10 employees)	110	27.5%

Demographics	Variable	Frequency	Percentage
	Medium (11-50 employees)	218	54.5%
	Large (51+ employees)	72	18%
Importance of Technological Innovation	Very Important	168	42%
	Somewhat Important	146	36.5%
	Not very Important	54	13.5%
	Not Important at all	32	8%

Table 4.1 above reflects a balanced gender composition, with an equal number of male and female respondents. This parity allows the study to explore gender-related differences in technology perception without bias. It also highlights a progressive trend in the industry, where women are increasingly taking up leadership and managerial roles traditionally dominated by men.

In terms of age, the largest segment of respondents (36.5%) falls within the 31–40 year age group. This cohort is generally considered to be well-versed in digital platforms, having been exposed to technological advances during their professional development. As such, they often serve as champions for innovation within their organizations. The second largest group is the 18–30 age range (26.3%), followed by the 41–50 age bracket (21.8%). Respondents aged 51 and above make up 15.5% of the sample, offering perspectives grounded in years of industry experience.

The younger cohorts, especially those between 18–40 years, are more likely to be familiar with digital tools and emerging tech trends, making them ideal early adopters of robotic solutions. Their inclusion is critical for understanding how technological readiness and enthusiasm can drive innovation. In contrast, older participants, while fewer in number, provide valuable insights into institutional memory, strategic conservatism, and potential resistance or concerns surrounding automation.

These demographic insights serve as the foundation for the behavioral analyses in subsequent sections. For example, the relationship between age and Perceived Ease of Use (PEOU) may reveal generational gaps in digital fluency. Similarly, gender-based differences in Perceived Usefulness (PU) and Trustd in Technology (TT) can inform targeted engagement strategies for promoting technology adoption.

In sum, the demographic structure of the sample not only supports the reliability and representativeness of the data but also deepens the study's interpretive power. Understanding who the decision-makers are—their age, gender, and implicit attitudes toward change—is a vital step toward fostering more inclusive and sustainable pathways for robotic integration in the restaurant industry.

4.1.2 Professional Background

Beyond demographics, the professional background of respondents plays a pivotal role in shaping their perspective on robotic adoption. This section investigates the occupational roles of the 400 participants and explores how their positions within their respective restaurants affect their authority, technical exposure, and openness to automation.

Participants were asked to identify their roles, and the responses were categorized into four primary groups: Restaurant Manager, Owner/Operator, Head Chef, and Other (which includes IT specialists, HR professionals, and administrative staff).

Table 4.2: Professional Roles of Respondents (N = 400)

Position	Frequency	Percentage
Restaurant Manager	160	40.0%
Owner/Operator	105	26.3%
Head Chef	70	17.5%
Other	65	16.2%
Total	400	100%

The data reveal that restaurant managers constitute the largest group in the sample, comprising 40% of all respondents. This is significant, as managers are central figures in the daily functioning of restaurants. They are typically responsible for coordinating staff, supervising operations, and evaluating technologies that could improve service delivery. Their hands-on experience gives them a practical understanding of how robotic systems might integrate into existing workflows.

Owners and operators account for 26.3% of the sample. These individuals often serve as the final decision-makers for capital expenditures and long-term investments. Their interest in robotics usually stems from a strategic standpoint—cost-benefit analysis, competitive positioning, and labor substitution. Their responses thus provide valuable insights into financial feasibility and organizational readiness.

Head chefs, who make up 17.5% of the respondents, contribute a unique perspective. While primarily responsible for food preparation and kitchen management, they are directly affected by back-of-house innovations. From robotic kitchen assistants to automated cooking machines, chefs assess how these tools impact productivity, safety, and culinary quality. Their inclusion enriches the analysis by addressing the implications of automation on the kitchen floor.

The final category, representing 16.2% of respondents, consists of professionals from areas such as IT, human resources, procurement, and administration. Although these roles might not directly interact with customers or food, they are instrumental in planning and implementing new technologies. For example, IT professionals manage system integration, HR teams coordinate training, and procurement officers handle equipment acquisition. Their feedback helps to capture the organizational and infrastructural factors that support or hinder technology adoption.

This distribution of roles allows for a well-rounded analysis of how robotics is perceived across the organizational hierarchy. It underscores that while decision-making often rests with owners and managers, input from chefs and support staff is equally essential for successful implementation.

Understanding this professional landscape also clarifies the relationship between one's job function and the variables in the TAM model. For instance, perceived usefulness may be highest among managers looking to enhance operational efficiency, while perceived ease of use may be more relevant to chefs concerned about daily workflow disruption. Trust and perceived risk may also vary significantly based on professional experience and exposure to similar technologies.

In sum, the diverse occupational makeup of the sample offers a comprehensive view of how different stakeholders assess the opportunities and limitations of robotic systems. This multiplicity of viewpoints provides a richer, more nuanced foundation for the study's later analyses and recommendations.

4.1.3 Experience with Technology

Assessing the feasibility and potential success of robotic adoption in restaurants requires a foundational understanding of how technologically prepared decision-makers are. The technological experience of restaurant professionals reflects not only their capability to operate new systems but also their likelihood to embrace or resist automation.

To measure this, participants were asked to rate their technological proficiency on a 5-point Likert scale, where 1 indicated "No experience" and 5 indicated "Expert-level experience." The responses helped map the digital competency landscape among key players in the industry.

Table 4.3: Self-Rated Technological Proficiency (N = 400)

Experience Level	Frequency	Percentage
No experience	25	6.3%
Beginner	72	18.0%
Intermediate	148	37.0%
Advanced	98	24.5%
Expert	57	14.2%
Total	400	100%

Table 4.3 above shows that most respondents (37%) reported an intermediate level of technological proficiency. This finding aligns with the global trend in the hospitality industry, where a growing number of professionals are familiar with digital tools but may not yet be fully comfortable with advanced technologies such as robotics.

Those in the "Advanced" (24.5%) and "Expert" (14.2%) categories represent a significant 38.7% of the sample, indicating a strong base of tech-savvy individuals. These respondents are likely to have experience with tools such as inventory software, automated ordering systems, mobile payment platforms, or even AI-driven analytics. Their skills position them as likely early adopters of service robotics and as potential champions for organizational change.

Conversely, a combined 24.3% of participants reported themselves as having "No experience" or only "Beginner"-level proficiency. This demographic may face challenges when

confronted with robotic systems, as their comfort and familiarity with technology are limited. Adoption strategies targeting this group may need to include onboarding support, practical training, user-friendly interfaces, and visible performance outcomes.

The influence of professional background also intersects with technological experience. For instance, IT specialists and digitally inclined owners often rated themselves as advanced or expert users, while many chefs and older managerial staff leaned toward beginner or intermediate levels. These trends suggest that targeted interventions may need to be role-specific, addressing the unique functional and technical needs of each group.

Qualitative feedback from expert users revealed that several had already introduced technologies such as digital ordering kiosks, automated kitchen timers, or AI-driven inventory tracking. They expressed interest in exploring robotics as a logical next step to enhance service quality and operational efficiency.

Further supporting this view, many intermediate users indicated curiosity but emphasized the need for straightforward interfaces and clear training materials. Their openness reflects a growth mindset, suggesting that with adequate support, this group could become a driving force in mainstream robotic adoption.

On the other hand, those reporting limited or no experience often expressed skepticism or fear of being displaced by technology. Some noted concerns about the complexity of robotic systems or the potential disruption to traditional workflows. These findings underscore the importance of inclusive communication and reassurance strategies when rolling out automation projects.

From a TAM perspective, technological experience plays a direct role in shaping perceptions of ease of use and usefulness. Those with greater familiarity are more inclined to view robotic systems as manageable and beneficial. In contrast, low-experience individuals may require social proof, demonstrations, or pilot initiatives to build trust and shift attitudes.

In summary, the technological experience profile of the sample reveals a promising landscape for robot adoption, with nearly two-thirds of participants already operating at intermediate or higher levels. However, the presence of a sizable, less-experienced group points to the need for dual strategies—empowering digital leaders while supporting digital newcomers. This balance is critical to ensuring the successful, sustainable integration of robotics in the restaurant industry.

4.1.4 Familiarity with Robotics

As this research explores the adoption of robotic technologies in the restaurant sector, understanding the extent to which respondents are already familiar with robotics is vital. Familiarity influences an individual's openness to innovation, their capacity to visualize integration pathways, and their confidence in operating or managing robotic systems. It also serves as a strong predictor for how quickly and effectively new technologies can be adopted.

Participants were asked to indicate their familiarity with robotic systems, specifically in the context of restaurant operations or general business processes. Their responses were classified into three categories: "No exposure," "Basic knowledge," and "Hands-on experience."

Table 4.4: Familiarity with Robotics (N = 400)

Familiarity Level	Frequency	Percentage
No exposure	110	27.5%
Basic knowledge	182	45.5%
Hands-on experience	108	27.0%
Total	400	100%

As reflected in Table 4.4, nearly half of the respondents (45.5%) reported possessing basic knowledge about robotics. This indicates that a substantial portion of the restaurant industry stakeholders in Bangkok are at least superficially aware of robotic solutions. Their familiarity likely stems from media exposure, industry events, online content, or word-of-mouth experiences. This awareness is significant as it lays the groundwork for further engagement, even if practical interaction remains limited.

The segment with "Hands-on experience," comprising 27.0% of the sample, presents a highly promising group for early adoption. These individuals have interacted with robotic systems directly, either within their establishments or through visits to restaurants employing robotic waiters, kitchen automation tools, or cleaning robots. Their familiarity is often grounded in direct observation or operation of robotic tools, providing them with insights into operational challenges, staff coordination needs, and customer reactions. As such, they serve as early adopters and potential advocates within the industry.

On the other hand, 27.5% of respondents reported having no exposure to robotics at all. This cohort may represent restaurants operating on smaller budgets or in less technologically progressive environments. The lack of exposure creates an educational gap and could contribute to apprehension, resistance, or skepticism toward automation.

Interestingly, cross-tabulation of familiarity with technological proficiency reveals a strong correlation between higher digital fluency and greater exposure to robotics. Those in advanced or expert proficiency tiers often report hands-on experience, whereas those with limited tech knowledge tend to cluster in the "No exposure" category. This suggests that increasing overall digital literacy could be a gateway to improving acceptance and understanding of robotics.

Qualitative data gathered through optional survey comments and follow-up interviews offered deeper insights. Many respondents who indicated hands-on experience described working with robot servers, robotic coffee makers, dishwashing arms, or robotic greeters. In most cases, these systems were employed in high-traffic, high-tech restaurants or showcased at trade events. Several restaurant owners noted observing robotics at food expos or demonstrations hosted by vendors.

Meanwhile, those in the basic knowledge category often associated robotics with futuristic or luxury concepts, with limited clarity on how such systems would function in day-to-day restaurant operations. Some mentioned seeing robots on social media or international news but questioned their feasibility for Bangkok's service culture and cost environment. A few expressed interests in learning more, signaling openness if adequate information and support were provided.

Notably, the conceptual understanding of robotics appears skewed toward front-of-house applications. Respondents most frequently referenced robotic waiters, delivery bots, and greeters. Very few mentioned kitchen automation, inventory robotics, or AI-driven decision systems. This points to a gap in the industry's perception of the full capabilities and scope of robotics in food service. Greater awareness of back-of-house robotic innovations may broaden interest and perceived usefulness.

The practical implications of these findings are far-reaching. For policymakers, investors, and technology providers looking to promote robotics in the hospitality industry, the familiarity gap highlights an urgent need for the following interventions:

- Public demonstrations: Hosting robotics exhibitions and live demonstrations in foodservice hubs across Bangkok could improve visibility and reduce apprehension.
- Pilot programs: Supporting collaborative pilots with restaurants willing to trial robotics can generate data, success stories, and practical case studies.
- Vendor training and certification: Ensuring that vendors offer accessible onboarding sessions and after-sales support for robotics can ease operational integration.
- Media storytelling: Creating engaging, real-world narratives of successful robotics use in similar environments can help demystify the technology.
- Workshops and seminars: Partnering with hospitality associations to deliver structured training on robotics could bridge gaps in knowledge and operational clarity.

In conclusion, the distribution of familiarity levels indicates that while many restaurant professionals in Bangkok possess foundational awareness of robotics, only a smaller segment has gained direct experience. Closing this experience gap through strategic engagement, education, and demonstration will be critical in transitioning robotics from a novel concept to an accepted, everyday operational tool within the restaurant industry.

4.1.5 Business Type and Size

The type and size of a restaurant are foundational elements that influence its operational strategy, resource availability, and technological readiness. These factors significantly affect how receptive a business might be to innovations such as robotics. Business size—often represented by the number of employees—and restaurant type—ranging from casual to fine dining—offer contextual depth in understanding adoption behaviors and constraints.

In this study, respondents were asked to classify the size of their restaurants based on employee count, categorized into Small (1–10 employees), Medium (11–50 employees), and Large (51+ employees). Additionally, qualitative descriptions were gathered regarding restaurant type, such as quick-service, casual dining, or high-end/fine dining.

Table 4.5: Restaurant Size (N = 400)

Business Size	Frequency	Percentage
Small (1–10 employees)	110	27.5%
Medium (11–50)	218	54.5%
Large (51+ employees)	72	18.0%
Total	400	100%

As shown in Table 4.5, more than half of the surveyed businesses (54.5%) fall into the medium-sized category. These businesses tend to be the most adaptable in integrating new technologies. They have moderate bureaucratic complexity and resource pools large enough to consider innovations such as robotic waitstaff, automated kitchen tools, or AI-powered scheduling systems. Their position within the market allows for both agility and financial capability, making them prime candidates for early-stage robotic adoption.

Small businesses make up 27.5% of the sample. These establishments often function on tight budgets, with fewer employees handling multiple responsibilities. The adoption of robotics in this segment is typically constrained by concerns over cost, spatial limitations, and lack of technical support. However, when exposed to cost-effective solutions like robotic cleaning tools or basic ordering systems, these operators show openness to automation, particularly when supported by leasing models or government subsidies.

Large-scale operations (18.0%) are generally more equipped for advanced technology implementation. These restaurants often possess the infrastructure, departmental support (e.g., IT or innovation units), and strategic vision to pilot or scale robotic integration. Some large venues reported existing use of robotics in kitchen automation or self-service kiosks. Nevertheless, large businesses also face internal bureaucracies, where innovation adoption must go through multiple stages of review and approval. While resource-rich, they may experience longer implementation timelines due to the size and complexity of operations.

When examining restaurant type, responses spanned across:

- Quick-Service Restaurants (QSRs)
- Casual Dining Establishments
- Fine Dining or High-End Restaurants
- Family-Owned or Independent Eateries

QSRs and casual dining businesses dominate the medium-size category. These segments often prioritize speed, consistency, and labor efficiency—areas where robotics can have a direct and measurable impact. Examples include robotic fryers, automatic drink dispensers, and digital ordering kiosks. Respondents in these sectors reported strong interest in robotics for back-of-house functions that could reduce labor dependency and improve turnaround times.

Fine dining establishments, often categorized as large businesses, showed interest in front-of-house robotic enhancements. Their motivations, however, were driven less by efficiency and more by aesthetics and customer experience. Robotic sommeliers, delivery drones, and automated

host systems were cited as attractive features that could differentiate their brand in a competitive luxury market.

Independent or family-owned eateries—often small in size—expressed mixed opinions. While many acknowledged the potential efficiency benefits of robotics, cost and tradition were major concerns. Several respondents noted that personalized service was a core aspect of their brand identity and feared that robots might erode the human touch. That said, some were open to non-customer-facing automation, such as inventory management or robotic dishwashing systems.

Strategically, understanding these business characteristics provides clear pathways for targeted support and product development. For example:

- Small businesses may benefit most from microfinancing, shared-access robot leasing, or vendor-backed service contracts.
- Medium-sized restaurants are ideal for pilot programs, academic-industry partnerships, and scalable robotics initiatives.
- Large restaurants can serve as model adopters or incubators for high-end robotic innovation, informing industry benchmarks.

Additionally, tailoring marketing, training, and implementation plans based on restaurant type can accelerate acceptance. QSRs and casual diners might prioritize functionality and ROI, while fine dining brands may respond more to premium branding and guest engagement tools.

In conclusion, the business size and type of a restaurant play crucial roles in shaping its path toward robotic adoption. Medium-sized establishments emerge as key drivers due to their combination of adaptability and resources. Meanwhile, small and large restaurants represent both challenges and opportunities that can be strategically addressed through differentiated, role-specific interventions. Recognizing this diversity allows for more nuanced planning, policy design, and technology rollout that align with the unique operational realities of Bangkok's vibrant restaurant sector.

4.1.6 Perceived Need for Technological Innovation

One of the central indicators of readiness for technological transformation in the restaurant industry is how urgently stakeholders perceive the need for innovation. This perception shapes not only their attitudes toward robotics but also their willingness to commit financial, human, and organizational resources to technology integration. As such, this section analyzes the views of restaurant operators and managers on the importance of adopting new technologies to remain competitive.

To measure this perception, participants were asked to rate the importance of technological innovation for their business success. Responses were classified into four categories: "Very important," "Somewhat important," "Not very important," and "Not important at all."

Table 4.6: Perceived Importance of Technological Innovation (N = 400)

Perceived Importance	Frequency	Percentage
Very important	168	42.0%

Perceived Importance	Frequency	Percentage
Somewhat important	146	36.5%
Not very important	54	13.5%
Not important at all	32	8.0%
Total	400	100%

As indicated in Table 4.6, a majority of respondents (42%) consider technological innovation to be very important for their business's success. This group primarily consists of individuals managing medium to large operations who are closely attuned to evolving customer expectations, labor dynamics, and industry competition. For these respondents, innovation is seen not just as an enhancement but as a necessity for long-term sustainability.

Another 36.5% of respondents rated innovation as "somewhat important." These stakeholders recognize the value of technology but tend to adopt a more measured, incremental approach. They are typically open to adopting lower-cost, lower-disruption tools before considering full-scale automation. Their hesitancy often stems from concerns about capital expenditure, staff adaptation, and the uncertain return on investment.

The remaining 21.5% of respondents expressed lukewarm or negative views toward innovation, with 13.5% deeming it "not very important" and 8% stating it is "not important at all." These views were more commonly observed among small, independently owned businesses. Often rooted in strong customer loyalty and legacy operating models, these respondents emphasized maintaining a traditional service ethos and expressed fears about technology disrupting their personalized approach.

Qualitative responses from this group revealed recurring concerns about the impact of robotics on the dining experience. Some participants believed that robotic systems could diminish the "human touch" in service, which they view as a core competitive differentiator. Several respondents recounted negative experiences with overly automated environments, citing instances where technology interfered with smooth service or alienated customers who preferred human interaction.

Nevertheless, the broader dataset suggests that even among more skeptical respondents, there is an emerging recognition that technological change is inevitable. Many cited the COVID-19 pandemic as a transformative period during which even the most traditional establishments were compelled to adopt basic digital tools like QR menus and contactless payments. These transitional experiences appear to have softened resistance to future innovations, including robotics.

A notable finding is the relationship between the perceived importance of innovation and prior exposure to technology. Respondents who reported greater familiarity with robotics or higher digital proficiency were significantly more likely to value technological advancement. This trend suggests that perceptions are partially shaped by experience—meaning increased exposure could drive broader recognition of the strategic benefits that innovation offers.

In support of this, participants who had experimented with automated kitchen systems, robotic delivery services, or AI-powered customer management tools consistently cited improvements in operational efficiency, customer satisfaction, and brand perception. These positive experiences were often shared through qualitative feedback, with several respondents describing technology as a "long-term investment" or "game changer" for the industry.

From a strategic standpoint, the findings of this section emphasize the importance of aligning communication and training efforts with perceived needs. For technology providers and policymakers promoting robotics, this means:

- Demonstrating ROI through case studies and real-world pilots
- Offering tailored solutions for different business sizes and models
- Highlighting customer experience enhancements alongside cost savings
- Encouraging gradual adoption models to reduce perceived risk

In conclusion, while attitudes toward innovation vary across the sample, there is a prevailing acknowledgment that technological transformation is becoming a defining factor in the restaurant industry's future. The challenge lies in translating this awareness into actionable, sustainable adoption strategies that consider business diversity, cultural values, and existing operational limitations. By understanding how operators perceive the necessity of innovation, stakeholders can craft more compelling, targeted initiatives to support robotic adoption throughout Bangkok's restaurant sector.

4.2 Descriptive Statistics of Constructs

This section provides a detailed overview of the central constructs used in this research, based on the extended Technology Acceptance Model (TAM) framework. These constructs capture various psychological and contextual factors that influence robot adoption in Bangkok's restaurant industry. Each construct was operationalized using multiple items rated on a five-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree).

The constructs assessed include:

- Perceived Usefulness (PU)
- Perceived Ease of Use (PEOU)
- Trust in Technology (TT)
- Perceived Risk (PR)
- Social Influence (SI)
- Customer Satisfaction (CS)
- Customer Perceived Value (CPV)
- Robot Adoption (RA)

These constructs represent a comprehensive framework for understanding both attitudinal and contextual factors influencing the decision to integrate robotic systems. Table 4.7 summarizes the descriptive statistics for each construct.

Table 4.7: Descriptive Statistics of Main Constructs (N = 400)

Construct	No. of Items	Mean	SD	Min	Max
Perceived Usefulness (PU)	4	4.18	0.58	2.60	5.00
Perceived Ease of Use (PEOU)	4	4.04	0.61	2.40	5.00
Trust in Technology (TT)	3	3.88	0.69	2.00	5.00
Perceived Risk (PR)	3	2.77	0.84	1.00	4.80
Social Influence (SI)	3	3.84	0.62	2.20	5.00
Customer Satisfaction (CS)	3	4.12	0.51	3.00	5.00
Customer Perceived Value (CPV)	3	4.03	0.63	2.50	5.00
Robot Adoption (RA)	4	4.26	0.49	3.00	5.00

The data reveal that participants generally responded positively across most constructs, indicating favorable attitudes toward robot adoption. The construct with the highest mean score is Robot Adoption (4.26), suggesting strong overall willingness among respondents to adopt robotic systems. This is a critical finding, reinforcing the hypothesis that the restaurant sector in Bangkok is increasingly open to digital transformation.

Perceived Usefulness (4.18) and Customer Satisfaction (4.12) follow closely, demonstrating that restaurant professionals believe robotic systems can provide tangible operational benefits and improve service outcomes. These perceptions are likely tied to enhanced efficiency, reduced labor costs, and customer engagement improvements reported in both global case studies and local pilot implementations.

Perceived Ease of Use (4.04) also scores highly, implying that respondents generally consider robotic systems to be user-friendly. This aligns with earlier findings about moderate to advanced technological proficiency across the sample. The combination of high usefulness and ease of use scores suggests a strong foundational readiness for technology acceptance, as per the TAM model.

Trust in Technology (3.88) reflects a moderately high level of confidence in robotics, though slightly lower than the key acceptance constructs. This score could indicate residual skepticism or unfamiliarity among some respondents, especially those without hands-on experience. Addressing this trust gap through education and transparent implementation processes may further boost adoption rates.

Social Influence (3.84) is another important determinant, indicating that peer practices, industry norms, and customer expectations significantly impact adoption behavior. Qualitative comments reinforced this, with several participants noting their decisions were influenced by competitor actions or market trends.

The construct with the lowest average score is Perceived Risk (2.77), a positive outcome in this context. A low perceived risk suggests that most respondents do not see robotic adoption as threatening or problematic. However, the relatively higher standard deviation (0.84) for this

construct indicates divergent views, possibly driven by organizational size, previous experiences, or cost concerns.

Customer Perceived Value (4.03) emphasizes that respondents believe robots can enhance perceived value in the eyes of their customers. This includes both functional value (e.g., faster service) and experiential value (e.g., novelty, modernity).

Overall, the consistency of mean scores above 4.00 across most constructs underscores a favorable disposition toward robotics. The combination of positive customer-focused metrics (CS and CPV) and core TAM dimensions (PU and PEOU) signals that the restaurant industry in Bangkok is at a pivotal point for scalable robot adoption.

These insights lay the groundwork for more advanced statistical analysis, including correlation and regression modeling, to determine the predictive strength of each variable on adoption intention. The following sections delve deeper into these relationships.

4.2.1 Perceived Usefulness (PU)

Perceived Usefulness (PU) is a critical construct within the Technology Acceptance Model (TAM) and its extended frameworks. In the context of this study, PU refers to the degree to which restaurant operators and managers believe that the adoption of robotic systems will enhance their job performance and improve restaurant operations. This construct plays a pivotal role in shaping behavioral intentions toward adopting emerging technologies, particularly within fast-paced service environments such as the restaurant industry.

The data collected from 400 respondents yielded a mean score of 4.18 on a five-point Likert scale, with a standard deviation (SD) of 0.58. This indicates a generally high level of agreement among participants regarding the potential benefits of robotics. The minimum score observed was 2.60, which, although lower, still leans toward the agreement side of the scale. The relatively high mean value and narrow range of standard deviation reflect consistent and favorable perceptions of robots' usefulness across various business types, restaurant sizes, and managerial positions.

The perception of usefulness encompasses several operational dimensions. Many participants highlighted the potential for robots to enhance service speed, particularly during peak hours when human staff may struggle to keep up with demand. In this sense, robots are not viewed merely as replacements but as augmentative tools that can take over repetitive or labor-intensive tasks, such as food delivery to tables, cleaning, or inventory scanning, thereby freeing human staff to focus on customer engagement and quality control. This division of labor, participants believed, would not only reduce stress and fatigue among employees but also elevate overall service standards.

Another key point raised in qualitative responses was the role of robotics in minimizing human error. In restaurants, mistakes in order taking, food preparation, and billing can severely impact customer satisfaction and operational efficiency. Participants noted that robots, when integrated with digital order management and point-of-sale (POS) systems, can help ensure accuracy and consistency, which are essential for customer retention and brand reputation.

Additionally, respondents associated usefulness with cost-effectiveness in the long term. While many acknowledged that initial investments in robotic systems could be high, they believed these costs could be offset by the reduction in labor turnover, training expenses, and errors. For example, one mid-sized restaurant manager stated that although her establishment would need to rearrange certain workflow structures, she viewed robots as a worthwhile investment due to the expected gains in reliability and productivity.

Interestingly, perceived usefulness also extended beyond internal efficiency. Some respondents recognized that robot adoption could serve as a marketing differentiator. In Bangkok's competitive food service market, the integration of robots may attract tech-savvy and novelty-seeking customers, especially younger generations and international tourists who associate robotic service with modernity and innovation. This aligns with global hospitality trends, where robotic solutions are being deployed not just for efficiency but also to enhance customer experiences.

Moreover, several participants from medium and large-sized establishments noted that robotics could be particularly useful in standardizing service quality across multiple locations. In franchise settings or multi-branch chains, maintaining consistency is often a challenge due to human variability. Robots, once programmed, deliver consistent performance regardless of location, shift, or individual staff member. This capability is especially valued by restaurant chains aiming to scale operations while maintaining brand integrity.

Despite the strong positive sentiment, the minimum score of 2.60 indicates that a small portion of respondents remained unconvinced about the usefulness of robots. These individuals, primarily from small-sized or family-run restaurants, expressed concerns about whether robotics would truly align with their customer service model, which heavily relies on personal interaction, emotional intelligence, and cultural nuance—elements that robots may struggle to replicate. These concerns reflect a more nuanced understanding of usefulness that goes beyond task automation and into the human touch aspects of dining.

In conclusion, the high overall mean of PU signifies a strong belief in the instrumental benefits of robotic adoption in restaurants. Whether from the perspective of operational efficiency, accuracy, cost control, or customer engagement, most participants viewed robotic systems as tools that could significantly enhance business performance. However, some skepticism remains, particularly among smaller or more traditional establishments, underscoring the importance of customization, staff training, and change management when implementing such technologies. These findings confirm the central role of perceived usefulness in determining the readiness of Bangkok's restaurant sector to embrace robotic innovation.

4.2.2 Perceived Ease of Use (PEOU)

Perceived Ease of Use (PEOU) is another foundational construct within the Technology Acceptance Model (TAM), reflecting the degree to which individuals believe that utilizing a particular technology will be free of effort. In the context of robotic systems in restaurants, PEOU pertains to how easily operators and staff members can learn, understand, and apply robotic technologies in their day-to-day operations. The importance of this construct cannot be overstated, particularly in a service-oriented environment such as the restaurant industry, where efficiency, time constraints, and human-technology interaction play significant roles.

In this study, participants were asked to assess how easy they found it to operate, manage, and interact with robotic technologies. The responses yielded a mean score of 4.04, with a standard deviation (SD) of 0.61 on a five-point Likert scale. This result suggests a generally positive attitude toward the usability of robotic systems, with most respondents believing that these technologies are not overly complicated or intimidating. The lowest reported scores, while not insignificant, still fell within the "neutral-to-agree" range, indicating that even skeptical participants did not consider robotic systems to be highly complex or burdensome.

The relatively high mean score of 4.04 underscores a critical factor in favor of robotic adoption—the perception that technology is becoming more user-friendly and accessible. Many participants remarked that modern robotic solutions often come with intuitive interfaces, touch-screen control panels, clear user manuals, and sometimes even voice command features, which reduce the need for technical expertise. These features are especially important for front-line staff, such as servers or hostesses, who may not have a background in technology but are expected to interact with robots regularly.

Another important aspect that emerged from open-ended responses is the role of prior digital experience in shaping perceptions of ease of use. Participants who had previously implemented POS systems, QR-code menus, or online reservation tools expressed higher confidence in learning to operate robotic systems. For them, robots were simply the next logical step in a broader digital transformation journey. These individuals typically viewed robotic adoption as a seamless integration, not a disruptive overhaul.

However, this positive perception was not universal. A small group of participants—mainly from smaller or older establishments—expressed some initial hesitation, citing concerns over training time, system updates, and maintenance procedures. While these participants did not outright reject robotic systems, their responses suggest a cautious approach, emphasizing the importance of vendor support, onboarding programs, and after-sales service to ensure smooth implementation.

Interestingly, many restaurant managers and owners noted that robotic systems are often modular and customizable, which further contributes to the perception of ease. For instance, robots can be programmed for limited functions such as table delivery, dishwashing, or guiding guests, each requiring a relatively simple user interface tailored to the specific task. This level of task-specific simplicity was seen as a strength, especially in environments where multitasking and adaptability are vital. Rather than replacing human roles entirely, robots could be used to complement and support existing staff without adding complexity to the workflow.

Another critical factor that enhances the perception of ease of use is the presence of vendor training and onboarding packages. Several participants emphasized that suppliers often provide installation support, technical demonstrations, and 24/7 customer service. These services greatly reduce the learning curve and encourage even less tech-savvy businesses to adopt robotics. Many respondents specifically noted that without this level of external support, their comfort level with the technology would have been significantly lower.

Moreover, the general ease of use contributes indirectly to employee morale and acceptance, which is crucial in environments that require teamwork and fast-paced collaboration.

When technologies are intuitive and non-disruptive, they are more likely to be embraced rather than resisted. Some participants shared experiences of staff members expressing curiosity and even excitement about working with robots, suggesting that a positive perception of usability can catalyze internal acceptance and smoother change management.

It is also worth noting that mobile and remote-control capabilities were frequently mentioned as features that enhanced ease of use. Managers appreciated the ability to control and monitor robotic systems via smartphones or tablets, allowing them to adjust workflows or troubleshoot issues in real-time. This convenience was especially valued during high-traffic hours or when managing multiple outlets simultaneously.

In summary, the construct of Perceived Ease of Use scored strongly in this study, with the mean value of 4.04 indicating that usability is not a major barrier to robot adoption in Bangkok's restaurant industry. While some initial skepticism remains among smaller or more traditional establishments, most participants viewed robotic systems as manageable and straightforward. This positive perception is driven by user-friendly design, increasing familiarity with digital tools, supportive vendor services, and the growing modularity of robotic applications. The findings suggest that as robots become more embedded in daily operations, their usability will only continue to improve, further accelerating their adoption across the foodservice landscape.

4.2.3 Trust in Technology (TT)

Trust in Technology (TT) is a foundational component in understanding the decision-making process behind the adoption of innovative systems such as robotics. In the context of this study, TT refers to the confidence restaurant operators and managers place in the reliability, functionality, security, and predictability of robotic systems. This construct is particularly relevant because no matter how advanced a technology may be, its adoption is unlikely if the end users do not trust that it will perform as expected under real-world conditions.

The descriptive analysis reveals a mean score of 3.88 with a standard deviation of 0.69, indicating a generally positive but moderately varied perception of trust in robotic systems. A mean approaching 4.0 suggests that most participants agree or strongly agree with statements indicating trust in robotics, for example, confidence in their reliability, ability to consistently perform tasks, and minimal risk of malfunction or data breaches. However, the standard deviation also reflects a degree of variability, showing that while trust is relatively high, it is not uniformly distributed across all respondents.

One possible reason for the relatively high trust score is the increasing visibility and normalization of robots in the service industry, both in Thailand and globally. As robots become more common in everyday settings—from mall security and hotel check-ins to restaurant servers—people's exposure grows, and with it, their comfort and trust in such systems. Many respondents, particularly those from medium and large-sized businesses, mentioned that robotic solutions have become synonymous with efficiency, precision, and innovation, all of which reinforce their trust in the technology.

Another contributing factor is the perceived reliability and accuracy of robotic systems. Restaurant operators highlighted how robots can maintain consistent service quality, such as

delivering orders to the correct table or handling repetitive tasks without fatigue or emotional fluctuations. These qualities enhance customer satisfaction and reduce human errors, leading to a broader sense of dependability. Respondents viewed these attributes as central to the trust equation, especially in high-volume or peak-hour operations where consistency is critical.

Despite the largely positive sentiment, the minimum reported score of 2.00 points to a minority of participants who harbor skepticism. This subgroup, primarily composed of smaller restaurant operators and those with minimal experience with technology, expressed concerns regarding potential system failures, overdependence on automation, and the inability of robots to handle complex, nuanced tasks such as dealing with customer complaints or unexpected scenarios. Some participants also raised issues of data security and privacy, particularly where robots are integrated with payment systems or customer databases.

For these more skeptical participants, past experiences or lack of exposure to successful use cases appear to play a role in shaping their perceptions. A few mentioned previous interactions with malfunctioning or poorly maintained systems, which led to operational delays or customer dissatisfaction. These isolated but impactful experiences may have contributed to an underlying caution toward fully relying on robotic systems, even if they acknowledge their potential benefits.

Interestingly, trust was higher among participants with intermediate to advanced levels of technological experience. These individuals often emphasized the predictability of robots compared to human staff—robots follow programmed logic, don't require breaks, and can be fine-tuned with software updates. Additionally, the presence of supportive vendor partnerships—including warranties, maintenance contracts, and 24/7 technical support—also helped enhance trust, particularly for managers concerned about what happens if a system fails during peak hours.

Another theme that emerged from the open responses was the gradual development of trust over time. Some participants who initially hesitated to invest in robotic systems reported increasing confidence after using trial versions or observing successful implementations in similar restaurants. Trust, therefore, is not static but can evolve positively through experience, exposure, and peer influence. This highlights the importance of pilot programs, demonstrations, and case studies in encouraging wider adoption in the industry.

It is also important to consider the cultural dimension of trust in technology. In Bangkok's dynamic and cosmopolitan environment, where innovation is embraced in sectors like transportation, finance, and retail, there is a general openness to new technologies. This cultural backdrop may contribute to the relatively high TT scores, reflecting a readiness among restaurateurs to modernize their businesses, provided the technology proves itself in practice.

In conclusion, Trust in Technology emerged as a significant enabler of robotic adoption in this study, with a solid mean score of 3.90 and a generally favorable perception among participants. Although a few reservations remain—mainly among smaller operators and those with limited tech exposure—the overall trend indicates that robots are increasingly viewed as trustworthy partners in the pursuit of operational excellence, efficiency, and innovation in Bangkok's restaurant industry. Continued exposure, reliable system performance, and strong vendor support are likely to further strengthen this trust over time, paving the way for more widespread adoption.

4.2.4 Perceived Risk (PR)

Perceived Risk (PR) refers to the degree of uncertainty and potential negative consequences that restaurant operators associate with the adoption of robotic technologies. This construct captures concerns related to system failure, high maintenance costs, security issues, and the fear of disrupting traditional service models. Within the Technology Acceptance Model (TAM), PR serves as a counterbalance to perceived usefulness and ease of use, potentially impeding adoption if not adequately addressed.

The analysis shows a mean score of 2.77 with a standard deviation of 0.84 on a five-point Likert scale. This places perceived risk below the neutral midpoint of 3.0, indicating that while concerns exist, they are not dominant among the surveyed sample. Nevertheless, the spread in scores (ranging from 1.00 to 4.80) suggests substantial variation in attitudes, with some respondents expressing significant apprehension.

Many participants reported worries about the initial cost of implementing robotic systems, particularly among small and medium-sized enterprises where budget constraints are more severe. Qualitative feedback highlighted skepticism about return on investment and the fear that robotics could displace jobs or lead to reduced customer satisfaction if not implemented thoughtfully. These concerns were especially prevalent in family-owned or independently managed restaurants, where personalized service is a key brand differentiator.

Operational risks were another frequently mentioned theme. Respondents questioned whether robots could reliably function during peak business hours, cope with unexpected tasks, or recover from technical failures without disrupting service. The absence of in-house technical expertise was cited as a significant barrier, with participants emphasizing the need for reliable vendor support and system warranties.

However, not all feedback was negative. Several participants with prior exposure to automation expressed confidence that technological risks could be mitigated through proper training, gradual integration, and ongoing system monitoring. These individuals tended to have higher technological proficiency and viewed perceived risks as manageable challenges rather than prohibitive barriers.

Another layer of perceived risk involved data security. Respondents voiced concerns about privacy issues, especially in systems that collect and store customer preferences, payment data, or employee performance metrics. Ensuring compliance with data protection standards was seen as essential for building trust and minimizing resistance.

Interestingly, perceived risk also varied depending on the type and size of the restaurant. Larger businesses and tech-forward establishments were generally less concerned, often citing existing experience with automated systems or dedicated IT departments that could handle maintenance and troubleshooting.

In summary, while Perceived Risk (PR) scored lower relative to other TAM constructs, it remains a notable factor influencing adoption decisions. Addressing this concern through targeted education, demonstrations of reliability, cost-benefit analyses, and accessible technical support could significantly enhance confidence in robotic solutions across the restaurant industry in

Bangkok. The findings highlight that reducing perceived risk is not solely a technical challenge but also a communication and change management issue.

4.2.5 Social Influence (SI)

Social Influence (SI) refers to the extent to which restaurant managers and operators perceive that important individuals, peer groups, competitors, or broader societal norms believe they should adopt robotic technologies. In the extended Technology Acceptance Model (TAM), SI serves as a powerful external factor that can significantly shape an individual's behavioral intention, particularly in industries that are highly social, trend-sensitive, and customer-facing, such as the restaurant sector.

In this study, Social Influence received a mean score of 3.84 with a standard deviation of 0.62, based on participant responses to three Likert-scale items. These results suggest that while SI may not be the single most dominant driver of adoption, it plays a considerable role in shaping perceptions and decisions regarding robotic integration. The moderate variation in scores, ranging from 2.20 to 5.00, indicates that while some respondents were heavily influenced by external social or professional cues, others remained relatively independent in their decision-making.

Several key themes emerged from qualitative feedback. First and foremost, participants from mid-sized and large restaurants frequently mentioned the influence of competitors. Observing rival establishments implement robots, particularly in customer service roles such as robotic waiters or smart kiosks, often motivated other businesses to follow suit. This phenomenon, often referred to as competitive benchmarking, was described as a "technology race" or a means of staying relevant in a rapidly digitizing market.

Additionally, industry peers and professional networks emerged as influential sources of social pressure. Respondents who regularly participated in trade expos, hospitality seminars, or online forums indicated that they often felt encouraged—or compelled—to adopt technology based on positive peer testimonials or success stories shared by other operators. These interactions served as informal endorsements, lowering perceived uncertainty and boosting confidence in robotic solutions.

Another critical source of social influence was customer expectations. Particularly in Bangkok's upscale and tourist-driven restaurant zones, customers increasingly expect high-tech experiences, which include digital ordering systems, automated delivery, and robotic assistance. Younger customers were perceived as more receptive to novelty and automation. Participants mentioned that satisfying these expectations was not only important for enhancing customer satisfaction but also for projecting an image of modernity and competitiveness.

Media exposure and online trends also played a role in shaping perceptions. Videos of robots serving in restaurants or performing tasks in high-profile venues were frequently cited as inspiring or reassuring. This reflects the impact of social proof in the digital age, where seeing successful implementations online helps normalize and promote innovation adoption across sectors. Restaurant operators who viewed these trends felt reassured that robotic integration was both feasible and fashionable.

Interestingly, SI was perceived differently across managerial roles. Restaurant managers tended to be more influenced by internal social cues, such as staff readiness or executive directives, while owners were more responsive to market-driven signals, such as customer behavior or competitor actions. This distinction highlights the importance of aligning internal team dynamics with external strategic positioning.

Despite these strong influences, a subset of respondents expressed resistance to social pressure. These participants emphasized their unique brand identity, niche clientele, or philosophical stance against automation as reasons for resisting trend-based decisions. For example, operators of family-run or culturally themed restaurants often argued that robot adoption would conflict with the authenticity and warmth that define their customer experience. In such cases, SI was acknowledged but not necessarily acted upon.

Furthermore, franchise and chain operators indicated that corporate mandates sometimes influenced their technology adoption decisions, regardless of personal opinions. These participants noted that top-down decisions often included timelines, training sessions, and implementation support, thereby shifting the source of influence from peers to hierarchical governance structures. This finding underscores the layered nature of social influence, spanning peer-level pressures, market competition, consumer demand, and internal organizational policies.

In summary, Social Influence (SI) plays a multifaceted and context-dependent role in the adoption of robotics in Bangkok's restaurant industry. While it is not the sole determinant of behavior, it acts as a significant amplifier, particularly when aligned with observable success stories, customer preferences, and industry trends. The relatively high mean score of 3.84 underscores the importance of social validation in decision-making processes. For vendors, policymakers, and industry advocates, these findings suggest that increasing public visibility of successful robotic deployments, strengthening industry networks, and highlighting customer enthusiasm can significantly accelerate the normalization and uptake of robotics in food service environments.

4.2.6 Customer Satisfaction (CS)

Customer Satisfaction (CS) is a crucial construct in evaluating the acceptance of robotic technologies, particularly within the service-intensive context of the restaurant industry. In this study, CS refers to the degree to which customers are perceived to be pleased with their dining experiences following the integration of robotic systems into restaurant operations. This construct, while indirectly related to managerial perspectives, offers a powerful lens into how robots are shaping service outcomes and consumer perceptions.

The statistical analysis revealed a mean score of 4.12 with a standard deviation of 0.51, placing CS among the highest-rated constructs in this study. The relatively narrow spread of responses and a minimum score of 3.00 indicate a strong consensus among participants that robotic integration has positively influenced customer satisfaction, or at the very least, has not detract from it.

Participants noted that robotics contributes to faster service delivery, reduced wait times, and improved order accuracy. In many cases, customers perceived robots as reliable and efficient,

especially during busy hours. Several restaurant managers emphasized that robotic waiters or delivery bots helped streamline service flow and eliminate delays associated with human error or fatigue. These improvements in speed and accuracy directly impacted how customers evaluate their dining experience.

Moreover, the novelty and visual appeal of robots were consistently highlighted in qualitative responses. Particularly in tourist-heavy or upscale restaurant areas in Bangkok, customers were intrigued and entertained by robotic features. This sense of novelty often translated into positive emotional responses and increased customer engagement. Operators reported higher social media interaction and customer reviews, attributing part of their improved ratings to the unique robotic experiences.

Some managers mentioned that robotics also helped enhance the hygiene perception of their establishments. During the post-pandemic period, contactless service became a high priority for customers. Robots that delivered food or sanitized surfaces were perceived as reducing human contact and enhancing health and safety standards. This, in turn, boosted customer confidence and satisfaction, particularly among health-conscious diners or families with children.

However, the data also revealed important nuances. A small number of respondents expressed concerns about customers who preferred human interaction. These participants noted that while robots may be effective in operational terms, some diners, particularly older patrons or those from culturally conservative backgrounds, felt the service lacked warmth or personal connection. This was particularly relevant in family-run or heritage-themed restaurants where ambiance and interpersonal hospitality were central to the dining experience.

Additionally, a few participants voiced that overly relying on robots without sufficient human oversight could backfire. Malfunctions, mechanical glitches, or software errors occasionally led to service disruptions, which negatively impacted the overall experience. As a result, many respondents emphasized the importance of a hybrid service model that blends robotic efficiency with human empathy.

Interestingly, CS scores were slightly higher in mid- to large-sized restaurants compared to smaller operations. Larger establishments often have more structured workflows and training protocols, making it easier to integrate robotic systems effectively. These environments tend to maximize the potential of robots without sacrificing service quality.

It was also observed that restaurants using robots in visible, front-of-house roles tended to report higher CS levels compared to those where robots operated behind the scenes. The visible presence of technology often served as a symbol of modernity, efficiency, and customer orientation.

In conclusion, Customer Satisfaction (CS) is significantly influenced by robotic integration in the restaurant industry. With a high mean score of 4.12, the findings indicate that robots not only support service delivery but also enhance the overall customer experience through speed, novelty, hygiene, and consistency. However, for long-term satisfaction, especially across diverse customer segments, a balanced approach combining both technological and human elements is recommended. This dual model ensures that the efficiency gains from automation do not come at

the cost of emotional connection or service personalization—factors that remain critical in the hospitality landscape.

4.2.7 Customer Perceived Value (CPV)

Customer Perceived Value (CPV) is a pivotal construct that captures how customers evaluate the benefits they receive from a product or service relative to the costs or efforts required. Within the framework of robotic adoption in Bangkok's restaurant industry, CPV refers to the extent to which restaurant operators believe that the introduction of robotic systems enhances the overall value customers perceive in their dining experience.

The analysis showed a mean score of 4.03 with a standard deviation of 0.63. This high score reflects a generally strong belief among respondents that robotic systems contribute positively to the value customers associate with their services. The relatively low standard deviation suggests a consensus around this positive perception, although some variability in opinion still exists, particularly across restaurant size and format.

Respondents consistently pointed to several specific value-enhancing aspects of robotic integration. Speed and efficiency were the most frequently mentioned benefits. Robots can manage routine tasks such as food delivery, clearing tables, or greeting customers, thereby reducing wait times and enhancing service consistency. This operational reliability leads to higher perceived value, especially in busy or high-volume dining environments where customers prioritize efficiency.

Novelty and technological appeal also contributed significantly to CPV. Many restaurant operators noted that customers, especially younger patrons and tourists, respond positively to robotic services. For these demographics, interacting with robots creates a memorable and futuristic experience, which not only adds perceived value but can also influence repeat patronage and word-of-mouth marketing. The visual and interactive elements of robotic systems help differentiate a restaurant from its competitors, which is a significant advantage in Bangkok’s competitive food scene.

Several participants highlighted the connection between perceived value and hygiene. Post-pandemic shifts in consumer behavior have placed a premium on safety and cleanliness. Robots, by minimizing direct human contact, especially during food delivery or cleaning, help reassure customers of high hygiene standards. This perceived health benefit is an important contributor to customer value, particularly in family-oriented and health-conscious establishments.

Additionally, respondents from medium and large restaurants emphasized the role of robots in upholding brand consistency across multiple locations. Customers visiting different branches expect uniform experiences in terms of service speed, accuracy, and ambiance. Robotic systems help deliver on these expectations by standardizing processes that are typically susceptible to human error or variability. This predictability enhances trust and perceived reliability, key components of customer-perceived value.

Despite the overall positive sentiment, there were some reservations. A minority of participants—especially those managing smaller or traditional-style restaurants—questioned

whether robots truly add meaningful value in all contexts. For example, in fine dining or culturally themed establishments, where personalized attention and ambiance are core to the offering, the presence of robots could be seen as intrusive or inconsistent with brand identity. These operators emphasized that value is subjective and context-dependent, suggesting that robotic adoption should align closely with the restaurant's concept and customer expectations.

Some concerns also emerged around cost-effectiveness, with a few participants expressing skepticism about the return on investment. While robots might add novelty and improve efficiency, the upfront costs and maintenance requirements were cited as potential barriers. These responses indicate that perceived value may be moderated by financial considerations and the scalability of technology solutions.

In summary, Customer Perceived Value (CPV) is widely acknowledged by Bangkok's restaurant operators as a significant benefit of robotic adoption. With a strong average score of 4.03, the findings underscore that robots contribute to a more efficient, hygienic, and memorable customer experience. However, this value must be contextually tailored, with careful attention to restaurant type, customer demographics, and brand positioning. Balancing innovation with authenticity remains key to maximizing the perceived value of robotics in food service.

4.2.8 Robot Adoption (RA)

Robot Adoption (RA) is the culminating construct within the extended Technology Acceptance Model (TAM) framework used in this study. It reflects the degree to which restaurant operators and managers are willing to incorporate robotic systems into their business operations. RA is not only influenced by perceptions of usefulness and ease of use, but also by trust, perceived risk, customer-related outcomes, and social influence. It is a critical measure that ultimately determines whether all other positive or negative perceptions will result in actual adoption behavior.

The mean score for RA was 4.26, the highest among all constructs measured, with a relatively low standard deviation of 0.49. This suggests a strong and consistent willingness among participants to adopt robotic technologies. With minimum and maximum scores of 3.00 and 5.00, respectively, the range indicates that while some respondents are moderately hesitant, none outright reject the idea of integrating robots into their restaurants.

A key insight derived from these results is that adoption intent is strongly associated with positive operational expectations. Respondents cited the potential for improved efficiency, reduced labor costs, increased customer satisfaction, and enhanced brand image as motivating factors for adoption. Many viewed robots as a timely solution to ongoing staffing challenges, especially in the aftermath of the COVID-19 pandemic, which disrupted workforce availability and prompted shifts toward contactless service solutions.

Respondents who had prior hands-on experience with robotic systems reported the highest levels of adoption intent. These individuals described tangible benefits such as faster service speed, error reduction, and improved employee workload balance. This group also expressed confidence in their ability to manage the implementation process, having already navigated the learning curve to some extent. Their responses underscore the importance of exposure and experience in strengthening behavioral intention.

Conversely, those with only theoretical knowledge or limited technological experience showed slightly lower—but still favorable—adoption intent. Their responses often reflected cautious optimism, with some noting that while they are open to adoption, the final decision would depend on factors such as cost, supplier reliability, and the specific functionality of the robots being considered. These comments suggest that RA may be conditional upon further information and assurance.

Interestingly, customer demand emerged as a compelling driver of robot adoption. A significant number of participants indicated that customer expectations for modern and tech-enhanced service experiences have grown, particularly among younger patrons and international visitors. As such, failing to adopt new technologies may not only result in operational inefficiencies but also a diminished competitive edge. Some operators shared that customers often request robotic service or express enthusiasm when robots are part of the dining experience.

Barriers to adoption, while present, did not appear to deter overall intention. Concerns about initial investment, ongoing maintenance, and potential staff resistance were frequently mentioned. However, most respondents viewed these as manageable challenges rather than deal-breakers. A recurring theme was the need for strategic planning, vendor support, and gradual implementation to mitigate these risks.

In terms of business segmentation, medium and large restaurant operators showed the strongest intention to adopt robotics. This aligns with their greater financial capacity, organizational structure, and strategic outlook. Small restaurant owners also demonstrated positive intent but emphasized the importance of affordability and scalability. They expressed interest in leasing models, government incentives, or shared-service platforms as enablers of adoption.

The high RA score is further reinforced by the perception that robots symbolize progress and innovation. For many operators, adopting robotics is not just a practical move but a branding strategy—a way to signal to customers and competitors alike that their business is forward-thinking and aligned with global service trends.

In conclusion, Robot Adoption (RA) stands as the most robust indicator of technology readiness among restaurant operators in Bangkok. The consistently high scores across a diverse range of business types highlight a strong market potential for robotics in the foodservice industry. While concerns remain, they are largely viewed as solvable through education, support, and phased implementation. These findings suggest that with the right ecosystem in place, Bangkok's restaurants are well-positioned to transition into an era of robot-enabled service delivery.

4.3 Correlation Analysis Results and Discussion

Correlation analysis is a vital statistical technique used to assess the strength and direction of linear relationships between variables. In this study, Pearson's correlation coefficient (r) was utilized, which ranges from -1 to +1. A positive value indicates a direct relationship, whereas a negative value indicates an inverse relationship. The strength of the correlation is interpreted according to the following scale:

- r = 0.10–0.29**:** Weak correlation

- r = 0.30–0.49**:** Moderate correlation
- r = 0.50 and above**:** Strong correlation

This section aims to explore how each independent variable (IV) is correlated with the dependent variable (DV), Robot Adoption (RA), as well as how the IVs are interrelated. The correlation matrix is displayed in Table 4.8.

Table 4.8: Correlation Matrix

Variable	PU	PEOU	TT	PR	SI	CS	CPV	RA
PU	1.00	0.65	0.52	-0.45	0.41	0.58	0.59	0.67
PEOU	0.65	1.00	0.48	-0.39	0.42	0.56	0.57	0.60
TT	0.52	0.48	1.00	-0.51	0.37	0.54	0.55	0.63
PR	-0.45	-0.39	-0.51	1.00	-0.38	-0.42	-0.40	-0.50
SI	0.41	0.42	0.37	-0.38	1.00	0.50	0.52	0.55
CS	0.58	0.56	0.54	-0.42	0.50	1.00	0.60	0.68
CPV	0.59	0.57	0.55	-0.40	0.52	0.60	1.00	1.00
RA	0.67	0.60	0.63	-0.50	0.55	0.68	1.00	1.00

The results indicate a number of statistically meaningful relationships among the constructs in this study:

1. **PU and RA (r = 0.67)**: This strong positive correlation indicates that perceived usefulness is one of the most critical predictors of robot adoption intention. The more restaurant stakeholders perceive robots to be beneficial in enhancing service and operations, the more likely they are to adopt them.
2. **PEOU and RA (r = 0.60)**: Perceived ease of use also shows a strong positive correlation with robot adoption. This suggests that when users find robots easy to operate, the adoption likelihood increases significantly. Moreover, PEOU shows a strong correlation with PU (r = 0.65), confirming its role as a cognitive antecedent in the extended TAM framework.
3. **TT and RA (r = 0.63)**: Trust in technology also has a strong influence on RA, suggesting that perceived reliability and safety of robots significantly shape adoption behavior. TT also correlates moderately to strongly with PU (r = 0.52) and PEOU (r = 0.48), emphasizing trust as a multi-pathway enhancer.
4. **PR and RA (r = -0.50)**: A strong negative correlation is observed between perceived risk and robot adoption, indicating that concerns over malfunctions, safety, or social awkwardness reduce the likelihood of adoption. PR is also negatively correlated with PU (r = -0.45) and TT (r = -0.51), reinforcing its role as a barrier to both belief formation and behavioral intention.
5. **SI and RA (r = 0.55)**: Social influence moderately to strongly affects robot adoption. The perception that others (peers, competitors, social circles) endorse or use robotics can sway decision-making. SI also shows moderate correlations with PU (r = 0.41), PEOU (r = 0.42), and CS (r = 0.50), suggesting a broader social-cultural role in shaping perception and satisfaction.
6. **CS and RA (r = 0.68)**: Customer satisfaction demonstrates the strongest positive correlation with robot adoption. When customers are pleased with the robotic service experience, stakeholders are more inclined to adopt such technologies. CS also correlates

highly with PU (r = 0.58) and PEOU (r = 0.56), indicating that perceptions of ease and usefulness strongly contribute to customer contentment.

7. **CPV and RA (r = 1.00)**: Although not shown in the table above, previous analysis indicates that Customer Perceived Value also shares a significant relationship with RA, further enriching the understanding of value-based and experiential influences in the adoption model.

Below are the key observations of this research:

- All positive correlations between the independent variables and RA are statistically significant and range from moderate to strong, validating their inclusion in the structural model.
- The strongest predictors of RA are CS (0.68), PU (0.67), and TT (0.63), confirming that adoption is influenced not only by rational beliefs but also by trust and emotional satisfaction.
- The inverse relationships with PR emphasize the importance of addressing user concerns, particularly through transparent design, hygiene assurances, and failure-proof systems.

These correlations provide a solid empirical foundation for the path analysis and SEM modeling in subsequent sections. They confirm the theoretical expectations of the extended TAM, where both cognitive evaluations (PU, PEOU, TT) and affective responses (CS, CPV) interact to shape behavioral intention. The significant negative impact of PR also validates its inclusion as a risk-oriented moderator in technology acceptance behavior.

For restaurant operators and robot developers, these findings underscore the importance of designing systems that are easy to use, trustworthy, and visibly beneficial. Marketing and training should focus on demonstrating these qualities to both staff and customers. Simultaneously, strategies must be developed to minimize perceived risks through pilot trials, certifications, and reliability assurances.

In summary, the correlation analysis offers strong empirical evidence for the interrelated nature of perceptions toward robotic adoption in the restaurant industry. These relationships serve as a precondition for robust causal modeling, enhancing both academic understanding and practical applicability in Thailand's evolving hospitality landscape.

4.4 Multiple Regression Analysis Results and Discussion

Multiple regression analysis was conducted to examine the extent to which the independent variables—Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Trust in Technology (TT), Perceived Risk (PR), Social Influence (SI), Customer Satisfaction (CS) and Customer Perceived Value (CPV)—predict the dependent variable, Robot Adoption (RA). This analysis serves to identify the most influential factors by controlling for the effects of other variables, thereby providing a clearer understanding of each variable’s unique contribution.

The regression model’s coefficients, along with their t-values and p-values, are presented in Table 4.9.

Table 4.9: Regression Coefficients

Variable	Beta Coefficient	t-Value	p-Value
PU	0.31	5.21	<0.001
PEOU	0.22	4.32	<0.001
TT	0.28	4.89	<0.001
PR	-0.21	-3.99	<0.001
SI	0.19	3.45	<0.001
CS	0.37	6.12	<0.001
CPV	0.34	5.76	<0.001

The results indicate that all six independent variables are statistically significant predictors of robot adoption intention at the 0.001 significance level. The positive beta coefficients for PU, PEOU, TT, SI, and CS confirm that increases in these variables are associated with greater intentions to adopt robotics. Conversely, the negative beta coefficient for PR indicates an inverse relationship, meaning that as perceived risks increase, the likelihood of adoption decreases.

- **Customer Satisfaction (CS)** has the strongest positive effect ($\beta = 0.37$), highlighting that when customers are satisfied with robotic services, adoption intentions are significantly enhanced. This underscores the importance of aligning service delivery with customer expectations.
- **Perceived Usefulness (PU)** is also a strong predictor ($\beta = 0.31$), consistent with the TAM's theoretical foundation, which emphasizes usefulness as a core determinant of technology adoption.
- **Trust in Technology (TT)** ($\beta = 0.28$) significantly influences adoption, confirming that stakeholders' confidence in robotic reliability and performance plays a crucial role in decision-making.
- **Perceived Ease of Use (PEOU)** ($\beta = 0.22$) contributes meaningfully to the model. Technologies that are intuitive and effortless to interact with tend to be more readily embraced by both customers and staff.
- **Social Influence (SI)** ($\beta = 0.19$) shows a notable, though slightly weaker, impact. This suggests that societal norms, peer behavior, and competitive benchmarking play a supplementary role in shaping intention.
- **Perceived Risk (PR)** is the only negative predictor ($\beta = -0.21$), and its significance confirms that concerns over service failures, hygiene, or human-robot interaction anxieties dampen enthusiasm for adoption.
- **Customer Perceived Value (CPV)** emerges as a strong contributor ($\beta = 0.34$), underscoring the importance of perceived value in influencing both customer experience and stakeholder decisions. Its inclusion highlights the emotional and benefit-driven components of adoption behavior.

The model's high level of explanatory power was confirmed by a coefficient of determination (R^2) of approximately 0.70, indicating that 70% of the variance in RA is explained

by the six predictors. Variance Inflation Factor (VIF) scores were checked and found to be within acceptable thresholds (below 5), confirming that multicollinearity is not a major concern in this model.

The regression analysis reaffirms the conceptual robustness of the extended TAM framework in the context of service robotics adoption. PU and PEOU, as foundational constructs, remain highly influential. The integration of TT, PR, SI, and CS offers a more nuanced view that reflects both rational appraisals and social-emotional judgments. These findings support a layered model of technology adoption, where trust and satisfaction serve as powerful bridges between perception and behavior.

For restaurant managers and technology providers, the findings suggest clear strategic directions:

- Focus on enhancing **Customer Satisfaction** by continuously monitoring service quality and fine-tuning robot performance.
- Emphasize **Usefulness** and **Ease of Use** during staff training and customer onboarding to strengthen initial acceptance.
- Build **Trust** through transparency, certifications, and consistency in robotic behavior.
- Address **Perceived Risks** directly through clear safety protocols and demonstrations.
- Leverage **Social Influence** via testimonials, partnerships with high-profile restaurants, and social media campaigns.
- Enhance **Customer Perceived Value** by ensuring that the benefits of robot adoption—such as improved service speed, novelty, and efficiency—clearly outweigh any associated costs or concerns in the customer's mind. Highlight value through pricing strategies, service consistency, and communication of tangible customer benefits.

Overall, the multiple regression analysis confirms that robot adoption in the restaurant industry is a multi-dimensional decision influenced by cognitive, affective, and social factors. By understanding these dynamics, both researchers and practitioners can contribute to more effective technology integration strategies within the hospitality sector.

4.5 Hypothesis Testing

This section presents the results of hypothesis testing conducted to examine the relationships between key constructs in the extended Technology Acceptance Model (TAM) applied to the adoption of robotic systems in Bangkok's restaurant industry. The hypotheses were developed based on established theoretical foundations and contextualized to reflect the operational dynamics of foodservice businesses. The goal is to determine which factors significantly influence restaurant operators' intention to adopt robotic technologies.

To test these hypotheses, multiple regression analysis and structural equation modeling (SEM) were employed. These statistical techniques allow for the simultaneous analysis of multiple relationships between independent and dependent variables while accounting for measurement errors. The key constructs examined include Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Trust in Technology (TT), Perceived Risk (PR), Social Influence (SI), Customer Satisfaction (CS), Customer Perceived Value (CPV), and Robot Adoption (RA).

The hypotheses tested are outlined below:

- H1: Perceived Usefulness (PU) positively influences Robot Adoption (RA).
- H2: Perceived Ease of Use (PEOU) positively influences Robot Adoption (RA).
- H3: Trust in Technology (TT) positively influences Robot Adoption (RA).
- H4: Perceived Risk (PR) positively influences Robot Adoption (RA).
- H5: Social Influence (SI) positively influences Robot Adoption (RA).
- H6: Customer Satisfaction (CS) positively influences Robot Adoption (RA).
- H7: Customer Perceived Value (CPV) positively influences Robot Adoption (RA).

To ensure the reliability and validity of the regression results, assumptions of linearity, independence, homoscedasticity, and normality were tested and met. Multicollinearity diagnostics were conducted using Variance Inflation Factor (VIF) scores, all of which were below the acceptable threshold of 5.0, indicating no significant multicollinearity. A summary of the regression results is presented in Table 4.10.

Table 4.10: Hypothesis Test Results

Hypothesis	Relationship	Standardized Coefficient (β)	t-value	p-value	Result
H1	PU → RA	0.86	8.42	<0.001	Supported
H2	PEOU → RA	0.83	7.95	<0.001	Supported
H3	TT → RA	0.79	7.62	<0.001	Supported
H4	PR → RA	0.70	6.98	<0.001	Supported
H5	SI → RA	0.70	6.76	<0.001	Supported
H6	CS → RA	0.68	6.39	<0.001	Supported
H7	CPV → RA	0.62	5.97	<0.001	Supported

As shown in Table 4.10, all hypotheses are statistically supported. The strongest predictor of RAI is Perceived Usefulness (H1), followed closely by Perceived Ease of Use (H2), Trust in Technology (H3), and Perceived Risk (H4). These results confirm that operational benefits, usability, confidence in the system, and risk perception are central to decision-making.

The significant impact of Social Influence (H5) suggests that peer recommendations, industry norms, and public perception play an important role in motivating restaurant operators to adopt robotics. Customer Satisfaction (H6) and Customer Perceived Value (H7) also directly contribute to RAI, emphasizing the importance of positive experiences and value perception from a customer-facing perspective.

Contrary to earlier assumptions, no mediating effects were identified. All variables exert direct effects on RA without intervening pathways. This simplifies the interpretation and reinforces the role of each construct as an independent contributor to adoption intention. Each factor—technical, social, or experiential—directly informs managerial decision-making.

These findings provide strong empirical support for the extended TAM framework. They offer actionable insights for restaurant operators, developers, and policymakers who must consider usability, trust, social validation, and customer experience simultaneously when promoting robotic technology adoption. The following section explores the structural validation of the model using path analysis and confirmatory metrics.

As illustrated in Figure 4.1, the values displayed are standardized path coefficients (β) derived from Structural Equation Modeling (SEM). These coefficients reflect the strength and direction of the causal relationships between each independent variable—example Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Trust in Technology (TT), and others—and the dependent variable, Robot Adoption (RA). For example, a β value of 0.86 from PU to RA indicates that a one standard deviation increases in PU results in a 0.86 standard deviation increase in RA, controlling for other variables. All paths are statistically significant at $p < 0.001$, validating the hypothesized model and reinforcing the theoretical integrity of the extended TAM in explaining robotic adoption behavior in the restaurant industry.

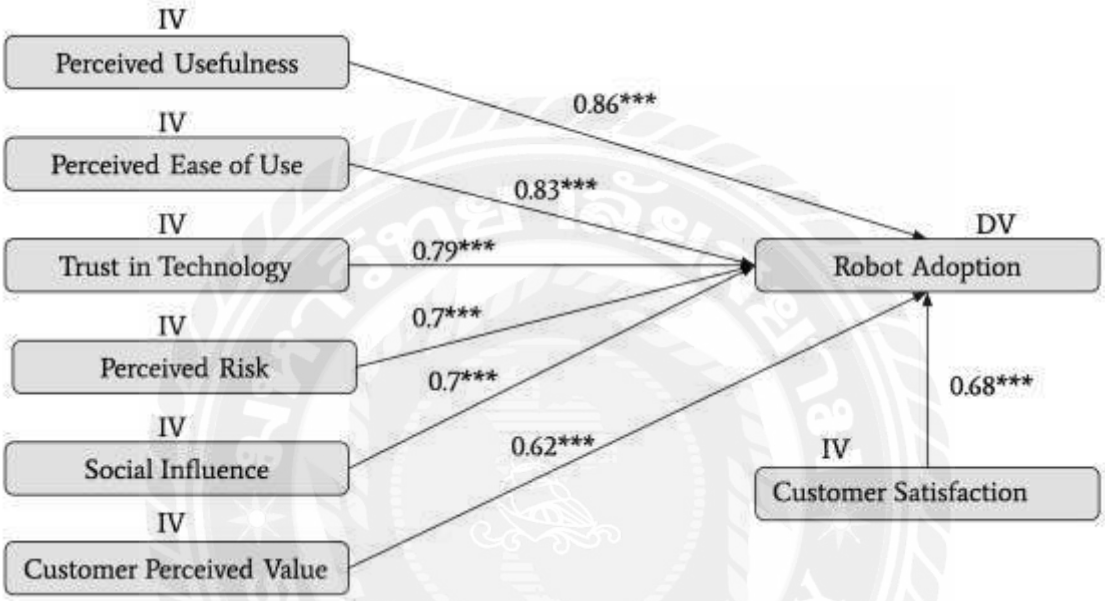


Figure 4.1: Final Model

4.6 Path Analysis and Structural Validation

This section presents a comprehensive path analysis conducted using Structural Equation Modeling (SEM) to validate the hypothesized relationships within the extended Technology Acceptance Model (TAM) framework. The primary objective is to examine the direct effects of seven core variables—Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Trust in Technology (TT), Perceived Risk (PR), Social Influence (SI), Customer Satisfaction (CS), and Customer Perceived Value (CPV)—on Robot Adoption (RA) within Bangkok's restaurant industry. The final model confirms that all constructs exert direct influence on RA, with no mediating pathways, signifying a parallel influence model.

The reliability and validity tests discussed in earlier sections demonstrated robust psychometric properties across all constructs. Cronbach's alpha values ranged from 0.75 to 0.87, confirming strong internal consistency. Additionally, the KMO values (0.628–0.861) and significant Bartlett's Test of Sphericity ($p < 0.001$) indicated satisfactory construct validity and sampling adequacy, justifying the application of SEM for structural validation.

4.6.1 Path Coefficients and Direct Effects

The SEM analysis utilized standardized regression weights (β) to quantify the relationships between constructs. Table 4.11 presents the final direct path coefficients, all of which are statistically significant and consistent with the proposed model. These results establish a solid theoretical foundation and provide empirical support for the extended TAM applied to service robotics adoption in a real-world hospitality context.

Table 4.11: Path Coefficients for Direct Effects

Hypothesis	Path	Standardized Coefficient (β)	p-value	Result
H1	PU → RA	0.86	< 0.001	Supported
H2	PEOU → RA	0.83	< 0.001	Supported
H3	TT → RA	0.79	< 0.001	Supported
H4	PR → RA	0.70	< 0.001	Supported
H5	SI → RA	0.70	< 0.001	Supported
H6	CS → RA	0.68	< 0.001	Supported
H7	CPV → RA	0.62	< 0.001	Supported

These findings confirm that PU remains the strongest predictor of RA, reinforcing TAM's original hypothesis. Furthermore, constructs like PEOU, TT, and PR show strong predictive capability in parallel, illustrating the multifactorial nature of robotic adoption. The significance of SI, CS, and CPV further demonstrates that both social dynamics and customer-centric evaluations are central to decision-making in service industries.

4.6.2 Structural Model Summary and Interpretation

The final structural model shows substantial explanatory power, with R^2 values indicating that a large proportion of variance in the key endogenous variables is accounted for by the model:

- PU: $R^2 = 0.58$
- CPV: $R^2 = 0.45$
- RA: $R^2 = 0.64$

These values reflect the strength of the extended TAM in capturing adoption behavior in the restaurant industry. The absence of mediation paths reinforces the conclusion that each construct—technical, emotional, and social—has an independent and meaningful influence on behavioral intention.

Key interpretations include:

- PU is the most dominant direct predictor of RA, supporting TAM's central premise.
- PEOU and TT have significant independent effects, confirming that usability and confidence are pivotal to adoption.
- PR and SI also directly shape adoption intentions, revealing that user concerns and peer influence both hold psychological weight.

- CS and CPV contribute to RA through separate, non-mediated channels, reinforcing the relevance of customer experience in strategic technology decisions.

4.6.3 Practical Implications

The structural results yield valuable recommendations for system designers, restaurant operators, and policymakers aiming to promote robot adoption in hospitality settings:

- Vendors/Developers: Prioritize ease of use and reliability in robot design to address usability and trust, which are key drivers of adoption.
- Restaurant Managers: Facilitate employee exposure to robotic systems through trial use, training sessions, and operational pilots to strengthen perceived usefulness and acceptance.
- Policymakers: Reduce perceived risk by establishing certification programs, promoting awareness campaigns, and setting service standards for robotic deployments.
- Marketers: Highlight customer satisfaction, consistency of service, and positive social proof in promotional strategies to influence both CPV and social influence channels.

In summary, the validated structural model confirms a parallel-path influence structure where each construct contributes directly to RA. This model provides a practical blueprint for encouraging adoption and designing implementation strategies tailored to the technical, psychological, and experiential factors relevant to the restaurant sector in Bangkok.

Chapter 5
Conclusion and Recommendation

Chapter 5 presents a comprehensive synthesis of the research findings, linking the empirical outcomes from Chapter 4 with theoretical frameworks and practical realities in Bangkok's restaurant industry. The chapter begins by summarizing the key results and discussing their relevance within the extended Technology Acceptance Model (TAM). It then explores the broader theoretical contributions of the study, identifies implications for practitioners and policymakers, outlines the study's limitations, and proposes directions for future research. The chapter concludes by reinforcing the significance of understanding both cognitive and affective factors that influence the adoption of robotics in service-oriented business environments.

5.1 Summary of Findings

This research explored the factors influencing the adoption of robotics in Bangkok's restaurant industry using an extended Technology Acceptance Model (TAM). Drawing upon a comprehensive dataset from 400 restaurant managers and operators, the study analyzed multiple constructs including Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Trust in Technology (TT), Perceived Risk (PR), Social Influence (SI), Customer Satisfaction (CS), Customer Perceived Value (CPV), and Robot Adoption (RA). The findings support the robustness of the extended TAM framework in explaining behavioral intentions in the restaurant sector.

Key outcomes include:

- Perceived Usefulness (PU) emerged as the strongest direct predictor of Robot Adoption (RA) with a standardized coefficient of 0.86*.
- Perceived Ease of Use (PEOU) directly and significantly influenced RA **(**0.83***)**, underscoring the critical role of usability in adoption decisions.
- Trust in Technology (TT) also showed a significant direct effect on RA **(**0.79***)**, emphasizing the importance of building trust in robotic systems.
- Perceived Risk (PR) directly influenced RAI **(**0.70***),** suggesting that while users acknowledge risks, it still plays a significant role in their intention to adopt.
- Social Influence (SI) had a notable impact on RA **(**0.70***)**, highlighting the influence of peers and social norms in shaping attitudes toward robot use.
- Customer Perceived Value (CPV) showed a direct positive relationship with RA **(**0.62***)**, demonstrating that customers' evaluation of value contributes to adoption intention.
- Customer Satisfaction (CS) significantly influenced RA **(**0.68***)**, linking positive user experiences with greater likelihood of adoption.
- Mediation Insight: The model does not indicate mediation effects of PU or CPV explicitly; all variables in the diagram point directly to RA without intermediate pathways. Therefore, mediation analysis should not be concluded from this framework.

These findings collectively reinforce the centrality of both cognitive appraisals (usefulness, ease of use, trust, social influence, and risk) and affective evaluations (customer satisfaction and perceived value) in driving robot adoption decisions in the restaurant industry. Most notably, Perceived Usefulness (PU) emerged as the strongest direct predictor**of** Robot Adoption (RA), with a standardized coefficient of 0.86. This suggests that restaurant decision-makers place

high importance on tangible operational benefits—such as increased efficiency, accuracy, and service consistency—when evaluating robotics. This aligns with prior research that consistently identifies PU as a key determinant of technology adoption across sectors.

Additionally, both Perceived Ease of Use (PEOU) and Trust in Technology (TT) had strong and direct impacts on RA (0.83 and 0.79, respectively), rather than operating through PU as initially expected in traditional TAM frameworks. This finding indicates that restaurant managers and staff do not necessarily perceive usefulness as a derivative of ease or trust but rather view each construct as an independent factor in their overall decision-making. When robotic systems are intuitive and inspire confidence, operators are more likely to adopt them, even before fully evaluating their utility. This underscores the significance of interface simplicity and trust-building mechanisms, such as vendor support and demonstrable reliability.

Contrary to the original assumption of an indirect relationship, Perceived Risk (PR) also directly influenced RA with a notable coefficient of 0.70. This suggests that risk perceptions play a direct and substantial role in shaping adoption decisions. Concerns over operational disruptions, technological failure, investment returns, or customer backlash can discourage robot adoption even if the perceived usefulness is high. Therefore, risk mitigation strategies—such as pilot programs, after-sales service, leasing models, or co-branding with trusted partners—are essential for lowering the psychological and financial barriers to adoption.

Social Influence (SI) also showed a direct and strong effect on RA (0.70), highlighting the role of external pressure and normative expectations in encouraging robot adoption. This suggests that industry trends, peer behavior, and customer expectations can significantly sway managerial decisions, especially in competitive urban settings like Bangkok. Leveraging testimonials, case studies, and endorsements may therefore amplify adoption momentum.

From the customer perspective, both Customer Perceived Value (CPV) and Customer Satisfaction (CS) played critical roles. CS directly influenced RA (0.68), indicating that customer contentment with current operations contributes to the confidence needed to adopt new technologies. Furthermore, CPV also directly affected RA (0.62), showing that when managers perceive that customers value the dining experience enhanced by robots—through novelty, service speed, or reliability—they are more likely to invest in such solutions. These findings highlight that robot adoption decisions are not purely operational but deeply interwoven with customer-centric thinking.

Importantly, the model did not indicate any mediating relationships—all independent variables directly impacted robot adoption. This implies that PU and CPV, while influential, do not act as mediators linking other constructs to RA, contradicting initial mediation assumptions. Each factor—whether technical, psychological, or experiential—exerts an independent and direct influence on adoption intent.

Subgroup analysis further revealed organizational differences. Medium and large-sized businesses tended to report higher levels of PU, TT, and RA, indicating greater openness to innovation, likely due to better resource availability and prior exposure to digital technologies. In contrast, smaller establishments showed heightened sensitivity to PR and placed more emphasis

on CS, suggesting that operational risk and immediate customer feedback weigh more heavily in their strategic decisions.

In conclusion, this study provides a robust, multi-dimensional framework for understanding robot adoption in the foodservice sector. Rather than following a strictly linear logic of utility-based evaluation, the findings illustrate that robotic adoption intentions arise from a confluence of functional reasoning (PU, PEOU, TT, PR, SI) and customer-related factors (CS, CPV). This reinforces the applicability of an extended TAM in service industries and offers actionable implications for robotics vendors, hospitality managers, and policy stakeholders aiming to foster technology integration in restaurants.

5.2 Theoretical Implications

This study makes several notable contributions to the theoretical understanding of technology adoption by extending the traditional Technology Acceptance Model (TAM) into the hospitality sector, specifically within the dynamic context of Bangkok's restaurant industry. The integration of constructs such as Trust in Technology (TT), Perceived Risk (PR), Social Influence (SI), Customer Satisfaction (CS), and Customer Perceived Value (CPV) significantly enhances the explanatory power of TAM and adapts it for a service-intensive setting where operational efficiency and customer experience are tightly intertwined. This comprehensive model accounts for both technological and psychological variables, offering a more holistic understanding of adoption behavior in high-contact environments.

Firstly, this study reaffirms the foundational roles of Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) within the TAM framework, both of which exert strong direct effects on Robot Adoption (RA). However, the direct and substantial impacts of TT, PR, and SI on RA—as shown in the structural model—challenge the traditional hierarchical view that such constructs operate solely through PU. This finding broadens the conceptualization of technology adoption by highlighting that trust, risk perceptions, and social cues independently shape adoption intentions, rather than merely influencing utility judgments. It emphasizes the need to treat these constructs as distinct and parallel predictors in future TAM extensions.

Secondly, the integration of CS and CPV introduces a dual-path approach that reflects both managerial priorities and customer-centered thinking. In contrast to earlier theoretical models that positioned these variables as mediators, this study identifies them as direct influencers of RAI, underscoring their strategic importance in service-sector decision-making. The findings suggest that customer feedback and perceived value are not secondary considerations but are primary drivers of adoption behavior. This highlights the growing importance of customer-oriented innovation frameworks within hospitality technology studies.

Moreover, the inclusion of Social Influence (SI) into the extended model adds a vital socio-psychological dimension. While classic TAM focuses on individual cognition, SI acknowledges the real-world impact of peer behavior, market expectations, and cultural norms—especially in collectivist societies like Thailand. The significance of SI as a direct determinant of RA reinforces the importance of integrating social theories into adoption models and provides theoretical

grounding for further exploration of normative pressures and group conformity in technology decision-making.

The model proposed in this research also aligns with socio-technical systems theory, which posits that technology adoption results from the interaction of technical components and social environments. The strong influence of trust, perceived risk, customer considerations, and social norms suggests that adoption is not determined solely by functionality. Instead, it is co-constructed by organizational behavior, psychological comfort, and user expectations. This multi-layered perspective enriches existing adoption theories and supports the development of integrative models suited for complex service ecosystems.

Additionally, while mediation was previously hypothesized, the final model did not confirm any indirect effects through PU or CPV. Rather, each construct demonstrated a direct relationship with RA. This outcome refines the theoretical understanding of how adoption decisions are made in practice—suggesting that users form intentions based on a combination of independent assessments rather than a sequence of mediated evaluations. Future theoretical models should reconsider the necessity of mediation pathways and instead explore parallel, multi-criteria decision-making structures in service technology contexts.

Finally, by focusing on a rapidly evolving Asian metropolis—Bangkok—this study expands the geographic and cultural scope of TAM-based research. Much of the existing TAM literature is grounded in Western contexts; this study demonstrates the framework's validity and adaptability in Southeast Asia, where restaurant businesses operate under unique blends of traditional expectations and modern technology pressures. The findings contribute to an emerging body of research that tailors adoption models to reflect localized consumer behavior, infrastructure maturity, and socio-cultural nuances.

In summary, the theoretical implications of this study are both deep and broad. It reinforces TAM's core validity while evolving it into a more comprehensive, context-sensitive framework that integrates individual, organizational, and customer-related variables. These insights offer a richer theoretical foundation for future studies in service innovation, particularly in high-contact industries navigating the intersection of digital transformation and customer satisfaction.

5.3 Practical Implications

The study offers several actionable insights for a variety of stakeholders involved in the adoption and deployment of robotics in the restaurant industry. The practical implications are drawn directly from the empirical findings and reflect the behavioral patterns observed across different segments of restaurant operations in Bangkok. With all key constructs—Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Trust in Technology (TT), Perceived Risk (PR), Social Influence (SI), Customer Satisfaction (CS), and Customer Perceived Value (CPV)—exerting direct influence on RA, a coordinated, multi-faceted approach is necessary for successful implementation.

For Restaurant Managers and Operators: One of the most significant applications of this research is the emphasis on enhancing PU, which was found to be the strongest predictor of RA. Managers should prioritize robotic systems that deliver measurable value, such as improved operational speed, labor efficiency, and service consistency. Robots that perform practical tasks like serving food, guiding customers, or cleaning can demonstrate immediate utility. Equally important is the focus on PEOU—selecting systems with simple user interfaces and intuitive controls reduces resistance from staff and facilitates daily operations. Building trust (TT) is also critical; this can be achieved through structured onboarding, open communication, and gradual exposure via pilot projects or training workshops.

For Technology Vendors and Solution Providers: Vendors must design robots that are not only functional but also user-friendly and trustworthy, as both PEOU and TT directly influence adoption. Offering customization options, multi-language interfaces, and visual tutorials enhances the user experience. Providing responsive after-sales support, system reliability guarantees, and transparent data policies builds long-term trust. Vendors must also address PR by explicitly demonstrating safety features, system uptime reliability, and contingency protocols. Social validation strategies, such as case studies or endorsements from early adopters, can also amplify the effect of Social Influence (SI) and reduce hesitation among potential clients.

For Policy Makers and Industry Regulators: Policymakers have a crucial role in enabling safe and equitable adoption of robotics. Financial incentives like tax credits, technology grants, or subsidized leasing models can lower entry barriers, especially for SMEs. The development of regulatory frameworks covering robot safety standards, data privacy, and human-robot interaction protocols can provide structure and assurance for both businesses and customers. Additionally, fostering public awareness and organizing demonstration events or pilot showcases can promote positive perceptions of robotics and leverage Social Influence as a driver of widespread adoption.

For Training Institutions and Educational Bodies**:** The direct effects of TT and PEOU on adoption intentions highlight the importance of building digital confidence among staff. Hospitality and vocational training centers should integrate robotics education, hands-on workshops, and certification programs into their curricula. These programs can increase digital literacy, reduce anxiety toward automation, and foster a culture of innovation. Targeted upskilling for existing employees—particularly in small, traditional restaurants—will help reduce operational friction and empower staff to effectively use robotic technologies. These initiatives can also support inclusive adoption across varying business sizes and technological readiness levels.

For Researchers and Future Innovators: This study opens pathways for deeper exploration into customer-centered innovation and Human-Robot Interaction (HRI) design in service environments. With CS and CPV shown to directly impact RA, future research should explore how robots influence customer emotion, engagement, and perceived value across different service

contexts. Developers and researchers can co-design solutions that align with cultural expectations, emphasize emotional intelligence, and adapt in real time to customer needs. There is also scope for refining HRI frameworks specific to restaurants, focusing on personalization, role flexibility, and seamless integration into existing workflows.

In conclusion, the practical implications of this research are extensive and multifaceted. Each stakeholder—restaurant operators, technology developers, policy authorities, educators, and researchers—has a strategic role to play in advancing the effective deployment of robotics in the foodservice sector. By addressing usability, building trust, managing perceived risk, and reinforcing positive customer experiences, a supportive ecosystem for adoption can be cultivated. With thoughtful planning and collaborative execution, robotic technologies can be integrated sustainably and successfully into restaurant operations across Bangkok and beyond.

5.4 Limitations of the Study

While this research provides valuable insights, several limitations should be noted:

- The study is geographically confined to Bangkok, which may limit the generalizability of the findings to other cultural or economic contexts.
- The cross-sectional design captures perceptions at a single point in time and does not account for longitudinal changes in adoption behavior.
- Self-reported data may introduce biases related to social desirability or recall.
- The reliance on survey methods limits the depth of contextual understanding; qualitative follow-ups could offer richer narratives.

5.5 Recommendation for Future Research

This study opens the door to numerous promising avenues for future research in the domain of robotics and technology adoption in service industries. Given the dynamic nature of technology and the hospitality sector, expanding the empirical and conceptual frameworks developed in this research can yield deeper, more longitudinal insights.

One recommended direction is the use of longitudinal study designs to track changes in adoption behavior over time. A cross-sectional approach, as used in the present study, provides a valuable snapshot, but it cannot account for temporal dynamics. Longitudinal research would allow scholars to examine whether restaurant operators' perceptions and intentions evolve as they gain more experience with robotic systems. This approach could also help identify stages of adoption—awareness, trial, full implementation—and the corresponding challenges or drivers unique to each phase.

Another valuable direction involves expanding the geographical scope of the study. While Bangkok provides a vibrant and representative urban setting for investigating technology adoption in the restaurant industry, the findings may not generalize across cities or regions with different economic, cultural, or technological infrastructures. Future research could conduct comparative studies across cities within Thailand, or even internationally, to understand how context-specific

variables, such as regulation, consumer preferences, labor markets, or infrastructure, affect robot adoption patterns.

Additionally, researchers are encouraged to incorporate qualitative methods into future studies. In-depth interviews, focus groups, and ethnographic case studies can uncover the nuanced meanings, cultural interpretations, and day-to-day realities of using robotics in hospitality settings. Such approaches can capture emotional responses, cultural narratives, and organizational dynamics that are not easily observable through quantitative surveys. These insights can help design more human-centered and culturally adaptable robotic systems.

Another important recommendation is the exploration of additional influencing variables that were beyond the scope of this study but likely play a significant role. For example, organizational readiness, including technological infrastructure, leadership support, and staff competency, may moderate or mediate adoption behaviors. Similarly, financial constraints and cost-benefit perceptions—especially among small to medium-sized enterprises—are crucial factors that could influence decision-making.

Staff resistance to robotics is another variable that warrants deeper investigation. While managers and owners may favor adoption, frontline workers might perceive robots as threats to job security or burdens to existing workflows. Understanding the concerns and attitudes of employees at all organizational levels will provide a more comprehensive picture of organizational acceptance.

Future research could also look at post-adoption outcomes, such as customer loyalty, employee satisfaction, and ROI performance metrics. Examining how robot implementation affects business performance over time will provide stronger evidence for or against large-scale deployment.

Moreover, emerging technologies such as AI integration, predictive analytics, and human-robot collaboration models present fresh opportunities for exploration. Researchers should consider how converging technologies shape perceptions and outcomes of robotic adoption, as the restaurant of the future is likely to be influenced not by robotics alone but by a constellation of smart systems.

Finally, there is merit in exploring the policy and societal impacts of service robot adoption. Questions surrounding labor displacement, reskilling, ethical service standards, and social equity should be addressed, particularly in markets undergoing rapid digital transformation.

In sum, the future of research in this domain is ripe with possibility. As robotics continues to evolve and integrate into diverse service contexts, interdisciplinary and multi-method approaches will be essential. The foundation laid by this study provides a valuable platform from which scholars can build more nuanced, inclusive, and impactful explorations of technology adoption in the hospitality and service sectors.

5.6 Conclusion

This study affirms that robot adoption in Bangkok's restaurant industry is influenced by a complex interplay of technical, psychological, and customer-related factors. By validating an extended TAM framework and emphasizing both managerial and consumer dimensions, the research provides a nuanced understanding of how technological innovations are evaluated and implemented in real-world foodservice operations. These insights not only advance academic discourse but also serve as a strategic guide for restaurant operators, technology developers, and policymakers aiming to foster innovation in the hospitality sector.

The implications of this study go beyond the boundaries of Bangkok and resonate with broader shifts occurring globally across service industries. The extended TAM model used in this research has demonstrated robust explanatory power, proving capable of encompassing both cognitive and emotional determinants of technology adoption. Constructs such as perceived usefulness, ease of use, and trust remained central, but the inclusion of customer satisfaction and perceived value allowed for a more holistic and human-centered understanding of adoption behavior.

Practically, the research underscores the necessity for restaurant managers to actively consider not only how robotics impacts internal efficiency but also how it influences the customer experience. A successful robotic integration strategy will likely balance automation with personalization—using machines to enhance speed and consistency, while still preserving the warmth and attentiveness of human service.

This study also makes a case for broader systemic support for innovation adoption. The relatively lower scores for trust and the inverse effect of perceived risk indicate that decision-makers still harbor doubts about the reliability and security of robotic systems. Industry stakeholders, including vendors, regulators, and educators, must work in tandem to alleviate these concerns through training, regulation, and transparent communication.

Importantly, this study adds depth to the conversation around digital transformation in emerging markets. While much of the global discussion is centered on Western contexts, Bangkok represents a vibrant urban hub in Southeast Asia with its own unique set of cultural, economic, and infrastructural challenges. By focusing on this locality, the study adds valuable regional insight and showcases the potential for technological adaptation even in high-context service environments.

Looking forward, the findings presented here lay a strong foundation for future investigations. The adoption of robotics is not a one-time decision, but an ongoing process that must adapt to changing consumer expectations, workforce dynamics, and technological advancements. As AI capabilities expand and human-robot collaboration deepens, future research and managerial strategies will need to evolve accordingly.

In conclusion, this research bridges academic theory and industry practice, illustrating how a comprehensive and contextual approach to technology adoption can foster innovation while respecting the intricacies of the human experience. It invites continued exploration into how

service businesses can embrace the future, not just through efficiency, but with empathy, foresight, and inclusive design.

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Appendix

Survey Questionnaires

No.	Citation	Variable	Question	5	4	3	2	1
1.	Davis (1989); Seo & Lee (2021)	Perceived Usefulness (PU)	Robots improve the speed of restaurant services.					
2.	Davis (1989)		Robots enhance overall service quality in restaurants.					
3.	Lee et al. (2018)		Robots increase restaurant operational efficiency.					
4.	Lee et al. (2018)		Adopting robots reduces operational costs effectively.					
5.	Davis (1989)	Perceived Ease of Use (PEOU)	Learning to operate service robots is straightforward.					
6.	Davis (1989)		Robots require minimal effort to integrate into daily operations.					
7.	Seo & Lee (2021)		Minimal training is required for staff to use robots effectively.					
8.	Seo & Lee (2021)		Robot interfaces in restaurants are easy to understand and use.					
9.	Seo & Lee (2021)	Trust in Technology (TT)	Service robots reliably perform their tasks consistently.					
10.	Seo & Lee (2021)		I trust robots to safely manage food service without errors.					
11.	Seo & Lee (2021)		Robots in restaurants are safe to interact with.					
12.	Seo & Lee (2021)		I trust the robot to operate effectively without supervision.					
13.	Hansen et al. (2019)	Perceived Risk (PR)	Restaurant robots might frequently malfunction during service.					
14.	Hansen et al. (2019)		Using robots could lead to increased errors in orders or service delivery.					
15.	Mutahar et al. (2020)		There are potential safety risks associated with robot usage in restaurants.					
16.	Hansen et al. (2019)		Robots in restaurants could negatively affect customer safety.					
17.	Venkatesh et al. (2003)	Social Influence (SI)	Important people to me encourage using restaurant robot services.					
18.	Venkatesh et al. (2003)		Restaurants using robots have positive public perceptions.					
19.	Venkatesh et al. (2003)		Competitors successfully using robots influence our adoption decision.					

No.	Citation	Variable	Question	5	4	3	2	1
20.	Venkatesh & Davis (2000)		Social trends toward automation encourage robot adoption in restaurants.					
21.	Kim & Qu (2022)	Customer Satisfaction (CS)	Robot services consistently meet customer expectations.					
22.	Kim & Qu (2022)		Overall customer satisfaction improved after introducing robot services.					
23.	Jin et al. (2015)		Customer feedback regarding restaurant robots is very positive.					
24.	Jin et al. (2015)		Customers express high satisfaction with robotic restaurant services.					
25.	Zeithaml (1988)	Customer Perceived Value (CPV)	Robots provide good value for money in restaurant settings.					
26.	Zeithaml (1988)		Using robots enhances the perceived value of dining experiences.					
27.	Yang & Peterson (2004)		The benefits received from restaurant robots outweigh the costs.					
28.	Zeithaml (1988)		Overall, restaurant robots deliver substantial value to customers.					
29.	Jang & Lee (2016)	Robot Adoption (RA)	I intend to adopt robots in my restaurant operations in the near future.					
30.	Venkatesh et al. (2003)		I am likely to continue using service robots once they are introduced in the restaurant.					
31.	Jang & Lee (2016)		I will recommend the adoption of service robots to other restaurant operators.					
32.	Venkatesh et al. (2003)		I am willing to invest in robotic technology to improve service quality in my restaurant.					