APPENDIX D

UNIVERSITI TUNKU ABDUL RAHMAN
FACULTY OF ACCOUNTANCY AND MANAGEMENT
UNDERGRADUATE FINAL YEAR PROJECT

Final Year Project Assessment Form - Report

Final Year Project Title:

ANALYSING THE EFFECTIVENESS OF REAL-TIME INVENTORY TECHNOLOGY IN OPTIMISING CENTRAL KITCHEN OPERATIONS

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No	Criteria	Excellent (8 - 10 marks)	Good (5 - 7 marks)	Fair (3 - 4 marks)	Poor (0 - 2 marks)	Awarded
1	**Title and Abstract**	Clear, concise, and informative; abstract summarizes all key elements effectively.	Title and abstract are clear but may miss some key elements.	Title and abstract are somewhat unclear or incomplete.	Title and abstract are unclear and do not summarize key elements.	
2	**Introduction**	Comprehensive background and context; clearly stated research question/hypothesis.	Adequate background; some context missing; research question/hypothesis is stated.	Background and context are vague; research question/hypothesis is unclear.	Background and context are missing or inadequate; research question/hypothesis is absent.	
3	**Literature Review**	Extensive review, critical analysis, and synthesis of relevant literature.	Adequate review with some analysis of relevant literature.	Limited review with minimal analysis of relevant literature.	Inadequate or no review of relevant literature.	
4	**Problem Statement & Objectives**	A clear, specific, and well-defined research problem was identified, including its significance and relevance. Clearly defined, specific, and measurable objectives.	Clearly stated problem, but may lack specificity or clarity in its significance. Objectives are stated but may lack specificity or measurability.	Problem statement is present but lacks clarity, specificity, or relevance. Objectives are vague or not well-defined.	The problem statement is unclear or missing. Objectives are absent or unclear.	
5	**Methodology**	Detailed, appropriate methods with clear rationale and feasibility.	Methods are outlined but some details or rationale may be lacking.	Methods are mentioned but lack clarity or rationale.	Methods are unclear, inappropriate, or not stated.	
6	**Results**	Results are clearly presented, well-organized, and thoroughly analyzed.	Results are presented but may lack organization or depth of analysis.	Results are unclear or poorly organized, with limited analysis.	Results are absent, unclear, or inadequately analyzed.	
7	**Discussion**	Insightful interpretation of results, connects to literature, discusses reasons for the findings.	Interpretation of results is present but may lack depth, some connection to literature.	Limited interpretation of results, minimal connection to literature.	Interpretation of results is absent or unclear, no connection to literature	
8	**Conclusion**	Comprehensive conclusion with discussions on implications supported by findings. Suggests future research.	Conclusion is present with key points somewhat summarized. Discussions on implications somewhat supported by findings. Suggests future research.	Weak conclusion, does not effectively summarize findings or suggest future research. Implications irrelevant to findings.	Conclusion is absent or very weak.	
9	**Writing Quality**	Excellent writing, free from errors, clear and professional.	Writing is clear but contains some errors or lacks professionalism.	Writing is unclear in parts, contains errors, and lacks professionalism.	Writing is unclear, contains numerous errors, and is unprofessional.	
10	**References**	Extensive and relevant references, properly formatted.	References are relevant but formatting is inconsistent.	Few references, some may be irrelevant or improperly formatted.	References are absent, irrelevant, or improperly formatted.	
					Total	

ANALYSING THE EFFECTIVENESS OF REAL-TIME INVENTORY TECHNOLOGY IN OPTIMISING CENTRAL KITCHEN OPERATIONS

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FACULTY OF ACCOUNTANCY AND MANAGEMENT

DEPARTMENT OF INTERNATIONAL BUSINESS

MAY 2025

ANALYSING THE EFFECTIVENESS OF REAL-TIME INVENTORY TECHNOLOGY IN OPTIMISING CENTRAL KITCHEN OPERATIONS

BY

SIM KAH KHAI

A final year project submitted in partial fulfilment of the requirement for the degree of

BACHELOR OF INTERNATIONAL BUSINESS (HONOURS)

UNIVERSITI TUNKU ABDUL RAHMAN

FACULTY OF ACCOUNTANCY AND MANAGEMENT
DEPARTMENT OF INTERNATIONAL BUSINESS

MAY 2025

DECLARATION

I hereby declare that:

(1) This undergraduate FYP is the end result of my own work and that due acknowledgement has been given in the references to ALL sources of information be they printed, electronic, or personal.

(2) No portion of this FYP has been submitted in support of any application for any other degree or qualification of this or any other university, or other institutes of learning.

(3) Sole contribution has been made by me in completing the FYP.

(4) The word count of this research report is 10,000.

Name of student:	Student ID:	Signature:
Sim Kah Khai	22UKB02769	

Date: 14 May 2025

ACKNOWLEDGEMENTS

iI offer my heartfelt gratitude to Puan Ezatul Emilia Binti Muhammad Arif, my final-year project supervisor, for her steadfast support, valuable insights and feedback, and patient guidance throughout my research journey for the past 6 months. I am just as grateful to Puan Nuraishah Raimee, my second examiner, for the valuations, feedback and recommendations during the FYP presentation. I thank Mr Muhammad Fadhirul Anuar Mohd Azami for the guidance in using tools such as SMARTPLS4. I am thankful to my friends for giving me guidance and techniques during the research. I am grateful to the participants who contributed towards my work, Lastly, I am greatly thankful for my family who has motivated me along the way and been a source of motivation throughout this research journey.

DEDICATION

I dedicate this research project to my family and friends for their support of my academic pursuits. Support and assistance from them have helped me enhance my knowledge and education throughout this journey. Making this journey an unforgettable experience to cherish.

I am also greatly thankful to my supervisor who has helped me gain knowledge on my research journey and career path. I am grateful for the time, effort and patience she has supported and guided me towards my professional and academic development.

Finally, I would like to dedicate this research to those who are influenced by the subject matter. It is my honour that this study can provide greater knowledge and understanding on online digital platforms activities.

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List of Abbreviations

UTAUT	Unified Theory of Acceptance and Use of Technology
F&B	Food and Beverage
FIFO	First-In-First-Out
PE	Performance Expectancy
EE	Effort Expectancy
SI	Social Influence
FC	Facilitating Conditions
IU	Intention to Use Real-Time Inventory Technology
PLS	Partial Least Squares
SEM	Structural Equation Modelling

PREFACE

This research project has been prepared as part of my final year project submitted in partial fulfilment of the requirement for the degree of Bachelor of International Business (Honours) in Universiti Tunku Abdul Rahman under the supervision of Puan Ezatul Emilia binti Muhammad Arif. This study aims to provide knowledge, results and findings about how real-time inventory technology can improve central kitchen optimization. The objective of this research is to investigate the business owner, manager, and staff intention to use real-time inventory technology by using the UTAUT model. This study aims to analyse the relationship between Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, and Intention to use real-time inventory technology.

ABSTRACT

This study investigates the role of real-time inventory technology in optimizing central kitchen operations within the food and beverage (F&B) industry. Central kitchens, designed to centralize food preparation and distribution, are pivotal in improving operational efficiency, reducing costs, and maintaining consistent quality. However, challenges such as inefficient resource utilization, excessive food waste, and lapses in inventory control continue to hinder their performance. Real-time inventory technology, which incorporates advanced systems like cloud-based platforms, offers a solution by providing continuous monitoring of inventory levels. This ensures timely replenishment, reduces spoilage, and enhances food safety. The research employs the Unified Theory of Acceptance and Use of Technology (UTAUT) framework to examine the factors influencing the adoption of this technology. The study evaluates key variables such as performance expectancy, effort expectancy, social influence, and facilitating conditions to understand their impact on user intention to adopt real-time inventory systems. The research employs a quantitative methodology, utilizing structured questionnaires distributed among central kitchen stakeholders in Malaysia. Data is analysed using descriptive and Partial Least Squares (PLS) tools to evaluate relationships between variables and their impact on intention to use. The findings of this research aim to provide actionable insights into how central kitchens can leverage real-time inventory technology to improve inventory management, reduce food waste, enhance food safety, and achieve higher operational efficiency. The study contributes to the growing body of knowledge on digital tools in F&B operations, offering practical recommendations for industry stakeholders to implement sustainable and efficient inventory practices.

Keywords: Real-time inventory, Central kitchen, UTAUT, Operational efficiency, Food Waste

CHAPTER 1: RESEARCH OVERVIEW

1.0 Introduction

This research aims to study and investigate how e-commerce integration impacts the optimization of central kitchen operations in the food and beverage (F&B) industry.

1.1 Research Background

The rapid development of technology, changing consumer perspectives, and the growing need for convenience have been the key drivers to the changeover of the food and beverage (F&B) industry (Kanberger et al., 2024). Having an inventory system in real-time significantly improves the operational efficiency of central kitchen operations. It provides immediate visibility into the amount of stock, which avoids overstocking and stockouts. It avoid manual errors and workload, allowing staff to focus on more critical tasks, it also helps to avoid wastage of food by tracking expiry dates and usage patterns (Khatri, 2025). The global inventory management software market is anticipated to grow from USD 2.31 billion in 2024 to USD 4.79 billion by 2032 at a CAGR of 9.6% during the forecast period (Fortune Business Insight 2025). Meanwhile, real-time inventory technologies such as automation, data analytics, and artificial intelligence have made new food preparation and inventory management methods possible into traditional ones.

The central kitchen is a hub for distributing semi-finished or cooked food to each location, where it is processed or reheated before being served to consumers (Phern & Sh, 2020). Across the globe, central kitchens have come up with the idea of an innovative way to reduce food waste and facilitate the delivery of food. Several names can exist together in a single kitchen, which allows for the efficient use of resources such as kitchen space and delivery logistics (Rout et al., 2024). This model aligns with urban needs for faster delivery and cost efficiency. At the same time, automation, artificial intelligence (AI), and data analytics are changing the way standard food and beverage businesses work, opening ways to be more productive and environmentally friendly (Kuppusamy et al., 2024).

Technology progressing at a rapid rate and all around us getting mechanized, individuals prefer keeping an eye and doing their daily chores using the intelligent gadgets they carry with them all the time instead of manually keeping track of and monitoring things (Lakshmi Narayan et al., 2019). It helps shifts in the F&B landscape present opportunities for businesses to innovate and improve their operations. Understanding these trends within both global and local contexts sets the stage for further exploration into optimizing central kitchen operations to thrive in this evolving environment (Jia et al., 2023).

1.2 Research Problem

The food and beverage (F&B) industry's rapid digitization and technology advancing, with the incorporation of e-commerce platforms, has revolutionized how companies conduct business around the world (Whitton et al., 2024). While this shift has brought numerous benefits, it has also introduced challenges that impede the optimal functioning of central kitchen operations. One pressing issue is the inefficiency in resource utilization (Jia et al., 2023). Central kitchens, despite their potential to streamline operations, often face difficulties in managing inventory constraints (Banaeian Far et al., 2023), procurement (Ssemanda et al., 2024), and delivery logistics (Ssemanda et al., 2024) effectively. Real-time invenory offering advanced tools, are not always integrated seamlessly, leading to underutilization of data and technology.

Additionally, the increasing demand for sustainability and waste reduction presents another challenge (Song et al., 2024). Food waste remains a significant problem in central kitchens, where excess inventory and poor monitoring lead to financial losses and environmental harm (Song et al., 2024). Though e-commerce technologies can provide solutions such as real-time inventory tracking and (Nir Kshetri, 2023) predictive analytics (Nir Kshetri, 2023), their adoption in central kitchens is limited or inconsistent. This gap hinders operational efficiency and cost management. The hospitality and food service sectors (including central kitchens) contribute significantly to the annual production of about 1.3 million tons of food waste (Sanju Bala Dhull et al., 2024). Food waste is a problem for the environment as well as the economy because it contributes to 8–10% of global greenhouse gas emissions (Sanju Bala Dhull et al., 2024). An estimated $940 billion is lost every year as a result of food waste in restaurants and commercial kitchens around the world (Viscardi & Colicchia, 2024). These losses could be significantly reduced by using technology to optimize food operations.

The rise of the food and beverage business has highlighted the operational issues of central kitchens, particularly in terms of maintaining efficiency and safety. As of 2024, over 50% of restaurant, including franchises, and traditional restaurant operators have adopted some form of inventory management software, indicating that nearly half still rely on traditional methods such as manual counts, spreadsheets, or paper logs (Bennett, 2025). Additionally, a study on Secret Recipe Subang Perdana showed that the outlet used stock books to monitor stock whereby the employees manually calculated stock during the close, this resulted in inefficiencies in terms of difficulties in ensuring product quality as well as issues due to damaged labels that contained crucial information such as expiry dates (Anuar, 2021). Furthermore, incorrect waste management increases health risks by causing environmental contamination and outbreaks of foodborne illness (Tao et al., 2024).

The First-In-First-Out (FIFO) method of using older inventory before newer inventory remains in practice even in Malaysian kitchens. A survey of food and beverage establishments in Malaysia conducted for exploratory purposes showed that the majority of outlets employed FIFO practices to manage their inventory (Ain, 2025), but these control procedures were not followed correctly and needed to be improved. Although FIFO prevents waste and keeps food safe, its manual application is not straightforward without proper training and facilities. Without standard procedures, a reliance on experience staff can lead to inefficiencies and potential food safety hazards (Ain, 2025).

These issues motivate the need for research into how real-time inventory systems can optimize central kitchen operations by improving stock accuracy, reducing food waste, and enhancing efficiency. Understanding their effectiveness can support better adoption and drive sustainable, data-driven practices within the food and beverage industry.

1.3 Research Objectives

The main objective of this study is to investigate the impact of real-time inventory on the optimization of central kitchen operations in the food and beverage (F&B) industry.

1.3.1 General Objectives

The main objective is to understand how real-time inventory impacts the optimization of central kitchen operations in the food and beverage (F&B) industry.

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1.3.2 Specific Objectives

1. To investigate the relationship between **Performance Expectancy** and **Intention to Use** real-time inventory technology in central kitchen operations.
2. To investigate the relationship between **Effort Expectancy** and **Intention to Use** real-time inventory technology in central kitchen operations.
3. To investigate the relationship between **Social Influence** and **Intention to Use** central kitchens real-time inventory technology in central kitchen operations.
4. To investigate the relationship between **Facilitating Conditions** and **Intention to Use** real-time inventory technology in central kitchen operations.

1.4 Research Question

1. Is there any relationship between **Performance Expectancy** and **Intention to Use** real-time inventory technology in central kitchens.
2. Is there any relationship between **Effort Expectancy** and **Intention to Use** real-time inventory technology in central kitchens.
3. Is there any relationship between **Social Influence** and **Intention to Use** real-time inventory technology in central kitchens.
4. Is there any relationship between **Facilitating Conditions** and **Intention to Use** real-time inventory technology in central kitchens.

1.5 Research Significant

This study contributes to the knowledge base in the application of real-time inventory technology in central kitchen operations. Because central kitchens are critical to the efficient and scalable nature of the food and beverage (F&B) industry, real-time inventory systems present a technological fix to correct long-standing issues such as inventory error, food wastage, and wasteful stock management. Through exploring the dynamic interplay of real-time inventory technology and critical operating outcome. Such as precision, food safety, waste reduction, and cost efficiency, this research provides theoretical and practical input into digital optimization techniques. Findings aim to aid central kitchen managers and decision-makers in the uptake of data-enabled technology solutions for enhanced control, responsiveness, and productivity. The research further investigates the value of system use friendliness, personnel readiness, and organizational backing for effective technological transition. In the case of Malaysia, where central kitchens expanded to meet rising demand for delivery service and mass food production, this research serves as a timely guidebook to help companies transition to wiser, more efficient practice. The results can also assist policymakers and corporate leaders in pushing for digital transformation, facilitating effective resource utilization, and enhancing food safety and environmental responsibility across the sector.

1.6 Conclusion

The researcher and business owner were encouraged to investigate the use of real-time inventory system to optimize central kitchen operations when the research problem and its significance were summarized. The research objective and questions have been stated.

CHAPTER 2: LITERATURE REVIEW

2.0 Introduction

This chapter included a list of the earlier study projects conducted by academics that the researcher had evaluated. It focused on discussing theories and reviewing relevant literature and variables.

2.0.1 Central Kitchen

Central kitchens with an enabling environment play a critical role in the promotion of synergy among connected industries, improving the efficiency of production, and driving the development of food industrialization; it is a centralized kitchen facility in which food is prepared in large quantities and distributed to various sites or outlets like restaurants, catering companies, or delivery-focused cloud kitchens (Jia et al., 2023). Central Kitchen uses standardized recipes and processes to ensure that customers receive uniform taste and quality across all outlets and maintains high food safety and hygiene standards (Noor & Mohd, 2020). By centralizing production, businesses benefit from economies of scale, allowing for bulk purchasing and streamlined processes, which reduce overall labor and overhead expenses. The technological innovation and industrialization of culinary food in central kitchens is reflected in prepared foods as an extension technology of preconditioned foods and industrially prepared culinary foods (Li et al., 2022). Present is also increased consumption of prepared foods that are semifinished or finished products from poultry, livestock, agricultural, and fish origins, and which are then processed together with other auxiliary ingredients and undergone preprocessing operations that include cutting, mixing, forming, rolling, and seasoning (Jia et al., 2023).

2.0.3 Real-Time Inventory Management

Real-time inventory refers to the process of continuously tracking and updating stock levels using technology-enabled systems (Setyawan et al., 2022). This approach allows businesses to maintain accurate, up-to-the-minute transparency into inventory availability, helping them manage resources efficiently and make informed decisions (Pilati et al., 2024). Unlike traditional methods, which rely on periodic inventory checks and manual record-keeping, real-time inventory systems use tools such as barcodes, RFID tags, and cloud-based software to automate data collection and synchronization (Kumar et al., 2024) (Pacheco et al., 2024). In the food and beverage (F&B) industry, real-time inventory management is particularly critical for ensuring product freshness, reducing food waste, and maintaining health and safety standards (Barto et al., 2024). By providing instant notifications on low stock levels, expiration dates, or discrepancies, these systems enable businesses to respond proactively to supply chain challenges. Real-time inventory is also vital in the e-commerce ecosystem, where consumer expectations for speed and accuracy necessitate precise stock monitoring to avoid overpromising or underdelivering (Shili et al., 2024). This technology not only improves operational efficiency but also enhances customer satisfaction (Kumar et al., 2024) by ensuring that products are always available and delivered on time (Wang et al., 2022).

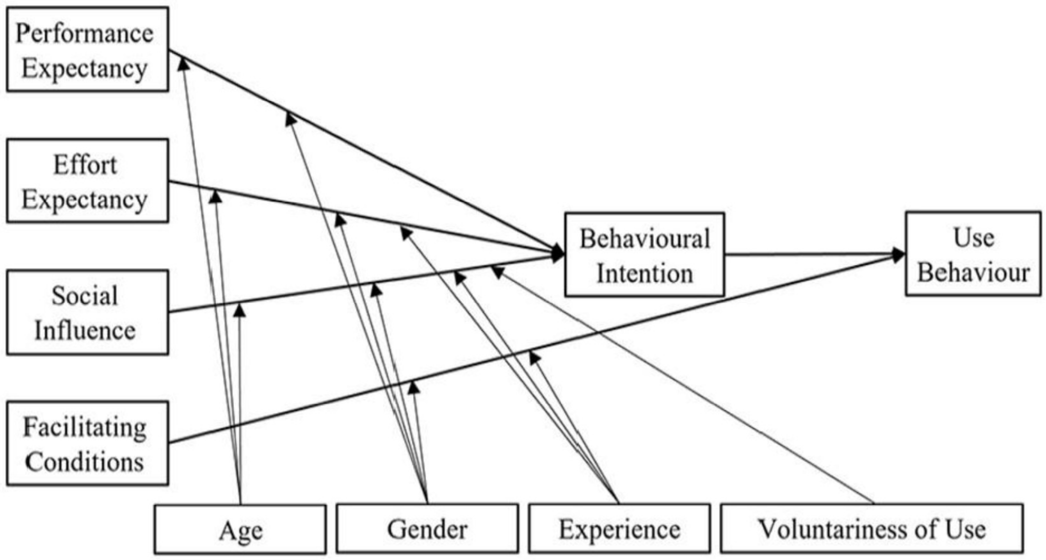
2.1 Underlying Theories

2.1.1 The Unified Theory of Acceptance and Use of Technology (UTAUT)

The Unified Theory of Acceptance and Use of Technology (UTAUT) is a popular framework used in technology adoption studies. (Rana et al, 2024). UTAUT is a model that determines the most significant factors that make up a person's decision in adopting and using a new technology (Xue et al., 2024). The UTAUT model employed the belief that the acceptance of the given technology will bring measurable improvement in some key aspects (Abdalla et al., 2024). Effort Expectancy is aimed towards the simplicity of using the technology (Abdalla et al., 2024). Social Influences is aimed towards competitors, or standard within an industry that drives the user towards adopting the technology (Abdalla et al., 2024). Facilitating Conditions is aimed towards technical and organizational infrastructure that is in place for the utilization of the system (Abdalla et al., 2024).

The widespread use of the UTAUT within numerous industries has established its broad application. It has been used in the study of the use of numerous technologies such as electric cars (Le et al., 2023), artificial intelligence products (Al-Sharafi et al., 2023), the Internet of Things (Scur et al., 2023), and electronic health devices (Cobelli et al., 2023)

Figure 2.1: Unified Theory of Acceptance and Use of Technology



(UTAUT)

Source: Xue et al. (2024)

2.2 Review of variables

2.2.1 Performance Expectancy (PE)

Performance Expectancy (PE) refers to the belief that adopting a particular technology will improve performance and productivity (Abdalla et al., 2024). In the context of central kitchens, this variable emphasizes how the use of a real-time inventory system can streamline operations, minimize inventory shortages, and reduce food waste, thereby enhancing overall efficiency. Individuals with a direct effect of intention to use the system are more likely to adopt it if they perceive clear benefits (Hamed M.H. Mujahed et al., 2024). The report said that the system made inventory management easier and more efficient, allowing users to complete stock audits within specified timeframes (Mwaisumo, 2020). This expectation aligns with the operational goals of central kitchens, making it a key variable in evaluating technology adoption.

2.2.2 Effort Expectancy (EE)

Effort Expectancy (EE) is the perceived ease of usage when adopting a particular technology (Abdalla et al., 2024). EE brings into perspective how a user-friendly interface and a rich functionality of a real-time inventory system is crucial (Gayam, 2019). Real-time inventory technology effort expectancy drives the intention to use by ensuring that the system is user-friendly and accessible. The consequence of such a greater effort expectancy is positively correlated with the intentions of the users to adopt the inventory system (Mwaisumo, 2020). Effort expectancy is a significant driver for technology acceptance because it directly has an impact on the willingness of the users when it comes to using and trusting the system (Abdalla et al., 2024), and makes real-time inventory systems user-friendly and adoptive in nature for the staff in order for them to efficiently manage the inventory.

2.2.3 Social Influence (SI)

Social Influence (SI) refers to the degree to which individuals perceive that important others, such as peers, industry leaders, or competitors, believe they should adopt a particular technology (Abdalla et al., 2024). When competitors, industry standards, or even supply chain partners demonstrate the effectiveness of such systems (Cobelli et al., 2023), central kitchen managers may feel a need to align with these practices to remain competitive and relevant. SI is to assess how the perceptions and recommendations of peers, industry standards, and competitors encourage users to adopt real-time inventory technology, influencing the intention to use. SI explores how industry standards, peer recommendations, and competitor practices encourage the adoption of real-time inventory systems to the research. Social influence highlights the external pressures that central kitchen owners decision-making in technology adoption (Bellet & Banet, 2023). For central kitchens, aligning with these social norms not only fosters credibility but also ensures operational parity with industry leaders.

2.2.4 Facilitating Conditions (FC)

Facilitating Conditions (FC) is the resources and support which facilitate use and posits that there is an organizational and technical infrastructure existing to provide support for and sustain the use of information systems and technology (Abdalla et al., 2024). It highlights the availability of the proper resources, for example, financing investment, technical support, and capacity building to provide a smooth installation and use of a real-time inventory system (Abdalla et al., 2024). FC motivates the intention to use technology through ensuring that central kitchen staff and managers have the support and infrastructure for the use and implementation of real-time inventory technology. It has been seen through research that the presence of facilitative conditions like organizational and technical support directly and significantly impacts the perception of the promise of new technologies at the user level, so it is an important determinant of implementation (Jabeen et al., 2022).

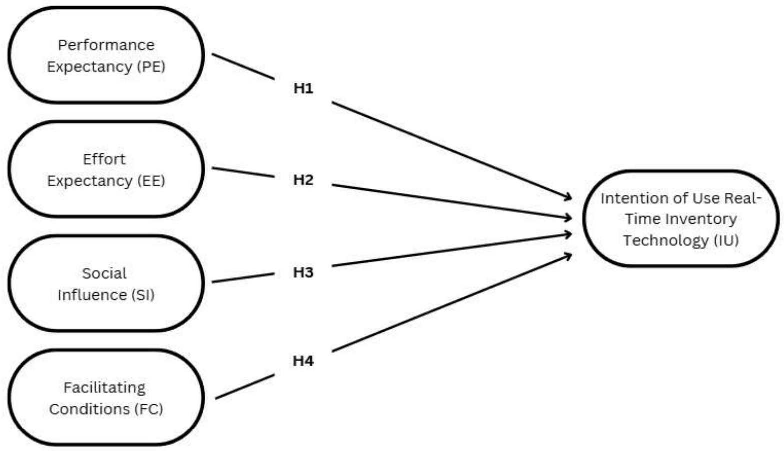
2.2.5 Intention to Use (IU) Real-Time Inventory Technology

Intention to Use (IU) refers to the likelihood or willingness of individuals to adopt and use a particular technology (Menon & K Shilpa, 2023). When staff and managers perceive that the system will improve efficiency, is easy to use, is supported by industry norms, and is backed by adequate resources, their intention to adopt the technology increases (Chao, 2019). Adopting a real-time inventory system requires not only recognizing its potential benefits but also committing to its implementation.

2.3 Conceptual frameworks

The theoretical framework for this study is built based on the Unified Theory of Acceptance and Use of Technology (UTAUT) model. In line with it, the dependent variable, which is the intent to use the system, is influenced by four important independent variables that are performance expectancy, effort expectancy, social influence, and facilitating conditions. The system's perceived capacity to enhance working procedure efficacy and reduce food waste is reflected in Performance Expectancy (McGaughy et al., 2024). Through the measurement of perceptions for use, Effort Expectancy ensures that employees starting from different technical proficiency levels can use the system (Mwaisumo, 2020). While Facilitating Conditions encompass the equipment, training, and support requirements for a flawless implementation (Mwaisumo, 2020), Social Influence underscores the work done by peer pressure and industry norms for encouraging usage (Mwaisumo, 2020). The parsimonious model focuses on the immediate relationship between the IVs and the DV, and it outlines a clear path to determine the important drivers for the adoption and implementation of real-time inventory systems within a central kitchen environment.

Figure 2.2: Conceptual Framework



Source: Developed for Research Purpose

2.4 Hypotheses Development

2.4.1 There is a Relationship between Performance Expectancy and Intention to Use Real-Time Inventory Technology

Performance expectancy plays a powerful role in the prediction of users' intention to use technology since it reflects the notion that the technology will better facilitate their performance. Performance expectancy is the strongest predictor of behavioral technology intention when the perceived benefits align the users' operational goals (Abdalla et al., 2024). On realizing the benefits, belief in the technology increases among users, and it has a favorable implication for them to adopt and utilize the technology (Singha Chaveesuk et al., 2023)

H1: There is a significant relationship between performance expectancy and intention to use real-time inventory technology.

2.4.2 There is a Relationship between Effort Expectancy and Intention to Use Real-Time Inventory Technology

Effort expectancy, referring to the level of ease involved with the usage of technology, is an essential factor that influences users' intention towards adopting and utilizing a system. The easier and more user-friendly the technology is found to be, the more they tend to adopt such technology (Gayam, 2019). Real-time inventory technology should be understandable and not need extensive learning in order to facilitate its adoption. Once users feel that the system is easy to work with and integrate into their routines, the extent of their resistance against using the technology is reduced, and their willingness towards utilization is enhanced (Singha Chaveesuk et al., 2023).

H2: There is a significant relationship between effort expectancy and intention of use real-time inventory technology.

2.4.3 There is a Relationship between Social Influence and Intention to Use Real-Time Inventory Technology

The intention to use and social influence are interrelated because people tend to be influenced by the opinions of others in their social or workplace environment. Social influence is most significant in the initial stage of adopting a technology when people are creating opinions concerning its utility (Xue et al., 2024). A positive endorsement, word of mouth, or trend in the industry is capable of building legitimacy and a sense of urgency, which makes people more inclined towards using the technology (Jain et al., 2022). Users tend to be motivated towards adopting real-time inventory technology if they sense that others among their peers or within the business arena of the same type as them enjoy its advantages.

H3: There is a significant relationship between social influence and intention of use real-time inventory technology.

2.4.4 There is a Relationship between Facilitating Conditions and Intention to Use Real-Time Inventory Technology

Facilitating conditions and intention to use are related because they offer the requisite support and resources that make the adoption of and efficient use of technology more viable. Facilitating conditions play an immense role in affecting users' intention to adopt technology when the users feel that they have the tools, skills, and support necessary to implement it into the workflow (Xue et al., 2024). Users' perception of these enabling factors diminishes both their perceived obstacles for using the system and increases their intention to adopt the technology when they feel certain that they have these factors in place (Jain et al., 2022).

H4: There is a significant relationship between facilitating conditions and intention of use real-time inventory technology.

2.5 Conclusion

Particularly, the conceptual framework, hypothesis development, and literature review have been examined and assessed. We'll talk about the research approach in the upcoming chapter.

CHAPTER 3: METHODLOGY

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3.0 Introduction

This chapter describes the research process that involved the collection of methods used to test the efficiency of real-time inventory technology in central kitchen operations. It elucidates the procedure adopted for the collection of accurate and propitious outcomes that support the objectives of the research as well as the hypotheses.

3.1 Research Design

Research design is the structured plan that guides the entire research process, ensuring that the study effectively addresses its objectives and research questions (Mwaisumo, 2020). It integrates various components, such as data collection methods, sampling techniques, and analytical strategies, into a coherent framework. The design provides a roadmap for systematically investigating relationships between variables, whether descriptive, exploratory, or causal in nature (Razi-ur-Rahim et al., 2024). In this chapter, the chosen research design will be qualitative research and

3.1.1 Quantitative research method

Quantitative researc aims to test hypotheses, demonstrate how variables relate to one another, and forecast hypothesis results. It implies a methodological analysis by applying statistical or computational techniques and procedures to the gathered data. For unbiased and trustworthy data, quantitative research techniques work best.

Consequently, quantitative research is the most effective research methodology. Additionally, a survey questionnaire created with Google Forms will be used for this study. Fair, moral, and prudent data collection shall be practiced. (What makes this approach the most effective one for this study?).

3.2 Data Collection

Data collection refers to the process of obtaining information from different sources in response to certain objectives or research questions (Jain, 2021). Data collection is vital in such domains as research, business decision-making, and strategic planning because it forms the basis of analysis and conclusions (Bhandari, 2020).

3.2.1 Primary Data Collection

Primary data collection will involve gathering original, firsthand data directly from the target population using structured methods such as surveys and questionnaires (Mazhar, 2021). The purpose of these tools is to gather opinions, experiences, and attitudes of respondents about the application of real-time inventory technology in central kitchen operations. Managers of central kitchens, employees, and business owners will be the target of the surveys, which will ask them to rate the technology's efficacy in a number of areas, including inventory control, operational efficiency, and food waste reduction. The researcher will be able to examine trends, connections, and the technology's overall efficacy in streamlining central kitchen operations thanks to the data gathered by these tools, which will offer insightful information about the adoption process, difficulties, and perceived advantages of real-time inventory systems.

3.3 Sampling Design

Sampling design refers to the process of selecting a subset of individuals from a larger population to represent the overall group.

3.3.1 Target Population

The research findings are more likely to be precise, targeted, and applicable to the particular situation under study when the target audience is clearly defined and pertinent. The appropriate target group makes it possible to conduct insightful research and produce reliable findings with real-world implications (Kamau & Riany, 2023). The population under target for this study is central kitchen managers, staff, and business owners in the food and beverage (F&B) business. They are most appropriate respondents to offer meaningful information on the implementation, effectiveness, and utilization of real-time inventory technology in maximizing central kitchen operations The focus will be on those actively using or considering the use of real-time inventory management systems to gather relevant and specific data related to the research objectives.

3.3.2 Sampling Size

Approximately 521,000 workers, including manager, kitchen staff, and business owner are working in the food processing industry in Malaysia (Statista, 2023), Central kitchen is a part of the food processing industry, it prepares foods and distributes food to multiple locations (Jia et al., 2023).

The ideal sample size for this research is around 384 people (Qualtrics, 2023).

Some important elements that must be considered before calculating the sample size include the population size, the margin of error, the assumed proportion (standard deviation), and the confidence level. The 384 sample size will only be produced once this has been incorporated into the computation format.

3.3.3 Sampling Frame and Location

It is essential that there is a sampling framework because it makes sure that the selected sample is a reflection of the population of interest and reduces bias and increases the validity of the findings of the research; a defined sampling framework enables one to obtain accurate data and facilitates sound statistical analysis that finally translates into more valid and generalizable findings (Ruiz, 2023). Therefore, using a questionnaire as a research method will be appropriate for determining the research objectives. Google Forms will serve as the medium for creating the questionnaire survey and facilitating its execution. To the degree that it is feasible, the goal and subject matter of the survey should be taken into account while determining the appropriate sample frame to minimize error. The population proportion, total population size, margin of error, and suitable confidence level were all taken into consideration while determining the recommended sample size.

The sample location defines the area where the data will be gathered. Participants who work in the central kitchen in Malaysia are the target of this study. First, since the Google Form was utilized to disseminate the questionnaire, a QR Code that provides access to the survey will be generated. In order to physically meet University Tunku Abdul Rahman

Sungai Long students and ask them to complete the questionnaire, researchers will give them the QR Code.

Additionally, at the same time, the questionnaire will be sent to the participants who are knowledgeable and experienced in the central kitchen. By completing the demographic section, participants will be able to identify if they are central kitchen employees. Consequently, the survey questionnaire will be distributed to the individuals who may be the target demographic in order to get data from them. In order to encourage people to share the questionnaire with others, it will be shared with restaurant owners, stuff, and managers, or the F&B Community. This is known as "purposive sampling," and it will be covered in the portion that demonstrates sampling methodologies.

3.3.4 Sampling Technique

The methods employed in the selection of individuals or units within a population for inclusion in the study go by the name of sampling techniques. They allow the researcher to make valid conclusions and guarantee that the sample mirrors the population. Probability sampling and non-probability sampling form the main sampling techniques. Since non-probability sampling selects the participants in a systematic way such that each individual stands a similar chance of being selected, this might cause bias. Probability sampling selects people in a random manner such that each individual stands a similar chance and yields a more representative sample (Qualtrics, 2023).

In this study, non-probability sampling is going to be employed because subjective criteria is going to be employed as opposed to random selection. There is a wide range of non-probability sampling methods, and the one that is going to be employed in this study is purposive sampling. This is perhaps due to the fact that easy sampling recruits participants according to their accessibility and proximity, allowing for prompt and efficient collection of data (Toru, 2019).

Purposive sampling is used as the sampling method in order to make sure participants with direct significance to the aims of the research are selected. Purposive sampling enables the researcher to specifically choose individuals with expertise and experience (Thompson, 2020) in running the central kitchen operations. This sampling ensures that the information that is obtained is extremely relevant towards the focus of the study of operational efficiency, technology uptake, and inventory control.

Applying purposive sampling to this research involves deliberately selecting participants with specific characteristics relevant to the study's objectives. In this case, the participants will primarily include central kitchen managers, business owners, and staff. These individuals are targeted because they possess firsthand experience and insights into the adoption and operational impact of such technology. The purposive approach ensures that the data collected is precise and aligned with the research focus on optimizing central kitchen operations through real-time inventory systems.

3.4 Questionnaire Design

The questionnaire for this research has been separated into 4 sections to evaluate the effectiveness of real-time inventory technology in optimising central kitchen operations.

Firstly, Section 1 retrieves demographic information, such as role in the central kitchen, year of experience, team size, use of real-time inventory technology, and comfortability by using digital tools, to provide a basic understanding of the participants. The second section introduces respondents to the topic they will be answering.

Section C analyses the independent variables of the research on performance expectancy, effort expectancy, social influence, and the facilitating conditions that affect the intention towards using the real-time inventory systems. In Section D, the dependent variable is analysed considering participants' intention towards adopting the technology as a whole. Lastly, the measurement tools used in the research are based on existing studies that are explained in 3.5.2 Measurement Instruments, thereby ensuring the reliability and validity of the obtained data.

3.5 Measurement

The measurement scale and measurement instruments will be demonstrated in this study segment.

3.5.1 Measurement Scale

Establishing the collection and analysis of variables requires the use of measurement scales. There are four different degrees of measurement, each with a different level of accuracy and complexity. The nominal scale only classifies data in a predetermined order, but the ordinal scale both ranks and categorizes data. The interval scale gives constant distances between data points, whereas the ratio scale includes all previous features with a meaningful zero point. Understanding these scales is essential because they specify the type of statistical analysis that may be applied to the data (Lee, 2024).

In this research, the measurement scales employed will include nominal and ordinal scales. A nominal scale will be used to classify categorical data, such as respondents' roles in the central kitchen, and whether they use a real-time inventory system, which lacks numerical significance. Respondents will provide demographic information through structured questionnaires, including team size and work experience, to facilitate categorical analysis supporting the study's objectives (Lee, 2024).

Meanwhile, the ordinal scale will rank responses to evaluate their relative positions without measuring precise differences between them. A 5-point Likert scale will be utilized to assess respondents' perceptions of real-time inventory systems, with options ranging from "strongly disagree" to "strongly agree." This method will provide a structured approach for analyzing attitudes and preferences, allowing insights into trends and patterns in the central kitchen industry (Lee, 2024).

3.5.2 Measurement Instrument

To create the questionnaire for this study, measurement instruments were used from prior research. According to Table 3.1, the variables and the measurement elements that correspond with them were extracted from a range of research publications.

Table 3.1: Variables and Measurement Components

Author(s)	Construct (Variable)	Item	Original Question

Author (year) (Mwaisumo, 2020)	Performance Expectancy	PE1	Using computer based system helps me to accomplish stock taking as quickly as possible
(Mwaisumo, 2020)		PE2	Using computer based system in inventory control increase ability of monitoring and tracking of stock.
(Mwaisumo, 2020)		PE3	Using computer based system increases chances of getting a good stock control and management.
(Mwaisumo, 2020)		PE4	Using computer based system increases accuracy in stock audit
(Cimino et al., 2024)	Effort Expectancy	EE1	My first impression of SMALLDERS digital platform could be described as clear, favorable and comprehensible
(Cimino et al., 2024)		EE2	It is applicable to me to become proficient in using a digital platform like SMALLDERS
(Cimino et al., 2024)		EE3	I think that a digital platform like SMALLDERS would be an easy tool for me to use
(Cimino et al., 2024)		EE4	Learning how to operate with a digital platform like SMALLDERS would be easy for me
(Dilupa Nakandala et al., 2024)	Social Influence	SI1	Other practitioners in my profession use Industry 4.0technologies
(Rana et al., 2024)		SI2	My classmates and coworkers have helped encourage me to use AI technologies.

(Albahli, 2023)		SI3	People who are important to me think that I should use optional online professional development training.
(Albahli, 2023)		SI4	In general, the organization or company have supported the use of optional online professional development training
(Reza et al., 2024)	Facilitating Conditions	FC1	I have the resources necessary to use the system
(Reza et al., 2024)		FC2	I have the knowledge necessary to use the system
(Reza et al., 2024)		FC3	I can get help from others when I have difficulties using the e-wallet
(Reza et al., 2024)		FC4	E-wallet is compatible for my business
(Han & Conti, 2020)	Intention to Use real-time inventory technology.	IU1	I think I'll use the telepresence robot in the near future.
(Han & Conti, 2020)		IU2	I am not certain to use the telepresence robot in the near future.
(Han & Conti, 2020)		IU3	I'm planning to use the telepresesnce robot in the near future.

Source: Developed for Research Purpose

3.6 Data Processing

Data processing is turning unprocessed data into information that can be used to make inferences for this study. There are several processes, such as editing, coding, and checking.

3.6.1 Data Checking

Data checking, which is carefully reviewing the information acquired to make sure it is correct, detailed, and consistent, is a crucial stage in the research process. This process comprises verifying that the data matches the expected formats, identifying and fixing any errors, and ensuring that no data is duplicated or missing. Researchers may make sure the dataset is reliable and valid in this study by closely analyzing the data to make sure its validity is important for producing reliable and accurate research findings. Verification of data also stops mistakes from spreading and endangering the results of the study (Tawfik et al., 2019).

3.6.2 Data Editing

Repetitively altering collected data with the goal of correcting errors, reducing inconsistencies, or removing superfluous information is known as data editing. This phase raises the bar for the research findings by making sure the data collected for this study is authentic, clean, and ready for analysis (Tawfik et al., 2019). To ensure that extraneous information, such as respondents who do not reside in the Klang Valley is eliminated and to increase the study's credibility, data editing will be used for the questionnaire created for this specific study.

3.6.3 Data Coding

By classifying responses and data segments and assigning numerical or symbolic codes to them, data coding converts qualitative data into a quantitative format for easier analysis. In the interim, this technique improves the efficacy of data analysis while decreasing the time required to identify patterns and trends (Tawfik et al., 2019).

For this research, the data coding will be shown in Table 3.2:

Table 3.2: Data Coding

Section 1: Demographic		
Q1	Role in the central kitchen	"Manager" is coded as "1" "Staff" is coded as "2" "Business Owner" is coded as "3" "Other (please specify)" is coded as "4"
Q2	Year of experience	"Less than 1 year" is coded as "1" "1–3 years" is coded as "2" "4–6 years" is coded as "3" "More than 6 years" is coded as "4"
Q3	Team size	"Less than 10" is coded as "1" "10–20" is coded as "2" "21–50" is coded as "3" "More than 50" is coded as "4"
Q4	Use of real-time inventory technology	"Yes" is coded as "1" "No" is coded as "2"
Q5:	Comfortability with using digital tools	"Not comfortable at all" is coded as "1" "Slightly comfortable" is coded as "2"

		"Moderately comfortable" is coded as "3" "Very comfortable" is coded as "4" "Extremely comfortable" is coded as "5"

Section 2: Current Practices and Awareness of Inventory Management Systems		
Q1	How familiar are you with the concept of real-time inventory systems?	"Familiar" is coded as "1" "Not Sure" is coded as "2" "Not Familiar" at All is coded as "3"
Q2	How frequently does your central kitchen monitor inventory levels?.	"Always" is coded as "1" "Not Sure" is coded as "2" "Never" is coded as "3"
Q3	How frequently does your central kitchen experience stock shortages? .	"Always" is coded as "1" "Occasionally" is coded as "2" "Never" is coded as "3"
Q4	How effective is your current inventory management system in preventing food waste?	"Effective" is coded as "1" "Not Sure" is coded as "2" "Ineffective" is coded as "3"
Q5	How confident are you in the accuracy of your current inventory records?	"Confident" is coded as "1" "Neutral" is coded as "2" "Not Confident at All" is coded as "3"

Source: Developed for Research Purpose

Lastly, the responses for each survey question from Sections 3, and 4 are coded as below:

- “Strongly Agree’ is coded as 1
- “Disagree” is coded as 2
- “Neutral” is coded as 3
- “Agree” is coded as 4
- “Strongly Agree” is coded as 5

3.7 Proposed Data Analysis Tool

The instrument used to analyze the data will be covered in this section of the study. The descriptive analysis tool and the Smart PLS tool are the appropriate instruments for doing analysis.

3.7.1 Descriptive Analysis Tool

One of the methods used to discern and elucidate the salient features of a data collection is descriptive analysis. It provides overviews of the data set and measurements, including the mean, median, and mode, which are indicators of central tendency, as well as range, variance, and standard deviation. Understanding the foundations of the data also aids in identifying patterns, trends, and distributions within the data set and enables the presentation of quantitative descriptions in an intelligible manner (Cote, 2021).

The information gathered from the survey questionnaire will be used in this study to create a pie chart, bar chart, or graph that illustrates the proportion of each response and draws a more reliable and accurate conclusion.

3.7.2 Smart PLS Tool

A software program called SmartPLS uses the Partial Least Squares (PLS) approach for Structural Equation Modeling (SEM). It helps researchers look at both direct and indirect effects between variables, making it perfect for sophisticated statistical analysis of complex models. SmartPLS is flexible for a range of research data types and is particularly helpful when managing tiny sample sizes.

The tools of the PLS (Partial Least Squares) were used in conducting the comprehensive statistical analysis of the survey data in this research. Cronbach's alpha that represents the internal consistency of the respondent and confirms the level of trustworthiness of the garnered data will be calculated to ensure the reliability of the survey. Correlation analysis is the subsequent stage of identifying the relationship in variables between the dependent variable (use intention), and the independent variables (Performance Expectancy, Social Influence, Facilitating Conditions, and Effort Expectancy)

To visualize these correlations, the diagrams will also be created using sPLS. The diagrams will assist in collecting the questions for every variable, after which they will be tested and analyzed. The bootstrapping tools will then be used to produce p-values, R-squares, and significance values to validate the findings. The finding is to identify the most influential factors affecting the intention to use real-time inventory technology in central kitchen operations, and this statistical validation ensures that the findings are not due to random variation but reflect meaningful relationships among the variable

3.8 Pilot Test

The pilot test involving 30 respondents (n = 30) was carried out to assess how reliable and valid the questionnaire is in measuring four independent variables and one dependent variable.

3.8.1 Pearsons Correlation Analysis for Pilot Test

Table 3.3: Pearson's Correlation Coefficient: IVs and DV (Pilot Test)

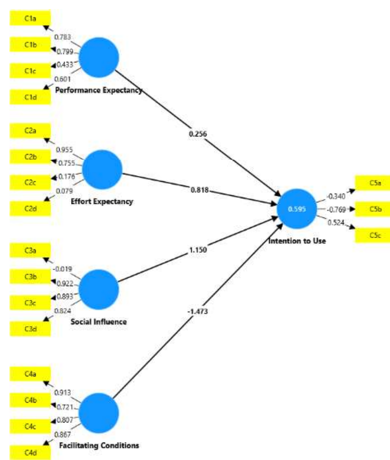
	Effort Expectancy	Facilitating Conditions	Intention to Use	Performance Expectancy	Social Influence
Effort Expectancy	1	0.73	0.473	0.537	0.516
Facilitating Conditions	0.73	1	0.316	0.681	0.885
Intention to Use	0.473	0.316	1	0.559	0.461
Performance Expectancy	0.537	0.681	0.559	1	0.753
Social Influence	0.516	0.885	0.461	0.753	1

Source: Developed for Research Purpose

Table 3.3 shows the ranges of all correlations. Effort Expectancy showed a moderate positive correlation with Facilitating Conditions (r = 0.73) and weak correlations with Intention to Use (r = 0.473), Performance Expectancy (r = 0.537), and Social Influence (r = 0.516). Facilitating Conditions had a strong positive correlation with Social Influence (r = 0.885), suggesting that environmental support and peer influence are closely linked, and also showed moderate correlation with Performance Expectancy (r = 0.621). Intention to Use correlated moderately with Performance Expectancy (r = 0.559), implying that perceived usefulness is a key driver of adoption, while showing weaker associations with other variables. Performance Expectancy and Social Influence also demonstrated a strong positive relationship (r = 0.753), highlighting the influence of social factors on perceptions of usefulness. These findings suggest promising connections among constructs, supporting the continuation of further analysis.

3.8.2 Structural model (path coefficient) of Pilot Test

Figure 3.1: Result Output Generated by SmartPLS 4 (Pilot Test)



Source: Developed for Research Purpose

Figure 3.1 shows that the path coefficient diagram illustrates the strength of relationships between the independent variables and the dependent variables. Effort Expectancy shows a strong and positive influence on Intention to Use with a path coefficient of 0.818, indicating it is a significant determinant in shaping user intentions. Performance Expectancy also positively impacts Intention to Use, albeit moderately (0.256). Interestingly, Social Influence displays a positive but unusually large coefficient (1.150), which may require further statistical scrutiny or model validation. In contrast, Facilitating Conditions shows a negative path coefficient (-1.473), suggesting an inverse relationship with Intention to Use in this pilot sample, which may reflect unique contextual factors or issues with construct validity. The R^2 value of 0.595 for Intention to Use implies that approximately 59.5% of its variance is explained by these four predictors, indicating a fairly strong model fit.

3.9 Conclusion

The concept of questionnaire construction is explained throughout this chapter, along with methods for analyzing the findings. Data processing will assist in making sure that the obtained data is appropriate for analysis by the data analysis tool. To determine whether the research's goals have been achieved, an analysis and proposal of the findings will be made in the following chapter.

Chapter 4 : Data Analysis

4.0 Introduction

This chapter will analyze and interpret the information gathered. 399 sets of data were gathered for this created research. Furthermore, the 399 sets of survey data will analyzed by PLS-SEM.

4.1 Descriptive Analysis

4.1.1 Descriptive Analysis: Demographic Profile

4.1.1.1 Role

Table 4.1: Role

Role				
	Frequency	Percentage	Cumulative Frequency	Cumulative Percentage
Staff	226	56.6%	226	56.6%
Business Owner	91	22.8%	317	79.4%
Manager	81	20.3%	398	99.7%
Others	1	0.3%	1	100%

Source: Developed for Research Purpose

Table 4.1 shows that 226 out of 399 (56.6%) respondents are staff. 91 out of 399 (22.8%) respondents are business owners and 81 out of 399 (20.3%) are managers. The role of others is only 1 respondent which is 0.3%.

4.1.1.2 Years of Experience

Table 4.2: Year of Experience

Year of Experience				
	Frequency	Percentage	Cumulative Frequency	Cumulative Percentage
Less than 1 year	77	19.3%	77	19.3%
1-3 years	133	33.3%	210	52.6%
4-6 years	135	33.8%	345	86.5%
More than 6 years	54	13.5%	399	100%

Source: Developed for Research Purpose

Table 4.2 shows that 77 out of 399 (19.3%) respondents have less than 1 year of experience. Following the group of 1-3 years of experience, it has 133 respondents (33.3%) Next up is the group of 4-6 years of experience, having 135 respondents (33.8%) while 54 out of 399 respondents (13.5%) from more than 6 years of experience.

4.1.1.3 Team Size

Table 4.3: Team Size

Team Size				
	Frequency	Percentage	Cumulative Frequency	Cumulative Percentage
Less than 10	64	16%	64	16.0%
10-20	140	35.1%	204	51.1%
21-50	146	36.6%	350	87.7%
More than 50	49	12.3%	399	100%

Source: Developed for Research Purpose

Table 4.3 shows that 64 out of 399 (16%) respondents have less than 10 workers in a team. Following the group of 10-20 workers in a team, it has 140 respondents (35.1%). Next up is the group of 21-50 workers in a team, having 146 respondents (36.6%) while 49 out of 399 respondents (12.3%) from more than 50 workers in a team.

4.1.1.4 Use of Real-Time Inventory

Table 4.4: Use of Real-Time Inventory

Use of Real-Time Inventory				
	Frequency	Percentage	Cumulative Frequency	Cumulative Percentage
Yes	197	49.4%	197	49.4%
No	202	50.6%	399	100%

Source: Developed for Research Purpose

Table 4.4 shows that 197 out of 399 (49.4%) respondents who selected Yes on their central kitchen used a real-time inventory system, while the other 202 out of 399 (50.6%) are No.

4.1.1.5 Comfortability in using digital tools

Table 4.5: Comfortability in using digital tools

Comfortability in using digital tools				
	Frequency	Percentage	Cumulative Frequency	Cumulative Percentage
Not comfortable at all	50	12.5%	50	12.5%
Slightly comfortable	100	25.1%	150	37.6%

Moderately comfortable	92	23.1%	242	60.7%
Very comfortable	98	24.6%	340	85.2%
Extremely comfortable	59	14.8%	399	100%

Source: Developed for Research Purpose

Table 4.5 shows that 50 out of 399 (12.5%) respondents are "not comfortable at all" in using digital tools. Following the "slightly comfortable" group, it has 100 respondents (25.1%). Next up is the group of "moderately comfortable" group, having 92 respondents (23.1%). Furthermore, the "very comfortable" group, has 98 respondents (24.6%) while 59 out of 399 respondents (14.8%) are "extremely comfortable".

4.1.2 Descriptive Analysis: Current Practices and Awareness of Inventory Management Systems

4.1.2.1 Real-time Inventory System Familiarity

Table 4.6: Real-Time Inventory Familiarity

Real-Time Inventory Familiarity				
	Frequency	Percentage	Cumulative Frequency	Cumulative Percentage
Familiar	117	29.3%	117	29.3%
Not sure	187	46.9%	304	76.2%
Not Familiar at all	95	23.8%	399	100%

Source: Developed for Research Purpose

Table 4.6 shows how familiar respondents are with the real-time inventory systems. Familiar getting 117 (29.3%) out of 399 respondents, while not sure has 187 (46.9%) respondents out of 399 respondents. The other 95 out of 399 (23.8%) respondents are unfamiliar.

4.1.2.2 Monitoring inventory levels

Table 4.7: Monitoring Inventory Levels

Monitoring inventory levels				
	Frequency	Percentage	Cumulative Frequency	Cumulative Percentage
Always	132	33.1%	132	33.1%
Not sure	182	45.6%	314	78.7%
Never	85	21.3%	399	100%

Source: Developed for Research Purpose

Table 4.7 shows how respondents frequently monitor inventory systems. Always has 132 (33.1%) out of 399 respondents, while not sure has 182 (45.6%) respondents out of 399 respondents. The other 85 out of 399 (21.3%) respondents are never

4.1.2.3 Stock Shortage

Table 4.8: Stock Shortage

Stock Shortage				
	Frequency	Percentage	Cumulative Frequency	Cumulative Percentage
Always	109	33.1%	109	27.3%
Not sure	188	45.6%	297	74.4%
Never	102	21.3%	399	100%

Source: Developed for Research Purpose

Table 4.8 shows how respondents frequently monitor inventory systems. Always has 132 (33.1%) out of 399 respondents, while not sure has 182 (45.6%) respondents out of 399 respondents. The other 85 out of 399 (21.3%) respondents are never.

4.1.2.4 Current Inventory System to Preventing Food Waste

Table 4.9: Current Inventory System to Preventing Food Waste

Current Inventory System to Preventing Food Waste				
	Frequency	Percentage	Cumulative Frequency	Cumulative Percentage
Effective	101	25.3%	101	25.3%
Not sure	173	43.4%	274	68.7%
Ineffective	125	31.3%	399	100%

Source: Developed for Research Purpose

Table 4.9 shows how respondents manage the current inventory system to prevent food waste. Effective has 101 (25.3%) out of 399 respondents, while not sure has 173 (43.4%) respondents out of 399 respondents. The other 125 out of 399 (31.3%) respondents are ineffective

4.1.2.5 Accuracy of current inventory system.

Table 4.10: Accuracy of current inventory system

Accuracy of current inventory system				
	Frequency	Percentage	Cumulative Frequency	Cumulative Percentage
Confident	110	27.6%	110	27.6%
Neutral	179	44.9%	289	72.4%
Not confident at all	110	27.6%	399	100%

Source: Developed for Research

Table 4.10 shows the accuracy of the current inventory system. Confident has 110 (27.6%) out of 399 respondents, while not sure has 179 (44.9%) respondents out of 399 respondents. The other 110 out of 399 (27.6%) respondents are ineffective.

4.2 Reliable Analysis

4.2.1 Before Pilot Testing

Table 4.11: Pilot Testing Cronbach's Alpha

	Item	Cronbach's alpha
Effort Expectancy	EE	0.585
Facilitating Conditions	FC	0.854
Performance Expectancy	PE	0.593
Social Influence	SI	0.661
Intention to Use	IU	0.483

Source: Developed for Research Purpose

Table 4.11 shows that Intention to Use (IU) has the lowest value of 0.483, which is unacceptable. Performance Expectancy and Effort Expectancy (PE, EE) have a value of 0.593 and 0.585 which is in the poor range. Furthermore, Social Influence (SI) has a value of 0.661 indicating questionable reliability. Finally, Facilitating Conditions (FC) has a good reliability of 0.854. The pilot test must have a minimum of 30 sample sizes to address potential issues that may occur. The pilot test must have a minimum of 30 sample sizes to address potential issues that may occur. Since the pilot test results indicated some issues with reliability, a larger size of respondents was necessary to ensure more accurate measurements.

4.2.2 After Pilot Testing

Table 4.12: Cronbach's Alpha

	Item	Cronbach's alpha
Effort Expectancy	EE	0.705
Facilitating Conditions	FC	0.795
Performance Expectancy	PE	0.75
Social Influence	SI	0.736
Intention to Use	IU	0.721

Source: Developed for Research Purpose

Figure 4.1: Range of reliability and its coefficient of Cronbach's alpha

No	Coefficient of Cronbach's Alpha	Reliability Level
1	More than 0.90	Excellent
2	0.80-0.89	Good
3	0.70-0.79	Acceptable
4	0.6-.69	Questionable
5	0.5-0.59	Poor
6	Less than 0.59	Unacceptable

Source: Zahreen Mohd Arof et al., 2018

The internal consistency of the questionnaire is assessed using Cronbach's alpha values. Better consistency and dependability are indicated by higher Cronbach's Alpha values. The Figure 4.1 shows that all the variables are within the acceptable value, all of the variables more than 0.70 are acceptable if the variables are lower than 0.7, it would be questionable, poor, and unacceptable (Zahreen Mohd Arof et al., 2018). It must refrain from changing or removing variables in the contents when its reliability levels are poor. From Table 4.12, FC are the highest reliable value with 0.795, almost good. PE, SI, IU, and EE are within 0.70-0.79, which is an acceptable reliability level, PE is the second highest value with 0.75. Next is SI with 0.736, and IU with 0.721. Lastly, EE has the lowest reliable value with 0.705. After collecting responses from 399 participants, Cronbach's Alpha values improved significantly.

4.3 Correlation Analysis

4.3.1 Pearson's Correlation Analysis

Table 4.13 Pearson's Correlation Coefficient: IVs and IU

	Effort Expectancy	**Facilitating Conditions**	**Intention to Use**	**Performance Expectancy**	**Social Influence**
Effort Expectancy	1	-0.218	0.7	0.749	0.602
Facilitating Conditions	-0.218	1	-0.306	-0.284	-0.159
Intention to Use	0.7	-0.306	1	0.771	0.597
Performance Expectancy	0.749	-0.284	0.771	1	0.673
Social Influence	0.602	-0.159	0.597	0.673	1

Source: Developed for Research

Figure 4.2: Interpretation of Correlation Coefficient

Coefficient Interval	Correlation
0.00 – 0.199	Very Weak
0.20 – 0.399	Weak
0.40 – 0.599	Medium
0.60 – 0.799	Strong
0.80 – 1.000	Very Strong

Source: Napitupulu et al., 2018

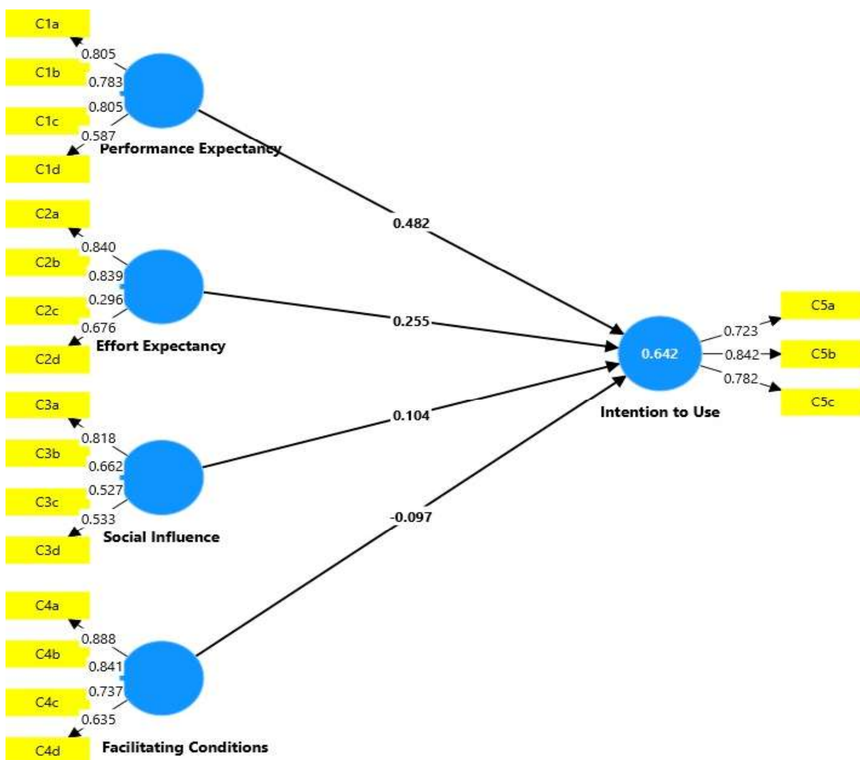
The direction and strength of a variable's connection are indicated by Pearson's correlation coefficient. Very strong correlation is defined as the coefficient between 0.80 and 1.00 in Figure 4.2, followed by strong correlation (0.60-0.79), medium correlation (0.40-0.59), weak correlation (0.2-0.39), and very weak correlation (0-0.19).

Table 4.13 presents the range of all correlations. The negative relationship of FC indicates that with a decrease in FC, the dependent variable (IU) decreases as well. This is perhaps because most of the participants chose 'Strongly Disagree' for FC items, reflecting that they feel there is a lack of required resources, assistance, or infrastructure. Therefore, their intention towards adopting or using the system is adversely affected. This finding highlights potential gaps in facilitating conditions that should be addressed to improve adoption rates. The table shows a strong relationship between EE and IU (0.7), EE and PE (0.749), EE and SI (0.602), IU and PE (0.771), and PE and SI (0.673). Medium correlations are SI and IU (0.597).

4.4 Structural Equation Modelling

4.4.1 Structural Model Assessment (Path Coefficients)

Figure 4.3: Result Output Generated by SmartPLS 4



Source: Developed for Research

Figure 4.3 shows that all of the IVs are significantly influencing IU, forming an equation of:

$$\boxed{IU = 0.482(PE) + 0.255(EE) + 0.104(SI) - 0.097(FC) + e}$$

The “e” represents the error term. This equation summarizes the relationship between the independent variables and IU, showing that PE has the strongest positive influence, followed by EE and SI, while FC has a slight negative effect on IU.

Table 4.14: Structural Model

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	Rejection of Null Hypothesis
Effort Expectancy -> Intention to Use	0.255	0.256	0.041	6.22	0	Rejected
Facilitating Conditions -> Intention to Use	-0.097	-0.098	0.02	4.721	0	Rejected
Performance Expectancy -> Intention to Use	0.482	0.481	0.05	9.577	0	Rejected
Social Influence ->	0.104	0.106	0.041	2.558	0.011	Rejected

Intention to Use						

Source: Developed for Research Purpose

Before we establish the significance of the relationship, we should note that the null hypothesis is rejected if the p-value is less than 0.05. A null hypothesis is not rejected if the p-value is more than 0.05. The Table 4.14 reveals that Effort Expectancy (EE) is 0, Facilitating Conditions (FC) is 0, Performance Expectancy (PE) is 0, and Social Influence (SI) is 0.011. The variables are less than 0.05. Even though Social Influence (SI) is significant (p = 0.011), the influence is weak compared with other variables, and hence the social factor might not play an important role in affecting user intention.

4.4.2 R-squared

From Figure 4.3, R-squared = 0.642, means that 64.2% of the variance in Intention to Use (IU) is explained by the independent variables (PE, EE, SI, and FC). The remaining **35.8%** is influenced by other factors not included in the model.

4.5 Hypothesis Testing

H1: Performance Expectancy positively affects Intention to Use Real-time Inventory Technology.

Table 4.14 indicates that the significance value of PE is 0.000 ($p < 0.05$). Hence, H1 is accepted, confirming a significant relationship between performance expectancy and intention to use real-time inventory technology.

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H2: Effort Expectancy positively affects Intention to Use Real-time Inventory Technology.

Table 4.14 shows that the significance value of EE is 0.000 ($p < 0.05$). Thus, H2 is accepted, confirming a significant relationship between effort expectancy and intention to use real-time inventory technology.

H3: Social Influence positively affects Intention to Use Real-time Inventory Technology.

Table 4.14 shows that the significance value of SI is 0.011 ($p < 0.05$). Thus, H3 is accepted, confirming a significant relationship between social influence and intention to use real-time inventory technology.

H4: Facilitating Conditions positively affect Intention to Use Real-time Inventory Technology.

Table 4.14 indicates that the significance value of FC is 0.000 ($p < 0.05$). However, the path coefficient is negative ($\beta = -0.097$), suggesting an inverse relationship. Hence, H4 is accepted, but the relationship is negative, indicating that better facilitating conditions may reduce the intention to use real-time inventory technology.

4.6 Conclusion

The results of the survey data analysis are shown in this chapter, together with an inferential analysis of the research variables and a descriptive analysis of the respondents. The theories have also been put to the test.

Chapter 5: DISCUSSION, CONCLUSION AND IMPLICATIONS

5.0 Introduction

The findings, implications, limitations, and suggestions for further study and outcomes are compiled and concluded in this chapter.

5.1 Discussion of Findings

5.1.1 Discussion of Descriptive Analysis

The demographic data reveal that the majority of respondents are staff working in the central kitchen, followed by business owners and managers. This distribution suggests that the survey captures diverse perspectives across various organizational levels, with a strong operational input from frontline staff. Most respondents have between 4 to 6 years and 1 to 3 years of experience in the central kitchen industry. This indicates that the sample consists of experienced individuals who are likely familiar with operational processes. Only a small percentage have more than six years of experience. This variety allows for insights from both seasoned and emerging professionals. The use of real-time inventory systems is nearly split. This indicates that the industry is at a transitional stage, with many organizations either in the early stages of adopting technology or hesitant to make the shift. Mostly comfortable to use digital tools.

Based on the responses, it is clear that there is a mix of awareness and understanding regarding real-time inventory management systems among central kitchen personnel. While some individuals are familiar with the concept and practices, many are still unsure or lack proper knowledge, which may hinder effective implementation. Inventory monitoring practices also vary significantly. Some central kitchens have consistent tracking habits, while others show uncertainty or lack regular monitoring procedures. This inconsistency could lead to operational challenges, such as stock shortages or inefficiencies in kitchen workflows. The issue of food waste and inventory accuracy also highlights gaps in the current systems being used. Many respondents are uncertain about the effectiveness of their inventory management tools, and confidence in the accuracy of inventory records is generally low. These findings suggest that more structured training, clearer processes, and user-friendly digital tools may help enhance performance and awareness in inventory handling.

5.1.2 Discussion of Inferential Data

Table 5.1: Hypothesis Result and Decisions

No.	Hypothesis	Path Coefficient	P-values	Decision	Relationship Direction
H1	There is a significant relationship between performance expectancy and intention to use real-time inventory technology	0.482	0.000	Hypothesis Supported	Positive
H2	There is a significant relationship between effort expectancy and intention to use	0.255	0.000	Hypothesis Supported	Positive

	real-time inventory technology				
H3	There is a significant relationship between social influence and intention to use real-time inventory technology	0.104	0.011	Hypothesis Supported	Positive
H4	There is a significant relationship between facilitating conditions and intention to use real-time inventory technology	-0.097	0.000	Hypothesis Supported	Negative

Source: Developed for Research Purpose

Table 5.1 summarizes the findings of the variables and the choice of hypothesis support. From the findings, performance expectancy, effort expectancy, and social influence all have a statistically significant and positive relationship with intention to use since their p-values are less than 0.05. Facilitating conditions also exhibit a statistically significant relationship with intention to use but with a negative path coefficient. This signifies an inverse relationship such that the lower the facilitating conditions, the lower the intention to use. Even with the negative path coefficient, the hypothesis is still supported according to the significance level.

There are a number of factors that might account for the fact that performance expectancy and effort expectancy play a significant role in affecting users' intention to adopt a real-time inventory system. Users tend to implement and make full use of the system if they perceive that the system is helpful for improving work performance and is convenient. This is particularly the case in the context of central kitchen environments where ease of use and efficiency matter most.

Social influence also plays a significant role, suggesting that recommendations or influence from colleagues, management, and competitors may contribute to users' decisions to adopt the system. While the influence is comparatively weaker, it still contributes meaningfully to behavioral intention.

Facilitating conditions showed a significant but negative relationship. This could be due to the fact that most respondents expressed disagreement with statements regarding the availability of resources, support, and system compatibility. When users perceive that their organization lacks the necessary infrastructure, knowledge, or technical support to implement and maintain the system, it may lead to resistance or reduced confidence in adopting the technology. This finding emphasizes the importance of organizational readiness in the success of system implementation.

All four hypotheses are supported, and facilitating conditions show an unexpected direction. Various factors, including respondent experience, company infrastructure, or training gaps could influence this result. Although the sample size of 399 is considered adequate, certain demographic or contextual differences may have affected perceptions, especially regarding internal support structures. Future studies should consider further segmentation or qualitative follow-ups to explore these attitudes in more depth.

The previous studies indicate that there is a negative correlation with Facilitating Conditions in UTAUT model due to insufficient technical skills, knowledge, and resources (ALBLOOSHI & ABDUL HAMID, 2021). A result of Abbad (2021) supported that Performance Expectancy had a significant impact on intention to apply the system; they felt that the system improved their performance and therefore increased their intention towards its adoption. Effort Expectancy is the level of easiness involved in the use of the system, if a technology is user-friendly and effortless to learn, people are more likely to adopt it (Aljojo & Alsuhaimi, 2020). The perceived ease of use influenced the users in being more inclined towards the system's acceptance (Aljojo & Alsuhaimi, 2020). Social Influence is the level up to which people feel that vital others (peers, organizations, stakeholders, and the management) expect them to apply the new system. According to Ramadhina et al. (2025) assume that social influence is the peer and societal pressures that influenced the user's choice of adopting the system.

5.2 Implications of Study

The findings from this study can be connected to real-world applications, particularly within the food and beverage industry, where inventory accuracy and efficiency are critical. Understanding what drives the intention to use real-time inventory systems allows businesses to make more informed decisions regarding technological implementation in central kitchen operations.

By acknowledging how expectations of performance and ease of use influence system adoption, businesses can take proactive steps to ensure that staff feel confident in the technology. Real-time inventory systems must demonstrate clear operational benefits such as reduced waste, improved stock visibility, and smoother kitchen workflows to encourage acceptance. These improvements can lead to better decision-making and more reliable kitchen performance.

Organizations must recognize the influence of both internal and external stakeholders on technology adoption. When management, operational staff, and industry competitors show strong support for the adoption of real-time inventory systems, it builds a positive environment for change. Encouragement from leadership and alignment among team members can significantly increase the willingness to adopt the system. This reinforces the importance of communication, shared vision, and strong leadership to drive successful integration in central kitchen operations.

Moreover, the availability of proper infrastructure, resources, and support directly influences employee confidence in using the system. Companies must provide compatible systems, technical help, and hands-on guidance to bridge the gap between technology and practical usage within kitchen operations.

Finally, this study provides useful insights for companies aiming to digitize their back-end operations. By understanding the factors that influence staff intentions, businesses can develop more effective implementation strategies that reduce resistance and promote long-term use. It also encourages developers to consider user feedback, creating systems that align with operational needs while enhancing the overall efficiency of central kitchen functions.

5.3 Limitations of the Study and Recommendations for Future Research

The research used a quantitative method employing self-completion questionnaires that might constrain the depth of insight into respondents' experiences and views. Respondents might have misinterpreted or misunderstood certain items, particularly technical terms that relate to real-time inventory systems, which might compromise the reliability of the data. Even if 399 usable responses were received, the sample is confined within one organizational or industrial context that might constrain extrapolation of the findings across industries or regions. The research mainly represents responses within one operational setting and might not capture the overall food business sector or SMEs across the world. A common method bias might result from the inherent dependence on a single method of data collection (i.e., surveys) from one collection source across a single occasion. This might result in an artificial inflation of the observed relationships between the variables.

Future research can adopt a mixed-methods approach by combining qualitative interviews with quantitative surveys. This would allow researchers to gain deeper insights into the reasoning and behavioral factors behind respondents' choices, especially for constructs like facilitating conditions and social influence. Furthermore, future research should explore additional or alternative theoretical models, such as the Technology-Organization-Environment (TOE) framework or the Diffusion of Innovations theory, to complement UTAUT and capture other relevant variables such as organizational readiness, cost concerns, or technological complexity.

5.4 Conclusion

This study on the effectiveness of real-time inventory technology in optimizing central kitchen operations has provided valuable insights into its potential to enhance operational efficiency, reduce food waste, and improve decision-making. By evaluating how real-time data can streamline inventory management, the research highlights the significant role of performance expectancy, effort expectancy, social influence, and facilitating conditions in influencing the adoption and usage of this technology. The findings suggest that real-time inventory systems offer substantial benefits in terms of inventory control, ensuring a more accurate tracking of stock levels, reducing stockouts, and optimizing purchasing decisions.

However, the study also identifies challenges such as initial implementation costs and the need for employee training to fully realize the potential of these systems.

In conclusion, real-time inventory technology presents a promising solution for central kitchens, improving operational workflows and enabling more accurate, data-driven decisions. Future studies could explore further advancements in technology integration, as well as how user adoption can be improved through tailored training programs and strategic change management.

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APPENDIX

Appendix 3.1

Dear Respondents,

I am Sim Kah Khai from the Bachelor of International Business (Hons) at University Tunku Abdul Rahman (UTAR). I am currently working on my final year project titled "Analysing the effectiveness of real-time inventory technology in optimising central kitchen operations".

This questionnaire aims to gather feedback on Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions related to intention to use. It how a real-time inventory system could optimize central kitchen operations for the organization. The survey consists of **three sections:**

- Section A: Demographics
- Section B: Current Practices and Awareness of Inventory Management Systems
- Section C: Opinions on real-time inventory toward it (Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Condition, and Intention to Use)

Your participation is entirely voluntary. Your responses will be kept STRICTLY CONFIDENTIAL and are used for academic purposes only. Additionally, this survey will be approximately 3 to 10 minutes to complete. Your response is much appreciated.

If you wish to enquire further regarding this research project, please do not hesitate to contact the researcher through email oscarsim528@1utar.my

Sincerely,
Tai Buo Ting

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3. You may access and update your personal data by writing to us at oscarsim528@1utar.my

- o You have notified me that I at this moment understood, consented and agreed per UTAR above notice
- o I disagree, my personal data will not be processed

Section A: Demographics

1. What is your role in the central kitchen?
   - Manager
   - Staff
   - Business Owner
   - Other (please specify)
2. How long have you been working in the central kitchen industry?
   - Less than 1 year
   - 1–3 years
   - 4–6 years
   - More than 6 years
3. What is the size of your central kitchen team?
   - Less than 10
   - 10–20
   - 21–50
   - More than 50
4. Does your central kitchen currently use a real-time inventory system?
   - Yes
   - No
5. How comfortable are you with using digital tools for work-related tasks?
   - Not comfortable at all
   - Slightly comfortable
   - Moderately comfortable
   - Very comfortable
   - Extremely comfortable

Section B: Current Practices and Awareness of Inventory Management Systems

(Questions to familiarize respondents with the topic)

6. How familiar are you with the concept of real-time inventory systems?
    - Familiar
    - Not sure
    - Not Familiar at All
7. How frequently does your central kitchen monitor inventory levels?
    - Always
    - Not Sure
    - Never
8. How frequently does your central kitchen experience stock shortages?
    - Always
    - Occasionally
    - Never
9. How effective is your current inventory management system in preventing food waste?
    - Effective
    - Not Sure
    - Ineffective
10. How confident are you in the accuracy of your current inventory records?
    - Confident
    - Neutral
    - Not Confident at All

Section C: Opinions on real-time inventory toward it

Please answer all questions in this section.

Please choose the likeliness of agreeing or disagreeing with each of the following questions based on a scale ranging from 1 (Strongly Agree) to 5 (Strongly Disagree)

Strongly Agree (SA)	Agree (A)	Neutral (N)	Disagree (D)	Strongly Disagree (SD)
1	2	3	4	5

No.	Statement	SA	A	N	D	SD
	Performance Expectancy					
1	Using a real-time inventory system helps reduce food waste in our central kitchen operations					
2	Using real-time inventory system improves our ability to predict inventory needs, enhancing stock availability.					
3	Implementing a real-time inventory system increases efficiency in monitoring and tracking stock levels					
4	Using real-time inventory system improves the accuracy of stock audits, reducing errors.					
	Effort Expectancy					
1	Troubleshooting issues with the real-time inventory system is clear, easy to understand, and accessible					
2	I believe I can become proficient in using the real-time inventory system with the available resources and support.					
3	The real-time inventory systems would be user-friendly and simple to navigate					
4	I believe the resources provided (e.g., training, guides) make it easier for me to operate the system effectively					
	Social Influence					
1	*Competitors motivate our organization to consider the use of real-time inventory systems*					

2	*Our management actively encourages the adoption of real-time inventory systems in our central kitchen operations*					
3	Operational staff in our organization believe that we should use a real-time inventory system to improve our central kitchen operations.					
4	In general, stakeholders support the adoption of a real-time inventory system in our central kitchen operations					
Facilitating Conditions						
1	Our organization has the necessary resources (e.g., financial, technical) to use a real-time inventory system.					
2	*Our organizations has the required knowledge and skills to operate a real-time inventory system effectively*					
3	*We have access to ongoing support and updates for the real-time inventory system, ensuring its functionality*					
4	The real-time inventory system is compatible with our central kitchen operations.					
Intention to Use						
1	I think our central kitchen will adopt a real-time inventory system in the near future					
2	I am uncertain whether we will adopt a real-time inventory system in the near future.					
3	I intend to support the planning of a real-time inventory system for our central kitchen operations in the near future.					

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