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Key Factors Influencing Technology Adoption for Food Loss Management in SMEs

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Abstract

Food loss is a pressing global issue, with significant economic, environmental, and social ramifications. Small and Medium Enterprises (SMEs), which constitute a substantial share of food production, often face higher levels of food loss during processing due to limited resources and production capacity. Digital technologies present a promising solution for managing food loss and enhancing sustainable food security. However, SMEs frequently encounter barriers, such as resource constraints, limited budgets, and inadequate technical expertise, when adopting such technologies. This study investigates the factors influencing the adoption of digital technologies for food loss management among SMEs in the food manufacturing industry by employing an integrated framework that combines the Unified Theory of Acceptance and Use of Technology (UTAUT) with the Technology-Organization-Environment (TOE) perspective. Data were collected through a census approach, using questionnaires emailed to representatives of food manufacturing SMEs registered with the Department of Business Development in the Bangkok Metropolitan Region, Thailand, yielding 371 usable responses. Confirmatory Factor Analysis (CFA) and Structural Equation Modeling (SEM) were utilized for data analysis. The findings revealed that performance expectancy, effort expectancy, and facilitating conditions, significantly impact the adoption of digital technologies, with facilitating conditions being the most influential factor. Conversely, social influence does not have a significant effect. The study highlights the importance of robust digital infrastructure, accessible technology specialists, and tailored training programs to enhance SMEs' digital adoption. Furthermore, promoting awareness of the benefits of digital technologies and ensuring user-friendly solutions can improve confidence, motivation, and operational efficiency, ultimately reducing food loss in SMEs.

Keywords: Digital technology; UTAUT; SMEs; food loss management

1. INTRODUCTION

Food loss is a pressing global issue with significant economic, environmental, and social implications (Intaratrakul & Pensupa, 2020). Although global food production often exceeds consumer demand, access to adequate supply remains a challenge. Approximately 840 million people suffer from chronic hunger, primarily due to poverty. This underscores that the issue is not a lack of food but rather inequitable access to available resources (Food and Agriculture

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Organization of the United Nations, 2018). Alarmingly, about one-third of all food produced is wasted, which could otherwise feed up to 1.8 billion people (Wongsaichia et al., 2022). Furthermore, food waste contributes to environmental degradation, emitting methane—a greenhouse gas 25 times more harmful than carbon dioxide—during decomposition (Broun & Sattler, 2016).

In response, the United Nations' Sustainable Development Goals (SDGs) emphasize the urgency of addressing food loss. Specifically, SDG 12 focuses on responsible production and consumption, with Goal 12.3 aiming to halve food loss by 2030 (Okayama & Watanabe, 2024). Achieving these objectives requires coordinated efforts across the food manufacturing sector, particularly through the development of innovative strategies to reduce food loss while enhancing operational efficiency.

In developing countries, SMEs in the agri-food supply chain contribute significantly to food loss. However, research on their operational impact remains limited (Kusumowardani et al., 2022). While large organizations have successfully implemented food loss reduction initiatives, SMEs, which dominate food manufacturing, experience higher levels of food loss during processing due to resource and capacity constraints (Bhageria & Vyas, 2023).

Although many companies have already adopted digital technology in their operations, this study emphasizes the importance of digital technology for SMEs in addressing the challenges of food loss. Digital tools such as blockchain, big data analytics, and the Internet of Things (IoT) facilitate process optimization and support sustainable food security (Digital Economy Promotion Agency, n.d.). However, limited research exists on the factors influencing the adoption of such technologies by SMEs. Unlike larger firms, SMEs face significant barriers, including constrained resources, budget limitations, insufficient technical expertise, and skill gaps among business owners and managers (Eiriz et al., 2019; Mohd Salleh et al., 2017).

This study investigates the factors influencing the adoption of digital technologies for food loss management in SMEs. To guide the analysis, it adopts the Unified Theory of Acceptance and Use of Technology (UTAUT), which has been widely applied to explain individuals' behavior in technology adoption, and extends it with insights from the Technology-Organization-Environment (TOE) framework (Baker, 2011) to account for broader organizational and environmental conditions. This integrated perspective is particularly relevant in the context of Thailand's food manufacturing sector, where SMEs often face resource limitations and external pressures that affect digital adoption. The findings are expected to provide both SMEs and policymakers with evidence-based strategies to reduce barriers, strengthen organizational readiness, and promote effective use of digital technologies for food loss management. Ultimately, this study contributes to the advancement of sustainable food systems and supports long-term operational efficiency within the SME sector.

2. LITERATURE REVIEW

2.1 The Use of Digital Technology in Managing Food Losses in the Food Manufacturing Sector

In this study, digital technologies are defined as advanced, data-driven tools designed to enhance monitoring, analysis, and decision-making processes, in food production and related supply chains, with the specific purpose of reducing food losses. These technologies go beyond basic digital applications such as social media platforms or standard accounting software and instead focus on innovations that directly support operational efficiency, food safety, and traceability. Within this scope, IoT plays an important role by using sensor systems to monitor environmental conditions such as temperature and humidity, thereby improving supply chain safety and ensuring product traceability (Kör et al., 2021). Likewise, radio-frequency identification (RFID) enables real-time monitoring during transportation, reducing risks of damage and spoilage by maintaining optimal storage conditions (Zhu, 2017).

Blockchain technology represents another important advancement, offering improved transparency and safety by recording and sharing environmental and logistical data across the supply chain. This not only prevents food damage and facilitates prompt recalls when required but also enhances trust and accountability among supply chain partners (Mangla et al., 2021). Several empirical studies further demonstrate the transformative impact of these technologies. For instance, Kayikci et al. (2022) illustrated the application of blockchain in tracking tuna supply chains, allowing verification of product origins and manufacturer details. Industry collaborations involving Walmart, Nestle, Unilever, and IBM, have also shown blockchain's potential to strengthen food safety and accelerate contamination detection. In addition, Afresh, a company specializing in fruit and vegetable supply chains, employs artificial intelligence (AI) to predict demand and optimize inventory management, reducing food waste by up to 25% (Department of International Trade Promotion, 2023). Collectively, these examples highlight how digital technologies, as defined in this study, can play a critical role in mitigating food loss in the food manufacturing sector.

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

Venkatesh et al. (2003) introduced the UTAUT by consolidating insights from eight established models of individual technology acceptance into a single comprehensive framework. UTAUT identifies four central determinants of behavioral intentions and usage—performance expectancy, effort expectancy, social influence, and facilitating conditions—which together explain a substantial proportion of variance in technology adoption. Owing to its robust empirical validation across diverse contexts, UTAUT has become one of the most widely applied models for examining individual-level adoption behavior. Nevertheless, its primary focus on individual perceptions and behavioral drivers may not fully capture organizational and environmental dimensions that are particularly relevant for SMEs, which often operate under resource constraints and external pressures. To address this limitation, the present study extends UTAUT by integrating the TOE framework, which highlights the role of technological readiness, organizational capabilities, and environmental conditions, in shaping adoption. This integrated approach provides a more holistic foundation for analyzing the adoption of digital technologies for food loss management, enabling the study to account for both behavioral and contextual influences.

Marikyan and Papagiannidis (2023) explained the key factors influencing technology adoption. Performance expectancy refers to the belief that using a system will improve work efficiency, enhance outcomes, provide motivation, and align with job requirements. Effort expectancy involves the perceived ease of use, including the system's complexity and ease of understanding. Social influence reflects how much individuals feel pressured by societal norms, cultural relationships, and social image, to adopt a technology. Facilitating conditions pertain to the availability of organizational and infrastructural support to ensure successful adoption. Behavioral intentions are mainly influenced by performance expectancy, effort expectancy, and social influences, while facilitating conditions directly impact actual usage behavior, emphasizing the importance of organizational support and infrastructure.

Performance expectancy is a critical determinant of behavioral intentions in adopting digital technology. Cimino et al. (2024) highlighted that users' expectations of improved efficiency and better outcomes significantly influence their intentions to adopt technology. Similarly, Toader et al. (2024) demonstrated that performance expectancy is the most significant factor influencing intentions to use blockchain-driven supply chain platforms. Based on the above literature, the following hypothesis is proposed:

H1: Performance expectancy influences the behavioral intention to use digital technology for food loss management.

Effort expectancy refers to the perceived ease of using a technological system, reflecting whether it is simple, intuitive, and easy to operate. Previous studies have consistently shown that effort expectancy plays a crucial role in influencing technology adoption. According to Sharma et al. (2023), users are less likely to adopt digital technology if it is perceived as more complex or difficult to use compared to their current methods. Toader et al. (2024) demonstrated that effort expectancy was a critical factor driving the intention to use blockchain-powered supply chain platforms, showcasing its relevance to advanced technologies in logistics.

In the context of food loss management, Kamonthip et al. (2022) emphasized the importance of user-friendly designs in household food waste management applications. They argued that systems must be responsive to user experiences and easily accessible to foster behavioral changes, such as reducing food waste and maximizing resource utilization. These findings highlight the critical role of effort expectancy in facilitating the adoption of digital technologies across various domains. Based on this body of research, the following hypothesis was proposed:

H2: Effort expectancy influences behavioral intentions to use digital technology for food loss management.

Social influence refers to how an individual's decision to adopt digital technology is shaped by the advice, behaviors, and expectations of influential people in their social or professional networks. It encompasses interpersonal relationships, cultural norms, and the perception that adopting technology enhances one's social image or status, highlighting the impact of societal and peer pressure on behavioral intentions.

Previous studies have emphasized the significant role of social influence in technology adoption. Chen et al. (2021) found that social influences positively affect consumers' intentions to use e-commerce platforms for purchasing fresh food. Similarly, Ramanathan et al. (2023) highlighted compliance with laws and stakeholder pressures as key factors in adopting IoT to reduce food waste, indicating that external influences shape organizational decisions. These findings underscore the importance of social influence in shaping behavioral intentions toward digital technology adoption. Based on this literature, the following hypothesis is proposed:

H3: Social influence influences behavioral intentions to use digital technology for food loss management.

Facilitating conditions refer to the perception that an organization's resources and infrastructure adequately support the adoption of new technologies. This construct emphasizes the importance of organizational resources, infrastructure, and environmental factors in enabling smooth adoption of technology. A lack of these resources can hinder the successful implementation and use of digital technologies.

Research has consistently highlighted the importance of facilitating conditions in technology adoption. Ali et al. (2023) demonstrated that these conditions significantly enhance IoT adoption and usage behavior in the food and beverage industry. Moreover, Joshi and Sharma (2022) emphasized that stakeholder skills, logistics infrastructure, and the availability of digital technology are critical success factors for leveraging digital technologies to create sustainable agricultural food supply chains. These findings highlight the importance of resource availability and organizational readiness in overcoming barriers to technology adoption. Based on this literature review, the following hypothesis is proposed:

H4: Facilitating conditions influence the use of digital technology in food loss management.

Behavioral intentions refer to users' intentions to adopt or continue using a system. In the context of technology adoption, they are influenced by the perceived value the technology provides, such as efficiency, convenience, or other tangible benefits. According to Venkatesh et al. (2003), UTAUT defines behavioral intentions as a determinant of increased system usage frequency, also referred to as usage behavior. A substantial body of research supports the positive relationship between behavioral intentions and actual usage behavior.

Khan et al. (2024) highlighted the critical role of behavioral intentions in predicting new technology usage behavior, emphasizing its importance as a precursor to adoption. Similarly, Batucan et al. (2022) noted that this could assess both the level of intentions to engage in specific behaviors and the willingness to use a system. These studies collectively highlight the integral role of behavioral intentions in shaping technology adoption and use. Based on these findings, the following hypothesis is proposed:

H5: Behavioral intentions to use digital technology influence the use of digital technology in food loss management.

2.3 Food Loss Management for SMEs in the Food Industry

In Thailand, SMEs constitute approximately 91% of food processing businesses, yet information on food loss management in these enterprises remains scarce (Food and Agriculture Organization of the United Nations, 2023). Research by Chen and Chen (2018) indicates that 97% of food lost in the industrial supply chain is recycled as animal feed, with 1.5% donated and 1.7% disposed of in landfills. Manufacturers also manage excess food by repackaging, offering discounts, or utilizing leftovers—such as vegetables and meat—for animal feed production. Additional efforts to extend the shelf life of perishable foods include collaborating with retailers on standardized packaging and labeling, which have proven effective strategies.

Kattiyapornpong et al. (2023) proposed guidelines for integrating food waste management into sustainability strategies. Key measures included sourcing fresh ingredients through farmer collaboration, efficient service planning and procurement, and proper storage techniques. These techniques involve the first-in, first-out system, clear labeling, and temperature control to prevent spoilage and over-purchasing. In production, strategies emphasize minimizing waste through efficient trimming, reusing materials to create new products, recycling, and donating, with the overarching goal of achieving zero food loss.

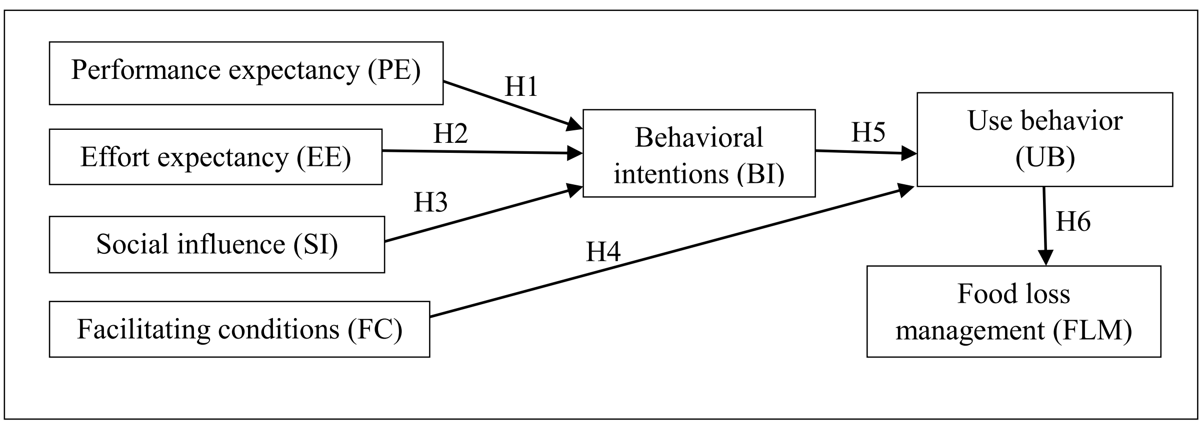
Digital technology is increasingly vital in reducing food losses. For instance, RFID prevents spoilage during transportation by enabling real-time monitoring of temperature and humidity (Zhu, 2017). Additionally, there are other new innovations such as time-temperature indicators on packaging which display environmental condition histories by permanently changing color when temperature limits are exceeded (Lehn et al., 2023; Yuvaraj et al., 2023). To explore how digital technology can reduce food losses during SME production processes, the following hypothesis was proposed:

H6: The use of digital technology influences food loss management.

The literature review informed the development of a conceptual framework that integrates the UTAUT with the TOE framework. UTAUT explains the relationships between individual-level factors—performance expectancy, effort expectancy, social influence, and facilitating conditions—and their influence on behavioral intentions and digital technology usage. To complement this perspective, TOE emphasizes the role of organizational readiness, technological context, and external environmental pressures, which are particularly relevant for SMEs in the food product manufacturing sector. Together, these frameworks provide a more comprehensive basis for examining the drivers of digital technology adoption for food loss management.

The conceptual framework therefore incorporates UTAUT constructs as key determinants of behavioral intentions and adoption, while also acknowledging organizational and environmental challenges that SMEs commonly face, such as limited resources, technical expertise, and external market pressures. This integrated approach not only strengthens the theoretical foundation but also enhances the practical relevance of the study by providing actionable insights for improving digital adoption in the sector. The proposed relationships are illustrated in Figure 1, which depicts the interactions among the variables and their expected impact on food loss reduction.

Figure 1 Conceptual Framework



3. RESEARCH METHODOLOGY

3.1 Population and Sample

This study aimed to examine the factors influencing the adoption of digital technology for food loss management among SMEs. The target population consisted of SMEs in the food manufacturing industry that were legally established and registered with the Department of Business Development and were located in Bangkok or its metropolitan area. This region was selected because it serves as the country's largest hub for food manufacturing businesses, hosting 15,759 companies and representing a substantial share of Thailand's food production activities. The concentration of SMEs in this area ensures access to diverse business types and operational scales, making it an appropriate setting for investigating digital technology adoption. Moreover, the Bangkok Metropolitan Region is characterized by higher levels of digital infrastructure, competitive pressure, and policy support compared to many other provinces, which provides a meaningful context for studying both the opportunities and barriers faced by SMEs. We employed a census approach, targeting all businesses that were currently in operation, resulting in a total of 3,711 eligible companies, while excluding those that were out of business. The sample size was determined using the formula proposed by Krejcie (1970), based on a population proportion of 0.5 and a 95% confidence level, yielding a required sample size of 375 companies. While the findings primarily reflect SMEs in the Bangkok Metropolitan Region, this area's central role in the national food manufacturing sector suggests that the insights can be cautiously generalized to similar SME contexts across Thailand, though regional differences are acknowledged as a limitation of the study.

Data collection involved distributing questionnaires to 3,057 companies with email contact information, followed by phone calls to encourage participation. Respondents included entrepreneurs, managers, or employees involved in decision-making in the company's production process, representing their respective SMEs. Over a one-month data collection period, 403 questionnaires were returned. After verifying the completeness and accuracy of the responses, 371 valid questionnaires were retained, resulting in a response rate of 12.14%. These responses were analyzed to address the research questions and achieve the study's objectives.

3.2 Instruments Used in the Research

The primary instrument employed in this study was a questionnaire designed to align with the research objectives and grounded in relevant concepts, theories, and previous studies. The questionnaire consisted of five sections. The first section gathered general information about the respondents and included six items. The second section collected general business information, containing seven items. The third section focused on factors influencing behavioral intentions and the use of digital technology in food loss management, with sixteen items developed based on the works of Shi et al. (2022) and Ali et al. (2023). The fourth section measured behavioral intentions and use behavior regarding digital technology in food loss management and featured four items for each construct. These items were adapted from the research of Ali et al. (2023), Chaiyakulwat (2018), and Nikolopoulou et al. (2020). The fifth section examined food loss management practices, comprising twenty-three items developed from the study of Kattiyapornpong et al. (2023).

To ensure the questionnaire's content validity, an expert panel evaluated its items for alignment with the research variables and objectives, following Polit and Hungler's (1999) guidelines and employing the Item-Objective Congruence (IOC) Index. The panel consisted of three experts: one academic from the Faculty of Agro-Industry and two entrepreneurs from food product manufacturing SMEs, each possessing over ten years of experience. All items achieved IOC values above 0.6, confirming their validity and relevance. Moreover, the questionnaire (see

Appendix) was reviewed and approved by the Research Ethics Committee of Kasetsart University (COE No: COE67/064) prior to data collection, in order to assure respondents of confidentiality.

Reliability testing was conducted using Cronbach's alpha coefficient, with a pilot test of thirty questionnaires yielding reliability coefficients ranging from 0.712 to 0.896, thereby exceeding the acceptable threshold of 0.7. Additionally, the external component weights (outer loadings) of each item were assessed for consistency. All items met the reliability threshold, except for item UB1, which was excluded due to an external component weight below 0.5. Overall, the validation and reliability processes confirmed the robustness of the questionnaire in measuring the intended constructs.

3.3 Statistical Data Analysis

Statistical software was used to analyze the data, employing descriptive statistics such as percentage, frequency, mean, and standard deviation, to summarize the questionnaire responses. The reliability and validity of the measurement model were assessed through multiple statistical methods. Composite reliability coefficients were used to evaluate the reliability of latent variables, while convergent validity was measured using the average variance extracted (AVE). Discriminant validity was tested using the Fornell-Larcker criterion to ensure sufficient distinctiveness between variables.

Pearson's product-moment correlation coefficient was applied to verify the preliminary relationships among variables, which is a critical prerequisite for structural equation modeling (SEM). Confirmatory factor analysis (CFA) was then conducted to evaluate the structural validity of the measurement model, ensuring its consistency with empirical data and its suitability for testing the research hypotheses. Finally, SEM was employed to examine the factors influencing SMEs' adoption of digital technology for food loss management. This comprehensive method enabled the simultaneous testing of relationships among multiple variables, providing robust insights into the drivers of digital technology adoption in the food manufacturing sector.

4. RESULTS

4.1 Descriptive Statistics Analysis

The descriptive statistics analysis of SME representatives in the food product manufacturing sector in Bangkok and its vicinity revealed key demographic and business characteristics. Most respondents were female (66%), aged between 31 and 40 years (83.6%), and held a bachelor's degree (98.7%). Most respondents reported an average monthly income ranging between 20,001 and 30,000 baht (84.1%) and occupied operator-level positions within their organizations (97.6%). In terms of professional experience, most respondents had between 6 and 10 years of work experience (58.2%).

From an organizational perspective, most businesses were classified as small enterprises, employing between 6 and 50 employees (72%). A significant proportion of these organizations reported an annual income ranging between 1.8 and 100 million baht (68.2%) and were categorized under the "other food product manufacturing industries" classification (31.5%). Most businesses operated as general partnerships (63.9%) and had been in operation for more than 10 years (62.3%). Geographically, most businesses were located in Bangkok Province (26.1%).

Analysis of the mean, standard deviation, and the levels of opinions regarding factors influencing SMEs' adoption of digital technology indicated an overall high level of agreement, with a mean score of 4.00. All factors were rated highly, reflecting positive perceptions of digital technology adoption among SMEs. Effort expectancy ranked highest, with a mean score of 4.15, emphasizing the importance of ease of use and simplicity in encouraging technology adoption. Performance expectancy followed, with a mean of 4.01, suggesting that SMEs perceived digital technology as a tool for improving efficiency and reducing losses. Social influence received a mean score of 3.97, highlighting the role of external support from stakeholders, such as partners and customers, in driving adoption. Facilitating conditions had a mean score of 3.87, underscoring the need for adequate infrastructure and technical support to ensure successful implementation. These findings demonstrate the importance of simplicity, efficiency, stakeholder support, and infrastructure readiness in driving SMEs' intentions to adopt digital technology.

Analysis of the mean and standard deviation for SMEs' behavioral intentions to use digital technology for food loss management showed an overall high level of intentions, with a mean score of 4.04. The highest-rated item was intentions to use digital technology to manage food loss in the future, with a mean score of 4.18. These findings suggest a strong positive inclination among SMEs toward adopting digital technology for food loss management. In terms of usage behavior, SMEs expressed overall satisfaction with the use of digital technology for managing food loss, as indicated by a mean score of 3.91. The highest-rated indicator was satisfaction with the use of digital technology in managing food loss, with a mean score of 3.99. These results reflect that SMEs have had positive experiences with digital technology and are ready to adopt it effectively for food loss management in the future.

The analysis revealed a high overall opinions among SMEs regarding food loss management, with a mean score of 3.97. These results indicate that SMEs place significant importance on various aspects of food loss management, particularly in purchasing and storage planning, which received the highest mean score of 4.07. This underscores an emphasis on controlling processes from the outset to effectively minimize food loss. Additionally, strategies related to reuse, recycling, donation, and disposal of food, scored a mean of 4.00, highlighting their critical role in reducing food loss and ensuring efficient resource utilization. Employee management and performance in the production process also scored highly, with a mean of 3.97, reflecting the active role of employees in mitigating food loss. However, food loss management policy received the lowest mean score of 3.85. This suggests that, while policies are recognized as important, there may be a need for further development to establish clearer and more comprehensive guidelines for food loss management. Detailed results are presented in Table 1.

Table 1 Mean, standard deviation (S.D.), and overall opinion levels

	Mean	S.D.	Level
Factors influencing the use of digital technology			
Performance Expectancy (PE)	4.01	0.714	High
Effort Expectancy (EE)	4.15	0.706	High
Social Influence (SI)	3.97	0.725	High
Facilitating Conditions (FC)	3.87	0.736	High
Overall Total	4.00	0.727	High
Behavioral Intentions (BI)	4.04	0.664	High
Usage Behavior (UB)	3.91	0.740	High
Food Loss Management			
Food Loss Management Policy (PLC)	3.85	0.722	High
Procurement and Storage Planning (PCM)	4.07	0.802	High

Management and Operational Practices by Employees in Production (PD)	3.97	0.715	High
Reuse, Recycling, Donation, and Disposal (RCC)	4.00	0.874	High
Overall Total	3.97	0.788	High

4.2 Measurement Model Evaluation

The reliability of the questionnaire was assessed using the Composite Reliability (CR) method, with a threshold of 0.7 or higher considered acceptable. The analysis revealed that all studied variables exceeded this threshold, confirming the reliability of the instrument and its suitability for data collection. Convergent validity was evaluated by calculating the Average Variance Extracted (AVE), with a minimum acceptable value of 0.5 as recommended by Fornell and Larcker (1981). The findings showed that all latent variables had AVE values greater than or equal to 0.5, demonstrating that each latent variable effectively explained the variance of its corresponding observed indicators and confirming the structural reliability of the research instruments.

Discriminant validity was assessed using the Fornell-Larcker criterion, which compares the square root of the AVE ($\sqrt{AVE}$) of each latent variable with its correlations with other latent variables. The results indicated sufficient discriminant validity, as the indicators for each latent variable were clearly distinct from those of other constructs. Additionally, the correlation coefficients between all pairs of observed variables were below the critical value of 0.85, as recommended by Kline (2023). Correlation coefficients exceeding 0.85 would indicate multicollinearity issues; however, no such problems were identified in this analysis. These findings confirm that the research instruments meet the required validity criteria and that the measurement model is appropriate for structural equation modelling. The results of the reliability and validity testing are presented in Table 2.

Table 2 Discriminant validity, composite reliability, and average variance extracted

Variable	1	2	3	4	5	6	7	CR	AVE
PE	0.727							0.809	0.524
EE	0.116**	0.715						0.810	0.525
SI	0.100	0.081	0.754					0.837	0.568
FC	0.288***	0.127**	0.076	0.752				0.835	0.566
BI	0.411***	0.217***	0.120**	0.257***	0.738			0.809	0.517
UB	0.283***	0.075	0.061	0.301***	0.281***	0.791		0.832	0.625
FLM	0.250***	0.04	0.094	0.205***	0.269***	0.344***	0.709	0.798	0.500

Denotes: *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$

4.3 Construct Validity and Measurement Model Analysis

Construct validity of the measurement model was assessed using Pearson's product-moment correlation coefficient, producing a correlation matrix for the observed variables. The correlation matrix, along with the mean and standard deviation of each subcomponent, was presented alongside the results of the model validity evaluation. Confirmatory Factor Analysis (CFA) was conducted for each subcomponent, using several criteria to evaluate the model's goodness-of-fit. A measurement model is considered a good fit if the following criteria are met: the relative Chi-square value (χ^2/df) is less than 3, the statistical significance is greater than 0.05, the Tucker-Lewis Index (TLI) is above 0.95, the Goodness-of-Fit Index (GFI) exceeds 0.90, the Comparative Fit Index (CFI) is above 0.90, the Incremental Fit Index (IFI) is above 0.90, the Root Mean Square Error of Approximation (RMSEA) is less than 0.08, and the Root Mean Square Residual (RMR) is less than 0.08.

The CFA results for the measurement model indicated that all latent variables adequately represented the factors influencing the adoption of digital technology for food loss management among SMEs. The structural validity analysis confirmed that the research instruments were valid and reliable. Based on the model fit indices, it was concluded that the measurement model was consistent with the empirical data, making it suitable for further analysis to address the research questions. Detailed results are presented in Table 3.

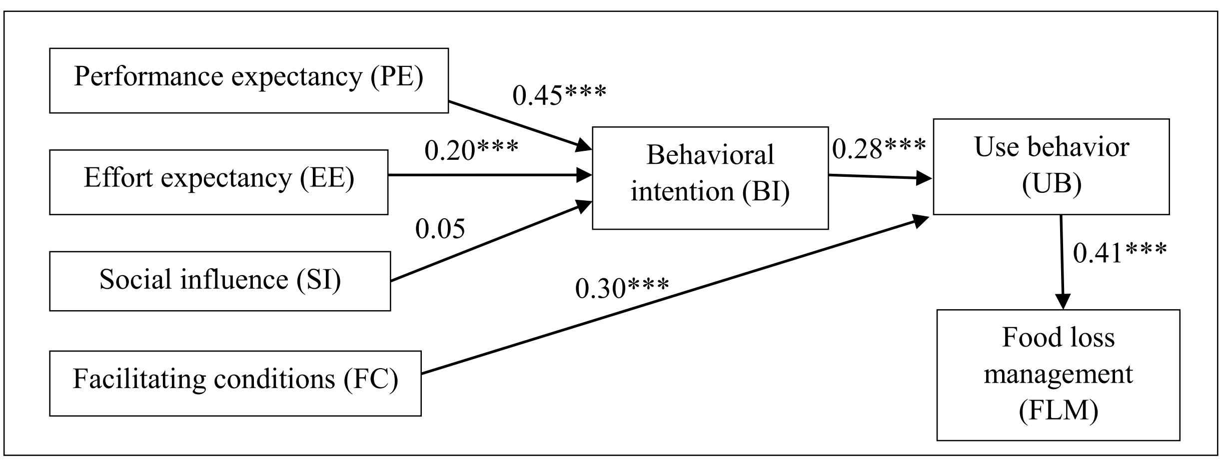
Table 3 Confirmatory Factor Analysis (CFA) of the measurement model

Fit Indexes	Acceptable Fit Interval	Measurement Model Result	Result
Relative Chi Square	< 3	1.739	Pass
GFI	> 0.90	0.903	Pass
CFI	> 0.90	0.948	Pass
IFI	> 0.90	0.949	Pass
RMSEA	< 0.08	0.045	Pass
RMR	< 0.08	0.025	Pass

4.4 Analysis of Research Hypotheses

The structural equation model (SEM) was used to analyze the factors influencing the adoption of digital technology for food loss management by SMEs. The hypothesis testing results are illustrated in Figure 2 and summarized in Table 4.

Figure 2 Measurement model demonstrating hypothesized relationships between all variables



Denotes: *p < 0.1, **p < 0.05, ***p < 0.01

Table 4 Summary of hypothesis-testing results

Hypothesis	Path Coefficient (β)	t-value	p-value	Result
H1	0.450	7.376	0.000*	Supports H1
H2	0.197	3.233	0.001*	Supports H2
H3	0.051	1.018	0.340	Does not support H3
H4	0.304	5.202	0.000*	Supports H4

H5	0.283	4.674	0.000*	Supports H5
H6	0.410	6.487	0.000*	Supports H6

Denotes: *Significance of path coefficients

The analysis revealed that performance expectancy and effort expectancy significantly influenced intentions to use digital technology for food loss management, with influence values of 0.450 and 0.197, respectively. These results indicate that SMEs are more likely to adopt digital technology if they believe it will improve operational efficiency, reduce food loss, and provide better returns, compared to traditional methods. Furthermore, simplicity and ease of use of digital technology encourage adoption, as SMEs are less inclined to invest in systems that are difficult to learn or operate.

Facilitating conditions were also found to significantly influence the behavior of using digital technology, with an influence value of 0.304. This suggests that when SMEs perceive they have the necessary resources and technical infrastructure to implement digital technology, their operations are streamlined, and their ability to manage food loss is enhanced. Adequate support systems within the organization further promote the adoption of digital technology.

The behavioral intention to use digital technology significantly influences actual usage behavior, with an influence value of 0.283. This finding implies that SMEs with a strong intention to adopt digital technology are more likely to integrate it into their practices. Additionally, the analysis revealed that the use of digital technology significantly impacts food loss management, with an influence value of 0.410, indicating that adopting digital technology directly improves SMEs' ability to manage and reduce food loss effectively.

Interestingly, the results showed that social influence does not significantly affect SMEs' decisions to use digital technology for food loss management. This suggests that external advice or perceptions, such as those from stakeholders or peers, do not play a substantial role in SMEs' decision-making processes regarding technology adoption. These findings highlight the importance of internal motivators, such as perceived efficiency, ease of use, or organizational readiness, over external social pressures in driving the adoption of digital technology for food loss management.

5. SUMMARY AND DISCUSSION

Food loss is a global issue that occurs at various stages of the supply chain, from raw material harvesting to distribution, emphasizing the need for innovative strategies to reduce waste and improve efficiency. Digital technology offers a promising solution for managing food loss and promoting sustainable food security. In Thailand, SMEs represent over 91% of the food production sector, making their adoption of digital technology essential for addressing food loss. However, SMEs face significant challenges, such as limited resources, budgets, and technical expertise, which hinder the effective implementation of digital solutions. This study utilized the UTAUT and TOE framework to examine the factors influencing SMEs in the food manufacturing sector to adopt digital technology for food loss management.

The findings indicate that performance expectancy significantly influences SMEs' intentions to use digital technology. SMEs are more likely to adopt technology when they perceive it as a means to enhance operational efficiency, reduce food loss, and provide better returns. This is consistent with Toader et al. (2024), who found that performance expectancy drives the adoption of blockchain-based supply chain platforms due to improved efficiency and cost reductions. This highlights the importance of clearly communicating the benefits of digital technology to SMEs to encourage adoption.

Effort expectancy was also found to positively influence intentions to use digital technology. SMEs are more inclined to adopt systems that are simple, user-friendly, and require minimal effort. This finding aligns with Inuzuka and Chang's (2023) work, which demonstrated that simplicity positively impacts the adoption of online food ordering systems. To ensure effective adoption, SMEs should prioritize selecting intuitive digital technologies and provide adequate training support for their employees.

An interesting finding of this study is that social influence did not significantly affect SMEs' intentions to adopt digital technology, which diverges from the expectations of the UTAUT and TOE frameworks. One possible explanation lies in the operational nature of many Thai SMEs, which tend to function independently and have limited involvement in formal business networks or strategic partnerships (Kattiyawong et al., 2019). In such contexts, external pressure or peer influence may have less weight in shaping decision-making processes. Cultural factors emphasizing autonomy in business operations may further weaken the role of social influences. This result highlights the importance of encouraging stronger inter-organizational networks to facilitate knowledge exchange, build trust, and strengthen SMEs' readiness to adopt digital technologies.

Facilitating conditions were found to positively influence SMEs' behavior regarding the use of digital technology. When SMEs perceive that their organization has the necessary resources, infrastructure, and technical support, they are more likely to adopt and effectively utilize digital solutions. This finding aligns with the research of Oktaviani et al. (2024), and Agarwal and Sahu (2022), who noted that well-developed infrastructure reduces barriers and increases user confidence. SMEs should therefore invest in technical resources, allocate budgets for technology adoption, and provide employee training to create an enabling environment for digital technology integration.

The study further confirms that behavioral intentions significantly influence actual technology usage behavior in food loss management. As Venkatesh et al. (2003) and Ali et al. (2023) highlighted, behavioral intentions are a strong predictor of technology adoption and usage frequency. SMEs with strong intentions to adopt digital technology are more likely to integrate these tools into their operations, thereby improving food loss management outcomes.

Finally, the findings reveal that digital technology usage behavior significantly influences food loss management. Technologies such as RFID and real-time monitoring systems facilitate improved service planning, procurement, and storage, thereby reducing spoilage and over-purchasing. Zhu (2017) demonstrated the effectiveness of RFID in preventing food loss during transportation, while Yang et al. (2024) highlighted the benefits of real-time temperature monitoring in reducing losses in vegetable and fruit handling.

This study underscores the importance of performance expectancy, effort expectancy, facilitating conditions, and behavioral intentions in driving the adoption of digital technology among SMEs. By addressing these factors and overcoming challenges, such as limited social influence, SMEs can effectively leverage digital technology to mitigate food loss. Doing so will not only foster sustainability but also support long-term growth in the food manufacturing sector.

5.1 Theoretical Contributions

This study advances the theoretical understanding of digital technology adoption in SMEs by integrating the UTAUT with the TOE framework. The findings confirm that performance expectancy, effort expectancy, and facilitating conditions significantly influence the intention to adopt digital technologies. These results reinforce UTAUT's explanatory power while also underscoring the importance of organizational readiness and supportive infrastructure, as emphasized in the TOE framework. SMEs are more likely to adopt digital solutions when they perceive clear operational benefits, find technologies user-friendly, and have access to adequate resources and digital skills.

Notably, the study reveals that social influence does not significantly affect adoption, diverging from the expectations of UTAUT. This deviation highlights the contextual uniqueness of Thai SMEs, many of which operate independently with limited reliance on external networks or institutional pressures. This finding points to the need for theoretical refinements when applying UTAUT in SME contexts and suggests that organizational and environmental factors may play a more decisive role than peer or societal influence.

By extending UTAUT and TOE, this study contributes a more holistic framework that captures both individual behavioral drivers and contextual determinants of adoption. It also identifies potential avenues for theoretical expansion, including the consideration of risk perception, management support, trust, and ethical orientations as complementary constructs. These insights not only broaden the theoretical basis for studying digital transformation in SMEs but also provides a foundation for future research to develop models better tailored to resource-constrained organizational environments.

5.2 Implementation Benefits

This research underscores the tangible benefits of adopting digital technology for food loss management in SMEs and provides a practical framework for improving organizational efficiency. For example, Ramanathan et al. (2022) demonstrated how Yumchop Foods, a UK-based frozen food manufacturer, utilized IoT and Big Data to enable real-time monitoring of temperature and humidity. This approach reduced food loss and maintained product quality, illustrating the transformative potential of digital technology in addressing inefficiencies in supply chain management. The findings suggest that facilitating conditions, particularly the presence of strong digital infrastructure, are the most influential factor in SME technology adoption. SMEs should prioritize investments in high-speed internet, modern equipment, and skilled personnel to enable effective and sustainable technology integration. Additionally, government support, such as providing digital technology investment funds and advisory services, is crucial to fostering a conducive ecosystem for digital transformation. Regarding performance expectancy, SMEs should increase awareness of the benefits of digital technology through targeted campaigns and strategic planning, ensuring alignment between employee needs and organizational goals. Cultivating a culture of continuous learning and collaborating with educational institutions to enhance digital literacy can further support technology adoption. In terms of effort expectancy, SMEs should focus on selecting user-friendly technologies and providing tailored training to employees. Technology providers should design intuitive products, offer clear user manuals, and ensure accessible customer support to simplify the adoption process. By addressing these factors, SMEs can maximize the potential of digital technology, effectively manage food loss, and position themselves for sustainable growth in the competitive food production industry.

5.3 Limitations and Future Research

This study examined the factors influencing SMEs' adoption of digital technology for food loss management but it has several limitations. Firstly, there is limited research specifically focused on the use of digital technology for food loss management in SMEs, restricting the availability of secondary data and potentially limiting a comprehensive understanding of the challenges and opportunities in this field. Secondly, the study is geographically confined to the Bangkok Metropolitan Region, which limits the generalizability of the findings to other regions in Thailand. Future research should expand to a national scale to capture regional differences and similarities in digital technology adoption for food loss management. Thirdly, the study focused on the UTAUT and TOE model and did not investigate other potentially relevant factors influencing technology adoption, such as user-specific characteristics, environmental factors, economic conditions, and legal frameworks. Future studies should explore these external influences and barriers to provide a more holistic understanding of digital technology adoption. Lastly, the research framework could be applied to other industries, to understand digital technology adoption in different contexts. This would help develop more targeted strategies for resource management, efficiency improvement, and sustainable practices across various industries. Addressing these limitations and exploring new research directions can advance knowledge on digital technology adoption, enhance food loss management strategies, and support the sustainable development among SMEs and in other sectors.

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7. APPENDIX

Survey indicators

Question	
Performance Expectancy (PE)	
PE1	Do you find digital technology useful in managing food loss.
PE2	Do you find digital technology increases the chance of achieving food loss management goals.
PE3	Do you find digital technology helps to manage food loss more quickly.
PE4	Do you find digital technology reduces food loss.
Effort Expectancy (EE)	
EE1	It is easy for you to use digital technology to manage food loss.
EE2	You do not think it takes long to learn to use digital technology to manage food loss.
EE3	You think it is easy to have skills in using digital technology to manage food.
EE4	You understand and can use digital technology to manage food loss.
Social Influence (SI)	
SI1	Someone important to you recommended that you use digital technology to manage food loss.
SI2	Someone you respect wants you to use digital technology to manage food loss.
SI3	People whose opinions you value, would like you to use digital technology to manage food loss.
SI4	People around you are successful in using digital technology to manage food loss.
Facilitating Conditions (FC)	
FC1	You have the knowledge necessary to use digital technology to manage food loss.
FC2	You have resources that support using digital technology to manage food loss.
FC3	You are ready to adopt digital technology to manage food loss.
FC4	You can ask for help from others when you have problems using digital technology to manage food loss.
Behavioral Intentions (BI)	
BI1	You intend to use digital technology to reduce food loss in the future.
BI2	You anticipate using digital technology to reduce food loss in the future.
BI3	You plan to use digital technology to reduce food loss in the future.
BI4	You will use digital technology when you want to reduce food loss.
Usage Behavior (UB)	
UB1	You frequently use digital technology to manage food loss.
UB2	You use digital technology to benefit your food loss management.
UB3	You use digital technology to make decisions about food loss management.
UB4	You find using digital technology to manage food loss a satisfying experience.
Food Loss Management Policy (PLC)	
PLC1	Your organization has a general policy on food loss management.
PLC2	Your organization has a policy to encourage customers to reduce food loss.
PLC3	Your organization has a policy to educate employees about food loss reduction.

PLC4	Your organization has a policy to collect food loss data.
PLC5	Your organization promotes the quality of life in the community and local areas through food loss management.
PLC6	Your organization organizes seminars/training on food loss management for employees, customers or partners.
Procurement and Storage Planning (PCM)	
PCM1	Your organization has a plan to reduce food loss.
PCM2	Your organization has a plan to stock ingredients in the appropriate amounts.
PCM3	Your organization has a plan to purchase ingredients to reduce amounts.
PCM4	Your organization has a first-in, first-out (FIFO) food plan.
PCM5	Your organization stores food at the appropriate temperature and location to slow down food spoilage.
PCM6	Your organization checks expiration dates regularly.
Management and Operational Practices of Food Loss by Employees in the Production Process (PD)	
PD1	Your organization's production process involves reducing food waste.
PD2	Your organization asks employees to reduce food loss.
PD3	Your organization uses near-expired food first.
PD4	Your organization distributes excess food to employees.
PD5	Your organization sells food waste as animal feed.
Food Loss Management through Reuse, Recycling, Donation, and Disposal (RCC)	
RCC1	Your organization has a plan to reduce food loss.
RCC2	Your organization donates excess food to external organizations.
RCC3	Your organization donates excess food to employees for free.
RCC4	Your organization donates food waste as animal feed.
RCC5	Your organization turns food waste into compost.
RCC6	Your organization turns food waste into organic fertilizer.