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The Impact of Quality Management Practices Towards Digital Transformation Readiness in the Food Industry

Halim-Lim, S.A.[1*], Mohd Asni, N.A.Z[1], Ismail, A.F.[1], Saryatmo, M.A.[2]

[1] Faculty of Food Science and Technology, Universiti Putra Malaysia, Serdang 43400, Malaysia
[2] Industrial Engineering Department, Universitas Tarumanagara Jakarta, Jl. Letjen S. Parman No. 1 Grogol Jakarta Barat, Jakarta 11440, Indonesia

*Corresponding Author: sarinalim@upm.edu.my

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Abstract: *This study investigates the influence of quality management practices (QMP) on digital transformation (DT) readiness within the food industry. A quantitative research approach was adopted, employing an online explanatory questionnaire distributed to 129 executives, senior managers, and quality managers in the food sector. Data analysis involved descriptive statistics, reliability analysis, multiple regression analysis, path analysis, and t-test analysis using SPSS and SmartPLS software. The findings reveal that most food companies implement QMP through certified programs like HACCP and ISO 9001. Current DT readiness in the industry is at an intermediate level ($\mu = 3.747$), with larger companies demonstrating higher readiness ($\mu = 4.633$). Importantly, a positive causal relationship exists between QMP and DT readiness ($p < 0.01$). While the study provides valuable insights, future research could explore the specific QMP elements most impactful on DT readiness within the food industry. Additionally, a broader geographical scope could enhance generalizability. The findings suggest that robust QMP fosters DT readiness in the food industry. This knowledge can guide companies in strengthening their quality management systems to facilitate successful digital transformation initiatives. This study contributes novel insights by exploring the link between QMP and DT readiness within the under-investigated context of the food industry. The results provide valuable guidance for food businesses aiming to leverage digital technologies while maintaining high-quality standards.*

Keywords: Quality Management Practices (QMP), Digital Transformation (DT), Food Industry, Digital Transformation Readiness, PLS-SEM

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1. Introduction

The food industry, like many others, faces a critical juncture in the era of Industry 4.0. Digital transformation (DT) offers significant opportunities to enhance efficiency, product quality, and customer satisfaction. However, successful DT implementation necessitates a strong foundation in quality management practices (QMP).

Quality Management Practices (QMP) have been a pillar in the food industry for decades, ensuring consistent product quality and adherence to regulatory standards (Prajogo & McDemmort, 2005). Traditionally, QMP encompasses both "soft" and "hard" practices. Soft practices emphasize leadership, supplier management, and customer focus (Amani & Ayham, 2021). Hard practices, on the other hand, focus on tangible tools and systems, like process management, continuous improvement, and employee training (Amani & Ayham, 2021). In the food industry, the QMP has extended to the assurance, monitoring, validation verification and continuous improvement and becoming a tool to ensure safe food, quality production, excellent processes, and a means of marketing. Since the QMP is implemented in the food businesses, the potential of its implementation promoting the DT in the food businesses should be explored (Ali & Johl, 2022).

Despite the established benefits of QMP, research gaps exist regarding its specific influence on DT readiness within the food industry. While studies have highlighted the importance of both hard and soft practices for successful change management (Uluskan, McCreery, & Rothernberg, 2018), limited research explores their statistical impact on DT implementation (Uluskan, McCreery, & Rothernberg, 2018).

Furthermore, research on QMP strategies in the Industry 4.0 context, particularly the integration of emerging technologies like big data and business analytics, remains scarce (Gunasekaran, Subramanian, & Ngai, 2019).

Additionally, challenges associated with DT implementation, such as inadequate planning, lack of expertise, and budgetary constraints, often stem from insufficient process management practices (Yusmadi et al., 2017). However, previous studies haven't established clear methods to assess process management sufficiency for DT readiness (Yusmadi et al., 2017).

This research aims to address these gaps by investigating the impact of QMP on DT readiness in the Malaysian food industry. We hypothesize that robust QMP implementation, encompassing both soft and hard practices, significantly contributes to an organization's ability to embrace digital transformation. This study will identify the specific QMP practices prevalent in the Malaysian food industry, assess their level of DT readiness, and statistically analyze the correlations between these factors. By elucidating this relationship, our research can guide food industry stakeholders in leveraging QMP as a strategic tool for successful DT implementation. This can ultimately enhance operational efficiency, improve food safety, and create a competitive advantage in the era of Industry 4.0.

2. Theoretical Background

Quality Management Practices (QMP) have been critical to the food industry for decades, ensuring consistent product quality and adherence to regulatory standards (Prajogo & McDemmort, 2005). QMP encompasses a set of principles and practices focused on continuous improvement. These practices are often categorized as "soft" or "hard" practices. Soft practices emphasize leadership, supplier management, and customer focus, fostering a culture of quality within the organization (Amani & Ayham, 2021). Hard practices, on the other hand, focus on tangible tools and systems, such as process management, continuous improvement initiatives, and employee training (Amani & Ayham, 2021). The successful implementation of both soft and hard QMP elements leads to numerous benefits, including production efficiency, reduced waste and defects, on-time product launches, and ultimately, improved customer satisfaction and sales growth (Kim-Soon et al., 2020).

However, the food industry has unique QMP considerations compared to other sectors. Beyond ensuring product functionality and meeting customer expectations, food safety is paramount. QMP plays a crucial role in maintaining safe food production practices and ensuring accurate

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labeling, minimizing health risks for consumers (Paiva, 2013). Additionally, QMP promotes continuous improvement activities across all operational areas, enhancing employee capabilities through training and fostering a culture of problem-solving (Shafiq et al., 2019). Furthermore, QMP practices can contribute to environmental benefits within the food industry. By optimizing processes and reducing waste, QMP can lead to lower production energy consumption (Yusr et al., 2017; Abbas, 2020). Studies have shown that QMP has been effectively utilized across various food industry segments to achieve market success and meet customer demands (Ahmad et al., 2017). Notably, Kim-Soon et al. (2020) highlight the importance of QMP for the operational and market performance of food manufacturers in Malaysia.

2.1 Quality Management Practices

The QMP can be reinforced by implementing the most relevant practices that can yield a higher positive impact on the organization's performance including leadership, customer focus, employee management, supplier management, process management, quality control and continuous improvement as presented in Table 1.

The concept of quality has long been vital in management theory. James (2008) defines it as the degree to which a product or service meets customer expectations, both explicit and implicit. Building on this foundation, Quality Management Practices (QMP) encompass a philosophy, and a set of tools aimed at achieving consistent product quality and exceeding customer demands (Canbay and Akman, 2023) As Prajogo & McDemmort (2005) posit, QMP represents a management model that integrates various organizational functions and processes through continuous improvement activities. This approach, heavily influenced by quality gurus like Deming, Juran, and Crosby (Prajogo & McDemmort, 2005), emphasizes a holistic view of quality management.

While these core definitions provide a solid foundation, it's crucial to acknowledge the unique challenges faced by the food industry. Paiva (2013) emphasizes the concept of "sustainability for consumer usage," highlighting the importance of not only meeting customer satisfaction but also ensuring product safety. This broader definition underscores the need for a more comprehensive QMP strategy in the food sector, where ensuring food safety and accurate labeling become paramount objectives (Paiva, 2013). Hence several hypotheses was tested to identify the factors of QMP in the food industry,

2.1.1 Leadership

Leadership plays a crucial role in fostering a culture of quality within food organizations. James (2019) defines leadership as empowering and developing employees, fostering a safe and supportive environment, and encouraging employee voice in decision-making (Homann et al., 2020). These leadership behaviors are critical for promoting employee engagement, a key driver of quality (Homann et al., 2020). While Canbay et. al. (2023) provides a positive view of leadership, it's valuable to acknowledge different leadership styles and their potential impact on QMP. Transformational leadership, for example, emphasizes innovation and continuous improvement, which may be particularly beneficial for the food industry facing dynamic consumer demands (Akanmu et al., 2023). Further exploration of leadership styles and their influence on QMP in the food context is warranted.

H1: Leadership has a positive and significant impact on QMP

2.1.2 Employee Training

Effective employee training is essential for successful QMP implementation. Zeng et al. (2017) highlight the importance of training methods such as small group problem-solving, employee suggestion schemes, and task-related workshops. These approaches go beyond basic skills development, fostering critical thinking and problem-solving skills crucial for maintaining consistent quality (Akanmu et al., 2023). Specific training needs for quality 4.0 within the food industry need to be studied further (Elg, et al., 2020). Training on food safety regulations, HACCP principles, and allergen management would be crucial for food companies. Additionally, exploring the effectiveness of different training modalities (e.g., online learning vs. on-site workshops) could be beneficial.

H2: Training has a positive and significant impact on QMP.

2.1.3 Process Management

Effective process management minimizes process variation and ensures consistent quality output (Zeng et al., 2017). Statistical process control (SPC) plays a vital role in this endeavor, allowing for real-time monitoring and identification of deviations (Abdul Halim Lim et al., 2015). Beyond SPC, a broader view of process management encompasses performance metrics like key performance indicators (KPIs) that track efficiency, innovation, and waste reduction (James, 2019). While SPC is a valuable tool, it's important to acknowledge the limitations of a purely quantitative approach. Process management in the food industry may also benefit from incorporating risk assessments and preventive maintenance practices to address potential quality issues proactively.

H3: Process management has a positive and significant impact on QMP.

2.1.4 Supply Chain Management

Effective supply chain management is critical for ensuring the quality and safety of food products. Manavalan and Jayakrishna (2019) emphasize the importance of a connected supply chain encompassing suppliers, manufacturers, and customers. Rigorous supplier audits and collaborative quality agreements are essential for mitigating risks associated with raw material quality (Alejandro et al., 2017). Additionally, robust traceability systems, as exemplified by Marks and Spencer's approach (2018), enable the identification and swift containment of potential food safety hazards. There are very little studies on the challenges of managing complex global food supply chains. Emerging technologies like blockchain may offer solutions for enhancing traceability and transparency within the food system (Kamble & Gunasekaran, 2019). Exploring the potential of such technologies for QMP in the food industry would be valuable.

H4: Supply chain management has a positive and significant impact on QMP.

2.1.5 Continuous Improvement

Continuous improvement, often represented by the PDCA (Plan-Do-Check-Act) cycle, is a cornerstone of QMP (Ladewski & Al-Bayati, 2019). Zeng et al. (2017) highlight the importance of employee involvement in this process, as their suggestions and feedback can be valuable sources of improvement. Additionally, data analysis plays a crucial role in identifying areas for improvement and measuring the effectiveness of implemented changes (James, 2019). While the PDCA cycle provides a structured framework, the review could delve deeper into specific tools and techniques used for continuous improvement in the food industry (Kim-Soon et al., 2020). For example, exploring the use of Six Sigma methodologies or lean manufacturing principles within the food context would provide further insights.

H5: Continuous improvement has a positive and significant impact on QMP.

2.1.6 Customer Focus

Customer satisfaction is a key objective of QMP in the food industry (James, 2019; Li et al., 2006). James, (2019) demonstrates the positive impact of customer satisfaction on profitability and overall performance. Understanding customer needs and expectations through feedback mechanisms and addressing customer complaints effectively are crucial aspects of customer focus in QMP (Akanmu et al., 2023).

H6: Customer focus has a positive and significant impact on QMP.

2.2 Readiness of Digital Transformation (DT) in the Food Industry

The concept of Industry 4.0, characterized by the integration of advanced digital technologies into business processes, presents a significant opportunity for the food industry. Digital Transformation (DT) refers to the strategic adoption of these technologies to fundamentally transform business activities and processes, ultimately creating greater value for customers (Higher Education Policy Institute, 2017; Vial, 2020). DT offers the potential to enhance efficiency, innovation, and customer focus within the food industry (Limani et al., 2019). There are few reasons why an organization may undergo DT, including being more resourceful, innovative, efficient, well-organized, customer-oriented, as well as positioning back the business towards industry 4.0 (Limani et al., 2019).

However, successful DT implementation hinges on an organization's readiness to embrace change. DT readiness reflects an organization's willingness and capability to adopt digital technologies (Uluskan et al., 2017). DT readiness also refers to the extent to which an organization is willing and able to implement that particular change, (Uluskan et al., 2017), which has become a critical assessment prior to the food business investing towards the change. This includes ensuring the workforce is adaptable and equipped with the necessary skills to navigate new technologies. Assessing an organization's DT readiness is crucial before embarking on significant digital investments.

Several models have been developed to assess an organization's preparedness for change, including DT readiness. These models often utilize the concepts of "readiness" and "maturity" to gauge an organization's current state and potential for improvement (Schumacher et al., 2016). Examples include the Capability Maturity Model, which evaluates processes across various departments (Pessl et al., 2017), and the Digital Readiness Assessment Maturity (DREAMY) model, which assesses digital competitiveness through a series of maturity levels (De Carolis et al., 2017). These models provide valuable frameworks for organizations to identify areas of strength and weakness in their DT readiness journey.

2.2.1 Top Management Commitment

Maskun et al. (2020) identified a dearth of digitalization knowledge, expertise, and infrastructure as primary barriers to digital transformation (DT). The critical role of top management in overcoming these challenges (Kuwormu et al., 2023). To foster a digital culture, top management should allocate financial resources for advanced digital infrastructure, recruit digital experts, and implement training programs (Akanmu et al., 2023).

H7: Top management support is an important indicator for DT readiness.

2.2.2 Employee Engagement

Effective DT requires active employee involvement characterized by problem-solving, creativity, and information seeking (Ladewski and Al-Bayati, 2019). Leadership and employee self-efficacy are crucial for fostering engagement. Leaders can enhance employee engagement by setting ambitious goals and empowering employees (Azim et al., 2019). Key indicators of employee engagement include involvement in decision-making, autonomy, and problem-solving opportunities (James, 2019).

H8: Employee engagement is an important indicator for DT readiness.

2.2.3 Emerging Technologies

Emerging technologies offer significant potential for enhancing various business functions, including marketing, finance, and production (Kumar & Kalse, 2020). For instance, QR codes integrated with artificial intelligence can optimize data management and forecasting (Lucato et al.,2019). In manufacturing, technologies such as vision systems and sensors can monitor resource consumption (Jagtap et al., 2020). Evaluating the compatibility, complexity, and potential benefits of new technologies is essential for successful implementation (Rotolo and Martin, 2015).

H9: Emerging technology is an important indicator for DT readiness.

2.2.4 Data Analytics Readiness

Data analytics readiness hinges on the availability of data, skilled personnel, and appropriate tools (Gurdur et al., 2019). Organizations must assess their technological infrastructure, human capital, and data management practices to determine their data analytics maturity. Establishing clear data policies and ensuring easy data accessibility are also critical components of data analytics readiness (Schumacher et al., 2016).

H10: Data analytics is an important indicator for DT readiness.

2.2.5 Process Innovation

Process innovation, characterized by the introduction of new elements into organizational processes, is essential for enhancing performance (Hong et al., 2019; Zeng et al., 2017). These innovations can be internally developed or acquired. Successful process innovation often involves the integration of new materials, tasks, workflows, or equipment (Zeng et al., 2017). Organizations with unique and valuable process innovations can gain a competitive advantage (Hong et al., 2019).

H11: Operation management is an important indicator for DT readiness.

2.2.6 Operations Management

Data-driven decision-making has long been a cornerstone of operational excellence. By analyzing data, organizations can improve process stability and efficiency (Abdul Halim Lim et. al., 2015, Schultz, 2006). Effective operations management encompasses supply chain management, resource planning, and inventory control, often facilitated through the implementation of quality management programs (James, 2019).

H12: Process innovation is an important indicator for DT readiness

2.3 Previous Works

This research builds upon a framework (Figure 1) to explore the impact of quality management practices (QMP) on digital transformation (DT) readiness in the food industry. The framework identifies four key QMP categories derived from Burli et al. (2012): leadership, employee training, process management, and supply chain management. Notably, the focus here is on practices directly influencing digital adoption, excluding customer focus and continuous improvement, which are addressed elsewhere in the literature. To assess DT readiness, the framework adopts product quality features established by Kim-Soon et al. (2020) and Rotolo et al. (2020). Based on this framework (Figure 1), the following hypotheses are presented:

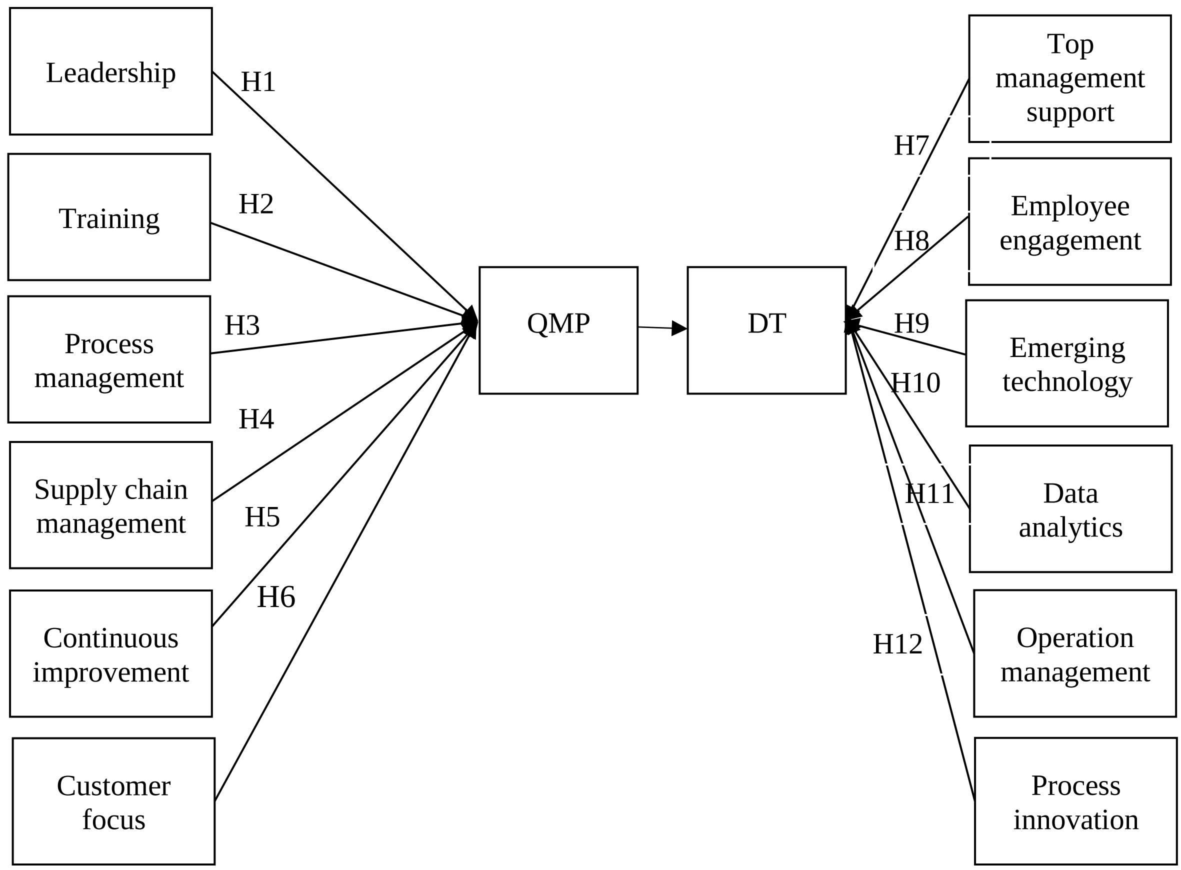

Figure 1: Conceptual Framework

Building upon the distinction between soft and hard QMPs (Zeng et al., 2017), this section explores the interplay between these practices and digital transformation (DT) readiness. Soft QMPs, encompassing leadership, employee involvement, and training (Zeng et al., 2017), are argued to have a direct influence on hard QMPs like process management (Sciarelli et al., 2020). This translates to a focus on soft QMPs fostering administrative DT, while hard QMPs drive technical DT, ultimately leading to improved performance (Sciarelli et al., 2020). Hence, for the food industry sector, the hypothesis of this study will be comprised as below:

Furthermore, the impacts of specific quality management programs like Lean, Six Sigma, and Total Quality Management (TQM) on DT readiness are examined. Lean, focused on value creation and process optimization (Sodhi, 2020), integrates well with Industry 4.0 (I4.0) technologies like lean automation (LA) (Tortorella et al., 2021). LA utilizes data collection, storage, and sharing facilitated by I4.0 to enhance operational performance (Xu et al., 2018; Tortorella et al., 2021). However, research suggests room for improvement in achieving advanced LA implementation levels (Tortorella et al., 2021).

Six Sigma, a data-driven methodology for error identification (Sodhi, 2020), might require prior DT implementation for successful application in the food industry (Uluskan et al., 2017). This highlights the importance of organizational culture and infrastructure alongside strong leadership for innovative Six Sigma adoption (Uluskan et al., 2017). Notably, the limitations of traditional Six Sigma statistical techniques in handling big data necessitate its evolution towards I4.0 technologies (Sodhi, 2020). Finally, TQM, with its focus on leadership, customer focus, and continuous improvement (Barros, 2014), while lacking conclusive evidence on its direct performance impact with I4.0 tools, demonstrates potential in enhancing data collection and process control within I4.0 manufacturing (Hassan & Jaaron, 2021). Additionally, TQM can facilitate the development of employee skills necessary for adopting green manufacturing practices within the I4.0 framework (Hassan & Jaaron, 2021).

3. Method

This research adopted three widely used valid and reliable instruments, which fitted and served the aim and objectives of the current study. The validity and reliability of these scales will be tested for the new context in our study. All the constructs of the model were measured using multiple items based on validated scales obtained from the existing literature, and the items were assessed via a five-point Likert-scale, ranging from strongly disagree to strongly agree. The two constructs measured were the following:

Quality management practices: to measure the level of QMP components, the reliable and valid instrument developed by Kim-Soon et al. (2020) was adopted. Meanwhile, the indicators for DT readiness are built from MITI Industry4wrd model consist of people, technology and process, which are supported by other previous studies (Uluskan et al., 2017; Zeng et al., 2017; Azim et al., 2019; Hong et al., 2019; James, 2019; Kumar and Kalse, 2020; Maskun et al., 2020; Rotolo et al., 2020; Kim-Soon et al., 2020). The final conceptual framework for guiding the analysis of this research is finalized as shown in Figure 1.

Individual affective commitment to change (IACC): IACC was measured by using Herscovitch and Meyer's (2002) instrument. TQM: in order to measure the level of implementation of TQM practices in AMOs, the valid and reliable instrument developed by Samson and Terziovski (1999) was utilised and adopted. In this instrument the empirical constructs are guided by and based on the principle criteria of the MBNQA.1 The findings from many empirical studies, such as Ahire et al. (1996), have demonstrated that TQM practices are strongly correlated to each other, supporting the synergy among the practices. Like many previous studies, the current study views TQM as a unidimensional set (or package) of practices. TQM is modelled as a single latent variable that is measured by six first-order latent variables, namely plan (Strategic Planning), info (Information and Analysis), peo (People Management), cust (Customer Focus), proc (Process Management) and lead (Leadership). All the items were assessed via a 5-point Likert-scale, ranging from 1 (strongly disagree) to 5 (strongly agree).

The research instrument, a questionnaire, was developed based on the existing literature (Hassan & Jaaron, 2021). It employed a six-point Likert scale with anchors ranging from "strongly disagree" to "strongly agree" to facilitate streamlined data analysis (Hassan & Jaaron, 2021).

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3.1 Sample and Data Collection

Firstly, the targeted population in this study is the employees from all departments in the food industry either they are a manager, a supervisor, an executive or a shop floor. This is because responsibility for quality was not specially assigned to quality department or quality officers only but every employee at each level and department plays an important role in achieving quality success (James, 2019). However, several conditions must be met before the food industry or the respondent can be chosen to be a part of the data collection process. The conditions to be met are as followed:

- Food industry selection:
  - Has a clear and well-established organizational structure.
  - Has a quality department, or quality control management activities with a quality officer and announced quality policy.
  - Has implemented digitization in daily operational steps.
- Sampling criteria:
  - Has working experience in the food industry
  - Aware of quality program and quality management activities

To ensure face and content validity, the questionnaire underwent review by academic professors and experts in the field of food industry QMPs. All of the experts considered that the questionnaire was appropriate, would achieve the aim of the study, and needed only a little editing. The proposed questionnaire was then adjusted and amended according to the feedback and comments of the experts. Additionally, a pilot study was conducted with 30 participants, including senior managers and quality department employees in the food industry. This pilot study aimed to assess the questionnaire's reliability by determining the clarity of the questions and identifying any necessary additions or removals.

The sample size was calculated using Daniel Soper Calculator. The anticipated sample size is set at 0.3 which is the medium number to be safe, the desired statistical power level is set at 0.8 because the common starting point for an acceptable risk is 20%, which returns a power level of 80% (Cross, 2019). Thus, 80% is a reasonable balance to be used in this study in order to minimize the sample size due to the limited time in running the survey. This study uses purposive sampling techniques which is also known as judgment, selective, or subjective sampling (Black, 2010). Purposive sampling is an effective sampling method when only a limited numbers of people can serve as primary data sources due to the nature of the research design and objectives).

The questionnaire consists of a total of 55 items that cover both QMP and DT readiness in the food industry. The calculation of this reliability test is done using SPSS19 based on an answered survey by 30 potential respondents. It can be concluded that all Cronbach’s alpha values are higher than 0.7, which means the items asked are reliable, highly reliable and very highly reliable when compared to Cronbach’s alpha guidelines by Kim-Soon et al. (2020).

3.2 Data Analysis

Data analysis was conducted using a combination of SPSS and SmartPLS software. Descriptive statistics were employed in SPSS to obtain the demographic profile of the participating companies and individuals (Pallant, 2020). Additionally, descriptive analysis was used to identify the current QMPs implemented within the food industry and the overall level of DT readiness. This involved calculating mean values from the six-point Likert scale responses (strongly disagree, disagree, slightly disagree, slightly agree, agree, strongly agree) (Pallant, 2020). To assess the model's reliability before further analysis, SmartPLS was utilized for reliability analysis. This analysis examined Cronbach's alpha, average variance extracted (AVE), factor loadings, and composite reliability.

SmartPLS was also employed to conduct path analysis, evaluating the relationships between the dependent variable (DT readiness) and the independent variables (individual QMPs). Path analysis helped to determine the individual contribution of each QMP variable to the different dimensions of DT readiness (human, technology, process). Finally, two-tailed independent t-tests were performed in SPSS to analyze DT readiness levels in the food industry based on company size and duration of QMP implementation. This enabled a deeper understanding of how QMP impacts DT readiness across varying company sizes.

4. Findings

4.1 Descriptive Analysis

Descriptive statistics were employed to analyze the demographic profile of the respondents, which included both individual and company characteristics (Table 1). The individual profiles captured gender, age, current department, position, years of experience in the food industry, and duration of employment in the current company.

Most respondents (76.0%) identified as female, with the remaining participants being male. Age distribution revealed a concentration in the twenties (72.9% between 20-29 years old). The other age groups included 30-39 years old (20.9%), 40-49 years old (4.7%), and 50-59 years old (1.6%). As the study investigated the impacts of QMP, unsurprisingly, the majority (66.7%) worked within the quality department. Other departments represented included research and development (14.0%), production (9.3%), and others (human resources, sales & marketing, engineering, packaging & distribution) collectively comprising 3.1% or less.

Regarding company positions, 62.8% of respondents held executive positions, followed by department managers (6.2%), senior/division managers (4.7%), supervisors (9.3%), and shop floor personnel (12.4%). The food industry experience primarily fell within the 4–10-year range (56.6%), with 31.8% having up to 3 years, 8.5% having 11-20 years, and 3.1% (4 respondents) exceeding 20 years. Interestingly, a disparity emerged between industry experience and current company tenure. The majority (72.1%) had been employed at their current company for only up to 3 years, with 24.0% working for 4-10 years, 1.6% for 11-20 years, and 2.4% for over 20 years.

Table 1: Company demographic profile

Demographic	Categories	Number of Response	Percentage (%)
Company size	Large	60	46.50
	Medium	33	25.60
	Small	29	22.50
	Micro	7	5.40
Type of food industry	Manufacturing	92	71.30
	Service	15	11.60
	Processing	12	9.30
	Retail	6	4.70
	Other	4	3.10
Type of food commodity	Vegetables and fruits	23	25.00

	Grains and rice	17	17.90
	Meat and poultry	16	17.40
	Eggs and dairy products	15	16.30
	Herbs and spices	13	14.70
	Seafood	8	8.70
Years of implementing QMP	Up to 5 years	48	37.20
	6-10 years	40	31.00
	11-20 years	26	20.20
	Above 20 years	15	11.60
Person responsible for QMP	Quality department manager	88	68.20
	Senior manager	12	9.30
	CEO	15	11.60
	Other	14	10.90

4.2 Validity and Reliability

The measurement model was assessed using the PLS algorithm in SmartPLS software to evaluate its reliability through factor loadings, Cronbach's alpha, composite reliability (CR), and average variance extracted (AVE) (Hair et al., 2017). According to Hair et al. (2017), acceptable factor loadings exceed 0.5, Cronbach's alpha and CR surpass 0.7, and AVE values are greater than 0.5. These criteria indicate strong internal consistency and convergent validity (Hair et al., 2017).

Table 2 presents the measurement model assessment results, including factor loadings, Cronbach's alpha, CR, and AVE. As shown, all factor loadings were above 0.5, with C14 exhibiting the lowest value (0.507). All Cronbach's alpha values exceeded 0.7, with continuous improvement showing the lowest score ($\alpha = 0.753$). Similarly, all CR values were higher than 0.7, with continuous improvement again having the lowest score ($\rho\_A = 0.823$). Finally, all AVE values surpassed 0.5, with continuous improvement registering the lowest value (AVE = 0.502). These findings demonstrate that all variables in the model possess acceptable reliability and converge validity, adhering to the established criteria by Hair et al. (2017). This paves the way for further data analysis.

Table 2: Results of measurement model assessment

Variables	Indicators	Loadings	Cronbach's alpha	Composite reliability	AVE
Leadership	L1	0.802	0.836	0.883	0.602
	L2	0.790			
	L3	0.787			
	L4	0.752			
	L5	0.745			
Employee training	ET1	0.720	0.850	0.893	0.627
	ET2	0.683			
	ET3	0.849			
	ET4	0.884			
	ET5	0.805			
Process management	PM1	0.720	0.829	0.878	0.590
	PM2	0.764			
	PM3	0.811			
	PM4	0.738			

	PM5	0.803			
Supply chain management	SCM1	0.849	0.876	0.910	0.671
	SCM2	0.871			
	SCM3	0.862			
	SCM4	0.820			
	SCM5	0.676			
Continuous improvement	CI1	0.841	0.753	0.823	0.502
	CI2	0.833			
	CI3	0.727			
	CI4	0.507			
	CI5	0.525			
Customer focus	CF1	0.810	0.872	0.908	0.663
	CF2	0.897			
	CF3	0.843			
	CF4	0.757			
	CF5	0.755			

Note: All values fit the reliability test with loadings more than 0.5, Cronbach's alpha more than 0.7, composite reliability more than 0.7, and AVE more than 0.5

4.3 Hypotheses testing

The path analysis revealed positive relationships between each QMP variable and DT readiness, with customer focus demonstrating the strongest association (p21 = 0.512). This was followed by supply chain management (p21 = 0.217), process management (p21 = 0.176), employee training (p21 = 0.159), leadership (p21 = 0.134), and continuous improvement (p21 = 0.047). Research hypotheses 7 through 12 examined the role of specific variables (top management support, employee engagement, emerging technologies, data analytics, process innovation, and operation management) in achieving DT readiness. Each variable was measured with four questionnaire items.

Similarly, the path analysis indicated positive relationships between these DT readiness variables and DT readiness itself. Data analytics exhibited the strongest association (p21 = 0.784), followed by employee engagement (p21 = 0.254), top management support (p21 = 0.249), emerging technologies (p21 = 0.245), process innovation (p21 = 0.226), and operation management (p21 = 0.201). Overall, the path coefficient of 0.331 suggests a moderate positive impact of QMP implementation on DT readiness.

While the path coefficients indicate positive relationships, further analysis was conducted to determine their statistical significance using t-values and p-values (Hair et al., 2014). A t-value exceeding 1.96 (5% significance level) and a p-value lower than 0.05 (5% significance level) are considered statistically significant (Hair et al., 2014). Only if both criteria are met can the corresponding research hypothesis be accepted. Table 3 presents the t-values, p-values, and the acceptance status of each research hypothesis.

Table 3: Results for individual simple linear regressions

Hypo-thesis	Relationship	Std. deviation	t-value	p-value	Statistically significant	Decision
H1	L > QMP	0.059	6.171	0.000	Yes	Accepted
H2	ET > QMP	0.066	6.052	0.000	Yes	Accepted
H3	PM > QMP	0.061	6.853	0.000	Yes	Accepted
H4	SCM > QMP	0.066	6.853	0.000	Yes	Accepted

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H5	CI > QMP	0.093	2.321	0.000	Yes	Accepted
H6	CF > QMP	0.069	7.446	0.000	Yes	Accepted
H7	DTR > TMS	0.073	6.828	0.000	Yes	Accepted
H8	DTR > EE	0.063	7.986	0.000	Yes	Accepted
H9	DTR > EDT	0.075	6.582	0.000	Yes	Accepted
H10	DTR > DA	0.016	54.278	0.000	Yes	Accepted
H11	DTR > PI	0.081	5.873	0.000	Yes	Accepted
H12	DTR > OM	0.066	6.742	0.000	Yes	Accepted
	QMP>DTR	0.062	5.309	0.021	Yes	

Note: All hypotheses are accepted because they fit significant the $t>1.96$ and $p<0.05$

Table 3 presents the t-values and p-values for each path coefficient in the structural model. All t-values exceeded the critical value of 1.96 (5% significance level), ranging from a minimum of 2.321 (CI > QMP) to a maximum of 54.278 (DTR > DA). Similarly, all p-values were lower than 0.05 (5% significance level), with all relationships showing a p-value of 0.000 except QMP > DTR ($p = 0.021$), which nonetheless remained statistically significant. These findings confirm the statistical significance of all relationships within the model, supporting the acceptance of all twelve research hypotheses.

This implies that leadership, employee training, process management, supply chain management, continuous improvement, and customer focus have a significant impact on QMP, as similarly displayed in food SMEs (Kim-Soon et al., 2020). Conversely, top management support, employee engagement, emerging technologies, data analytics, process innovation, and operation management all emerged as significant indicators of DT readiness, corroborating prior research (Kempler & Matthew, 2016; Zeng et al., 2017; Azim et al., 2019; Hong et al., 2019; Maskun et al., 2020; Rotolo et al., 2020; Jangtap et al., 2020; Kumar & Kalse, 2020). Consequently, the path analysis validates all twelve research hypotheses established based on the existing literature.

Furthermore, this study specifically aimed to investigate the relationship between QMP impacts and DT readiness in the food industry. The path coefficient confirmed a positive relationship between these variables (0.331), with a statistically significant t-value (5.309) and p-value (0.021).

Following the confirmation of relationships between variables, including the impact of QMP on DT readiness, further analysis using SPSS was conducted to determine the level of QMP implementation and DT readiness in the Malaysian food industry. Descriptive statistics were employed to calculate the mean for each QMP and DT readiness variable (Pallant, 2020).

Table 4 shows the mean scores for each QMP variable. Customer focus emerged as the most implemented variable ($\mu = 4.977$), followed by supply chain management ($\mu = 4.955$), employee training ($\mu = 4.901$), process management ($\mu = 4.760$), leadership ($\mu = 4.744$), and continuous improvement ($\mu = 4.429$). Notably, customer focus had the highest overall mean values and a mode of 6, indicating practices like customer feedback platforms, product-related problem solving, and utilizing customer requirements as a quality foundation. Conversely, continuous improvement appeared to be the least implemented variable, with a mode of 4 and no significant differences in mean values. Practices associated with continuous improvement in this study included frequent internal audits, equipment upgrades and redesigns, and process and product performance analysis.

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Table 4: QMP variables implementation level

Variables	Mean	Std. deviation	Mode
Leadership	4.744	1.178	4
Employee training	4.901	1.062	6
Process management	4.760	1.127	4
Supply chain management	4.955	1.132	6
Continuous improvement	4.429	0.769	5
Customer focus	4.977	1.035	6

Table 5 presents the mean scores for the DT readiness variables. This study emphasizes the crucial roles of people (top management support and employee engagement), technologies (emerging technologies and data analytics), and processes (operation management and process innovation) in achieving DT readiness. As shown in the table, all variables have a mode of 4, indicating a slight level of implementation with no substantial mean value differences. Operation management exhibited the highest mean score ($\mu = 4.727$), followed by employee engagement ($\mu = 4.605$), data analytics ($\mu = 4.595$), emerging technologies ($\mu = 4.564$), top management support ($\mu = 4.436$), and process innovation ($\mu = 4.314$). Operation management practices included integrating quality programs into operational flows, combining digital technologies within operations, and prioritizing preventive measures over corrective actions. Process innovation, with the lowest mean score, encompassed practices like increased technology reliance compared to labor, standardized instructions for digital technologies, and utilizing digital monitoring systems for waste, water, and energy.

Table 5: DT variables readiness level

Variables	Mean	Std. deviation	Mode
Top management support	4.436	1.323	4
Employee engagement	4.605	1.100	4
Emerging technologies	4.564	1.112	4
Data analytics	4.595	1.156	4
Operation management	4.727	1.117	4
Process innovation	4.314	1.276	4

Examining Tables 4 and 5 reveals the most implemented variables within QMP and DT readiness in the food industry. Interestingly, the overall mean values displayed minimal variations between the highest and lowest scores, suggesting a general trend of moderate implementation for both QMP ($\mu = 4.57$ to $\mu = 4.98$) and DT readiness ($\mu = 4.31$ to $\mu = 4.73$). This finding helps address research questions 1 and 2 by indicating that the food industry practices QMP at a moderate to strong level (mode 4 to 6) and exhibits moderate progress towards DT readiness (mode 4).

Finally, the path analysis yielded R^2, f^2, and Q^2 coefficients to assess model fit and predictive relevance (Hair et al., 2014;). R^2 values exceeding 0.75, 0.50, and 0.25 are considered strong, moderate, and weak in predicting accuracy, respectively. Similarly, f^2 values are categorized as strong, moderate, and small effect sizes at 0.35, 0.15, and 0.02, respectively. Lastly, Q^2 coefficients greater than zero indicate predictive relevance.

Table 6: R^2, f^2, and Q^2 coefficient for the path analysis.

Variables	R^2	f^2	Effect size	Q^2	Predictive relevance
L	0.13	0.15	Moderate	0.07	Yes
ET	0.16	0.19	Moderate	0.10	Yes
PM	0.18	0.21	Moderate	0.09	Yes
SCM	0.22	0.28	Moderate	0.13	Yes
CI	0.05	0.05	Moderate	0.02	Yes
CF	0.26	0.36	Strong	0.17	Yes
TMS	0.25	0.33	Moderate	0.15	Yes
EE	0.25	0.34	Moderate	0.14	Yes
EDT	0.25	0.33	Moderate	0.14	Yes
DA	0.78	3.63	Strong	0.53	Yes
PI	0.23	0.29	Moderate	0.17	Yes
OM	0.20	0.25	Moderate	0.12	Yes

Table 6 summarizes the R^2, f^2, and Q^2 coefficients for each variable. Data analytics emerged as the only variable with a strong predictive accuracy ($R^2 = 0.78$). The f^2 values ranged from 0.05 to 3.63, signifying moderate to strong effect sizes for most variables. Encouragingly, all variables exhibited predictive relevance with Q^2 values exceeding zero.

5. Discussion

The results from this study coincide with other studies that complex QMP implementations, such as Six Sigma, necessitate a shift towards DT within food manufacturers for successful quality practices (Uluskan et al., 2017). Similarly, Hassan and Jaaron (2021) demonstrated that TQM implementation positively influences the I4.0 revolution by enhancing data collection and facilitating process improvement and control within manufacturing.

Leadership is frequently acknowledged as a crucial element in propelling digital transformation. Nevertheless, alternative research indicates that within the food business, the emphasis placed by executives on upholding conventional quality management methods might occasionally impede the progress of innovation. Brady and Davies (2021) conducted research that suggests that leaders in the food sector may be hesitant to adopt digital technologies that are seen as disruptive or risky due to their strong focus on compliance and aversion to risk. This contradicts the notion that leadership in quality management unambiguously endorses digital transformation, indicating instead that leadership may need to adapt to accommodate both the objectives of upholding quality and promoting innovation.

Employee training is crucial for ensuring that the staff is proficient in adjusting to emerging technologies. Nevertheless, several research suggest that the profitability of investing in digital skills training may not always meet the anticipated levels within the food business. A study conducted by Smith et al. (2020) revealed that personnel in the food manufacturing industry face difficulties in incorporating new digital technologies into their everyday workflows, despite undergoing comprehensive training programs. This challenge arises from the deeply rooted character of conventional methods. This discovery questions the belief that providing employees with training in quality management will automatically result in enhanced readiness for digital transformation. It emphasises the possible requirement for more customised or gradual training methods.

Process management in the food sector primarily focusses on ensuring strict adherence to standardised procedures and regulatory requirements. Although essential for guaranteeing the safety and excellence of food, several experts contend that it can also impede the progress of digital innovation. According to a study conducted by Lu and Watanabe (2021), the inflexible management structures in the food industry can impede the implementation of adaptable digital technologies that necessitate more agile process adjustments. This is in opposition to the idea that effective process management automatically promotes digital preparedness, suggesting that a more equitable strategy may be required - one that permits standardisation while also facilitating adaptability for digital projects.

The relationship between quality management and digital transformation in the field of Supply Chain Management is intricate. Although Hobbs (2021) and other studies highlight the capacity of digital tools to improve supply chain transparency and efficiency, there are also notable obstacles that need to be considered. An illustration of this is the study conducted by Nasir et al. (2020), which emphasises that the incorporation of digital technologies in food supply chains is frequently hindered by the differing degrees of technological acceptance among various participants, particularly small-scale suppliers. The uneven implementation of these standards can result in interruptions instead of the expected enhancements in efficiency, thereby confounding the connection between quality management techniques and the preparedness of supply chains for digitalisation.

Continuous Improvement is a fundamental aspect of both quality management and digital transformation; however, the interpretation and use of these principles can vary considerably. Continuous improvement in quality management typically emphasises gradual modifications to current procedures, but digital transformation may necessitate more drastic alterations. According to a study conducted by Chandrayan et al., (2023), organisations in the food industry that excessively prioritise small improvements may fail to recognise the significant impact that digital technology can have on their operations. This discovery indicates a possible conflict between the objectives of ongoing enhancement in quality management and the requirement for more radical alterations to accomplish digital transformation.

The importance of prioritising customer needs is becoming more widely acknowledged in order to achieve successful digital transformation, especially as consumer tastes continue to change. Nevertheless, several academics contend that the conventional emphasis on product uniformity and excellence within the food sector can clash with the necessity for adaptability and swift innovation. Zaki's (2019) research highlights that although digital tools can offer useful insights into consumer behaviour, the stringent quality requirements prevalent in the food industry can impede the company's agility in responding to these insights by introducing new product options. This viewpoint questions the belief that emphasising customer satisfaction in quality management methods will automatically result in improved preparedness for digital advancements. Instead, it proposes that a more adaptable approach may be required.

Overall, the PLS-SEM findings suggest that quality management techniques have a notable influence on the readiness of digital transformation in the food industry. However, it is important to consider these results in light of previous research that identifies possible contradictions and obstacles. The food sector's conservative attitude, influenced by regulatory requirements and the requirement for consistency, can both facilitate and limit digital transformation initiatives. In order to reconcile the disparity between conventional quality management and the requirements of the digital era, it is imperative to take into account not only the facilitating elements but also the possible hindrances and inconsistencies that may

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emerge. This necessitates a more refined strategy for quality management, which strikes a harmonious equilibrium between the imperative for adherence and uniformity, and the imperative for adaptability and ingenuity essential for digital transformation.

6. Conclusion

This section synthesizes the key findings in relation to the three research objectives: (1) identifying quality management practices (QMP) in the food industry, (2) determining the level of digital transformation (DT) readiness, and (3) evaluating the impact of QMP on DT readiness. The analysis confirmed the statistical significance of all twelve research hypotheses, signifying their relevance and acceptance.

The study acknowledges limitations including the sample size, respondent selection (excluding digital or engineering departments), and the adapted DT readiness model derived from various literature sources. Future research recommendations include expanding the sample size, incorporating respondents from both quality and digital departments to gauge the impact of QMP on DT readiness more effectively, and utilizing a well-established DT readiness model developed specifically for the food industry.

Despite these limitations, the study offers valuable contributions to the food industry. It highlights the importance of implementing both soft and hard QMP approaches for achieving DT readiness. Furthermore, the study successfully establishes a positive relationship between QMP and DT readiness, addressing a previously debated topic in the literature. Finally, the statistically validated, indirectly developed DT readiness model based on existing literature serves as a valuable reference point for future research on evaluating DT readiness in the food industry.

Building on this study's insights, several recommendations are offered for future research investigating the impact of QMP on DT readiness in the food industry. Future studies should employ larger sample sizes calculated using established methods and collaborate with relevant agencies to reach a broader range of food industry professionals. Including respondents from digital and engineering departments alongside quality management personnel would provide a more holistic perspective, strengthening the link between QMP and DT readiness. As the field matures, established and industry-specific QMP and DT readiness models are likely to emerge. Future research should consider adopting these published models for potentially higher reliability and stronger statistical significance.

This study offers valuable contributions to the food industry and the ongoing discussion regarding QMP and DT readiness. The findings highlight the importance of a comprehensive QMP strategy that incorporates both soft and hard approaches. Soft QMP practices, as analyzed in this study, include leadership, employee training, and customer focus. Hard QMP focuses on process management, supply chain management, and continuous improvement. Recognizing the interplay between both dimensions is crucial for DT readiness, which necessitates not only technological advancements but also competent employees and a new company culture.

This study contributes to the debate on the QMP-DT readiness relationship. While previous research suggested an indirect connection, this study establishes a positive direct relationship through path analysis within the food industry context. Additionally, the study demonstrates that companies with longer QMP implementation periods exhibit a higher level of DT

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readiness. It further identifies various practices that contribute to this positive impact, including certifications and methodologies like HACCP, ISO 9001, GMP, TQM, Lean, and Six Sigma. Finally, this study presents an adapted DT readiness model derived from existing literature. The model incorporates three core dimensions: people (top management support, employee engagement), technology (emerging technologies, data analytics), and processes (operation management, process innovation). The model's reliability and the positive relationships between the adapted variables suggest its potential as a valuable reference point for future research on evaluating DT readiness in the food industry.

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