INFLUENCING FACTORS ON SMART MANUFACTURING INTEGRATION OF DIGITAL TECHNOLOGY ADOPTION OF FOOD MANUFACTURERS IN MANDALAY

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Abstract

The purpose of this research is to investigating factors of smart manufacturing integration of digital technology (SMDT) adoption of food manufacturing companies in Mandalay. The conceptual framework is presented on how perceived value, perceived cost, perceived compatibility, perceived market transparency, strategic road mapping for smart manufacturing, transformational leadership, imposition by environment influence on SMDT adoption and implementation. This study employed the quantitative method using the questionnaire. Prior to data collection, the content validity was tested with Item-Objective Congruence (IOC) and Cronbach alpha. The samples of 500 respondents were collected from online and offline survey by using multistage sampling with probability and non-probability sampling including judgmental sampling, stratified random sampling, snowball sampling and convenience sampling to reach target respondents. The study applied the Structural Equation Model (SEM) and Confirmatory Factor Analysis (CFA) to analyze the data and confirm goodness-of-fit of the model and hypotheses. The results indicated that most variables have significant influence on SMDT adoption except perceived costs, perceived compatibility and imposition by the environment. SMDT adoption exhibited the strongest influence on SMDT implementation. Additionally, the company decision for adopting SMDT among Myanmar food industry determines a collection of technological, organizational and environmental factors. In conclusion, the study will potentially benefit for Myanmar Agri- food manufacturing enterprises' owners, by adopting digital technology in digital 4.0.

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Introduction

In digital era, the industrial transformation is referred to Industry 4.0 which can be explained as the integration of cyber-physical systems in production and logistics as well as the application of the Internet of Things (IoT) in industrial processes. It covers the impact on the value chain, business models, services and workplaces (Kagermann, Wahlster & Helbig, 2013). Smart Manufacturing (SM) has recently and rapidly changed the way of business operations (Qu et al., 2016). It offers customized product development, efficient management of manufacturing resource planning, specific control of manufacturing processes, automatic monitoring of manufacturing processes, proactive maintenance and quality control (Tao & Qi, 2017; Zheng, Xie, Dai, Chen & Wang, 2018). All these advantages result in an overall improvement in the performance of a manufacturing system, including decision-making capabilities for people and machines (Wang, Wei, Qiao, Lin & Chen, 2018).

Chau and Tam (1997) proposed a model using the technology-organization-environment framework (TOE) and adding product-specific characteristics to explore open (software) system standard adoption. This research developed a model based on TOE and adding products-specific characteristics: (1) external environment, for instance, strategic road-mapping for manufacturing digitalization, (2) organizational technique such as information technology (IT) infrastructure complexity, system satisfaction, system develop formalizations and (3) open system characteristics including perceived benefits, perceived barriers, interoperability, and interconnectivity.

Myanmar Population is approximately over 56 million in 2020. The construction and manufacturing are major sectors and manufacturing is the fastest growing sector in Myanmar. Mandalay city is the fastest growing regions in the country where has 11,244 of small and 839 of large enterprises, totaling of 12,083 enterprises (Asian Development Bank, 2019). Mandalay Smart City is the fifth of the top ten smart cities in the south-east Asia as reported by Lago (2020). In addition, Mandalay is a second city after Yangon where it has a large number of food manufacturers especially confectionery with around 162 factories in the city. During COVID-19 pandemic, manufacturers in Mandalay must move quickly to adopt and implement smart manufacturing projects to survive and accelerate smart manufacturing for future competitiveness.

The problem statements are the main constraints for small and medium enterprises to accomplish smart manufacturing which are (1) budget restraints, (2) undeveloped IT infrastructure on the well transition of Industry 4.0 technology, (3) Not adequate high-level management guidance for digital knowledge and support on the necessary budget, (4) lack of workforce skills, and (5) technical uncertainty and resistance due to immature standards and procedures (Wischmann Wangler & Botthof, 2019).

This study focuses on factors influencing smart manufacturing integration of digital technology (SMDT) adoption in Myanmar's food enterprises in Mandalay which would answer that statement of problems stated in this study. There are seven factors that could influence enterprises' SMDT adoption including perceived value, perceived cost, perceived compatibility, perceived market transparency, strategic road mapping for manufacturing digitalization, transformational leadership of food manufacturing, and imposition by the environment.

Literature Review

Smart Manufacturing Adoption

Smart manufacturing means "the application of the Internet of Things in industrial processes, as well as the integration of physical, cyber systems in production and logistics" (Kagermann, Wahlster & Helbig, 2019). It was generalized as the mobilization of physical and virtual systems using information and communication technologies to facilitate manufacturing processes, including the consumption of new resources, advanced semi-automatic machines, auxiliary systems, and industry technology virtualization. The smart manufacturing integration of digital technology (SMDT) adoption requires the change from manual operations to advance digital technology, as depicted by Liao, Deschamps, Loures and Ramos (2017). Technologies such as machine-to-machine communication, industrial sensors, big data analytics, cloud data are essential for Industrial Internet of Things and Services (IIoTS). Artificial Intelligence (AI) is crucial for IIoTs because it supports industrial operations to improve efficiency and reliability (Da Xu, He & Li, 2014).

Perceived Value

Kopp (2020) defined the perceived value in marketing terminology as the assessment of a product or service quality by the consumer and their ability to meet their needs and expectations. Ulaga and Chacour (2001) stated that it is an attempt to influence customers' perceived value of a product by explaining the innovative qualifications and how it is better than its competitors. Perceived value can also be measured by the price that the consumer is willing to pay for a good or service such as aesthetic design, accessibility, or convenience. According to Ghobakhloo and Ching

(2019), the results suggested that perceived value of SMDT is a significant determinant that positively influence SMDT adoption. Therefore, the perception of SMDT value is more likely to enhance the adoption of smart manufacturing and the following hypothesis of SMDT is formulated as:

H1: Perceived value of SMDT has significantly influence on the smart manufacturing adoption.

Perceived Costs

Perceived cost is defined as the cost that incorporates in using technology including transaction cost, equipment cost, applications download cost and access cost (Wu & Wang, 2005). The perceived costs feature money, time and employees (Benjangjaru & Vongurai, 2018). Agarwal and Teas (2001) argued that price can encourage financial sacrifice through a greater and positive understanding of product quality. Ghobakhloo and Ching (2019) indicated that SMDT adoption remains expensive for most SMEs due to smaller manufacturers have limited financial resources. According to Tornatzky and Klein (1982), technologies are more likely to be adopted it was perceived to be low-cost. Moreover, Prause (2019) mentioned that if perceived cost of the advanced manufacturing technologies is low, they should be adopted more. Therefore, previous studies have led to the following hypothesis:

H2: Perceived costs of SMDT has a significant influence on smart manufacturing adoption.

Perceived Compatibility

The definition of perceived compatibility is the degree to which information digital technology compatible with large to small enterprises' current technology infrastructure, culture, values, and preferred working practices, as explained by Ghobakhloo and Ching (2019). Therefore, the compatibility of innovation has had a strong impact on the adoption of innovation (Armstrong, Kotler & Da Silva, 2006; Ozer & Acikdilli, 2012). Moreover, Ghobakhloo and Ching (2019) stated that perceived compatibility has significant influence on SMDT adoption. Rogers and Singhal (2003) suggested that compatibility (both technological and organizational) and complexity (ease of use or learning an IT innovation) of the technological innovation were important technological factors upon influencing the adoption decision. Referring to stated studies, the following hypothesis was concluded as:

H3: Perceived compatibility of SMDT has a significant influence on smart manufacturing adoption.

Perceived Market Transparency

Market transparency can be defined as the ability of stakeholders to access trading process information, such as price, order size, trading volume, risk, and identity of the trader (Foucault, Pagano, Roell & Röell, 2013). Market transparency refers to the availability of knowledge and solutions for technology implementation. It is reflected in government efforts (Prause, 2019) to promote information, develop public-private partnerships (PPP), and build measures to compare technology solutions from various providers. According to Wischmann Wangler and Botthof (2019), market transparency refers to the availability of information about new technologies that will solve issues for companies. Prause (2019) postulated that the higher the market transparency, the more likely advanced manufacturing technologies will be adopted. From these supported studies, the following hypothesis has been formulated:

H4: Perceived Market Transparency of SMDT has a significant influence on manufacturing adoption decision.

Strategic Road Mapping

The definition of a strategic road mapping is a time-based strategy where is an organization, where it wants to go, and how it will get there. A strategic road map is a bridge or link between strategy and implementation. It visualises the key achievements which must be achieved over a certain period to meet the outcome of the strategic vision of the organization (Gindy, Cerit & Hodgson, 2006). Ghobakhloo and Ching (2019) presented the results that strategic road mapping for manufacturing digitalization is the most significant determinant of adoption. Therefore, Gilchrist (2016) explicated that a strategic road map for adoption ensures that businesses can capitalize on the benefits that will be brought about by new technology adoption such as physical infrastructure, workforce competency, decentralization, horizontal and vertical integration. Therefore, the researchers can form the following hypothesis:

H5: Strategic Road mapping for manufacturing digitalization has a significant influence on smart manufacturing adoption.

Transformational Leadership

According to Tuna, Ghazzawi, Tuna and Catir (2011), transformational leadership's definition is a leadership characteristic or action that infers leaders who build creative vision and use a powerful communication platform to share their own thoughts with employees/followers. To achieve high performance through self and organizational identity, transformational leaders' serve as a role model to inspire employees (Conger & Kanungo, 1988; Jaruwanakul, 2021; Sosik & Godshalk, 2005). Seyal (2015) found significant relationship between transformational leadership and technology adoption and transformational leader can encourage knowledge acquisition, retention and sharing. According to Alos-Simo, Verdu-Jover and Gomez-Gras (2017), transformational leadership is positively related to adaptive culture. This motivates the researcher to formulate the following hypothesis:

H6: Transformational leadership of SMDT has a significant influence on smart manufacturing adoption.

Imposition by the Environment

Imposition refers to a situation in which a person expects another person to do something they do not want or that is not comfortable. The imposition by environment reflects the influence practiced of business partners, customers and society on large and SMEs to adopt SMDT for the improvement procedure, connectivity enhancement and efficient sharing on data, (Riemenschneider, Harrison & Mykytyn, 2003). Ghobakhloo and Ching (2019) indicated that SMDT is significantly influenced by environmental imposition, which means the pressure on environment to produce digitalization can affect the decision to adopt SMDT. These investigations can lead to conclusion of the following hypothesis:

H7: Imposition by environment of SMDT has a significant influence on smart manufacturing adoption.

Implementation

Successful implementation of technologies requires skilled employees to achieve new and higher efficiency of operation and machine maintenance to improve level of product quality commitment (Osterman, 1994; Phyu & Vongurai, 2020), which has an impact on SMDT adoption. Ghobakhloo and Ching (2019) also observed the implementation of AI, AVR, autonomous robots, and high-performance computing powered CAD in which these applications provide organizational improvement and productivity. According to Ghobakhloo and Ching (2019), the further study has explored how various determinants have influenced the implementation of SMDT among SMEs. Some recent studies showed that lesser cost of technology, the faster it can be adopted and implemented in an organization (Ghobakhloo, Arias-Aranda & Benitez Amado, 2011). The assumptions above can lead to the following hypothesis:

H8: SMDT adoption has a significant influence on implementation.

Research Framework

The conceptual framework is developed from previous research frameworks. It is adapted from three theoretical models. Firstly, Ghobakhloo and Ching (2019) studied that technological context (perceived value, perceived costs, perceived compatibility), organizational context (strategic road mapping for SM) and environmental context (imposition by the environment) are significantly affected on SM adoption. Secondly, Alos-Simo et al. (2017) verified that transformational leadership has positive impact on e-business adoption. The third research was explored from Prause (2019) which conducted the research of market transparency that related to the adoption level of industry 4.0 as shown in Figure (1).

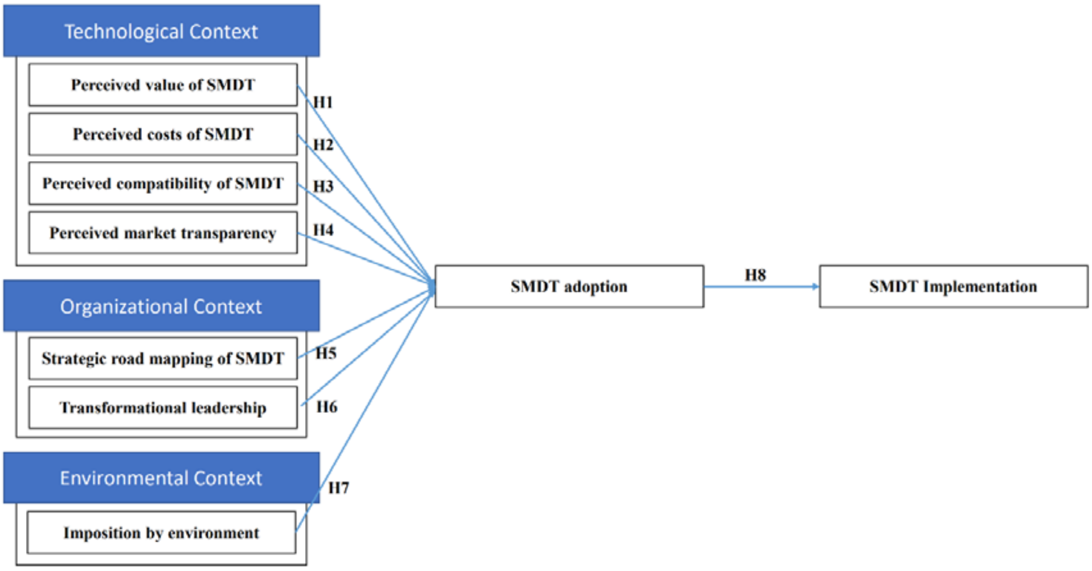

Figure 1 The conceptual framework of influencing factors on smart manufacturing integration of digital technology (SMDT) adoption and implementation.

This research aims to investigate the key influencers of perceived value (PV), perceived cost (PC), perceived compatibility (PCP), perceived market transparency (PM), strategic road mapping (SR), transformational leadership (TL) and imposition by environment (IE) in Myanmar. Additionally, the study examines the relationship between each variable to relate these factors influencing smart manufacturing adoption (SMA) and implementation (SMI).

Research Methodology

Population and Sample Size

Researchers selected three companies including large to small size of food manufacturing enterprises in Mandalay, Myanmar, targeting the total employees of 700 people per obtained data directly with human resources department of each company. Per recommended by Kline (2011) of minimum sample size of 200, data was collected from 500 employees of three businesses in this study as it has been widely accepted in most research.

Sampling Technique

This study applied quantitative approach using multistage sampling procedure. Firstly, nonprobability with purposive sampling was carried out by selecting three well-known food manufacturing industries in Mandalay, Myanmar, targeting 500 employees who have more than 5 years working experience. Second step is probability sampling with stratified random sampling, using number of total employees and calculating the ratio of sample size for each company as shown in Table 1. Thirdly, purposive sampling (chosen target employees), snowball sampling (suggesting them to spread the questionnaire to their peers) and convenience sampling (using online and offline survey by phone call and email).

Table 1 Population and Sample Size by Company

	Company Name	Approximate Employee Size	Percentage	Sample Size of Research
1	Myint Myint Khin	300	43	215
2	U Ka Ka family Co. Ltd (Tea Leaves)	300	43	215
3	Ah Yee Taung	100	14	70
	Total	**700**	**100**	**500**

Research tools and data collection

Before collecting the data, the questionnaire was constructed from prior literatures. The validity was tested by Index of Item-Objective Congruence (IOC), using three experts who have knowledge of SMDT and are high-level executives in Myanmar food manufacturing companies (Rovinelli & Hambleton, 1977). Afterwards, Cronbach's alpha reliability test was conducted with the the trial sample of 35 participants. The questionnaire design was composed with three parts including screening questions, five-point Likert scale, scaling from strongly agree of 5 to strongly disagree of 1, which was used for forty measuring items and demographical information including gender, age, educational level and job title.

Results and Discussion

Demographic Information

According to Table 2, most respondents were female with 60.8% and male with 39.2%. For the age of respondents, the major group was under 30 (Generation Z) years old, representing 44.8%, whereas 46-60 (Generation X) was 33.6%, over 60 (Baby Boomers) was 9.6%, and 30-45 (Generation Y) was 12%. In terms of education, 63.2% of employees have a diploma, while Bachelor's was 20.8%, Associate's degree was 15.2%, Master's was 0.8% and 0% of the respondents have Ph.D. Job title showed that there is 67% of employee level, 31% in Middle management level (Director or Manager) and 2% in top management level (Chief level)

Table 2 Demographic Characteristics of Respondents

Demographic and Behavior Data (N=500)		Frequency	Percentage (%)
Gender	Female	304	60.8
	Male	196	39.2
Age	< 30 - Generation Z	224	44.8
	30-45 - Generation Y	168	33.6
	46-60 - Generation X	60	12
	Over 60 – Baby Boomers	48	9.6
Education	Diploma	316	63.2
	Associate degree	76	15.2
	Bachelor’s degree	104	20.8
	Master’s degree	4	0.8
	Ph.D.	0	0.0
Job title	Top management level	10	2
	Middle management level	155	31
	Employee	335	67

Confirmatory Factor Analysis (CFA)

Confirmatory factor analysis (CFA) examined factors affecting smart manufacturing integration of digital technology (SMDT) adoption in this study. CFA revealed that all items in each variable are significant. Factor loading, indicating that discriminant validity has been established. Guidelines recommended by Hair Black, Babin, Anderson, & Tatham, 2006) is also employed in defining the significance of factor loading of each item and acceptable values in defining the goodness of fit. Factor loadings are more than 0.50 and the p-value is less than 0.05. In addition, the Composite Reliability (CR) is more than the cut-off point of 0.7, and the Average Variance Extracted (AVE) is accepted at 4.0, as recommendation from Fornell and Larcker (1981) in Table 3. The results of convergent validity testing showed that Cronbach’s alpha and Composite reliability of each construct ranged from 0.721 to 0.927 (as of Table 3), all Alpha values were greater than the recommended level of 0.70 (Iacobucci, Grisaffe, Duhachek & Marcati, 2003), indicating high level of reliability. CFA model showed all acceptable model-fit values including p-value of 0.000, CMIN/df of 1.465, GFI of 0.907, AGFI of 0.891, NFI of 0.901, CFI of 0.966, TLI of 0.962, RMSEA of 0.031 and RMR of 0.022 as demonstrated in Table 5. As a result, the convergent validity and discriminant validity were certified.

Table 3 Confirmatory Factor Analysis Result, Composite Reliability (CR) and Average Variance Extracted (AVE)

Variable	Source of Questionnaire	Number of Items	Cronbach's Alpha	Factors Loading	CR	AVE
Perceived value (PV)	Ustundag and Cevikcan (2017).	5	0.824	0.654-0.778	0.827	0.490
Perceived costs (PC)	Schröder (2016)	3	0.721	0.604-0.753	0.724	0.469
Perceived compatibility (PCP)	Kagermann et al. (2013)	4	0.804	0.590-0.773	0.810	0.519
Strategic road mapping (SR)	Chofreh, Goni and Klemeš (2017)	3	0.794	0.613-0.828	0.803	0.580
Imposition by environment (IE)	Ghobakhloo et al. (2011)	3	0.894	0.845-0.872	0.894	0.737
Transformational leadership (TL)	Bass (1999)	5	0.927	0.829-0.869	0.928	0.720
Perceived market transparency (PM)	Wischmann et al. (2019)	4	0.776	0.638-0.736	0.778	0.469
SMDT adoption (SMA)	Thames and Schaefer (2017);	5	0.829	0.687-0.726	0.829	0.492
SMDT Implementation (SMI)	Small and Yasin (2000)	8	0.874	0.593-0.736	0.875	0.468

Note: CR = Composite Reliability, AVE = Average Variance Extracted, *=p-value<0.05
Source: Constructed by author

Additionally, the discriminant validity among the constructs were assessed based on the criteria recommended by Fornell and Larcker (1981). The square root of the AVE should exceed the correlation shared between the construct and other construct in the model. As shown in Table 4, the square root of all the AVE estimates for each variable from 0.684 to 0.858 were greater than the inter-construct correlations; thus, therefore, the discriminant validity is supportive. Moreover, the factor correlations per illustrated in Table 4 did not exceed 0.80 can be presented that the correlation is not very strong among nine pairs of variables in this research. Thus, the multicollinearity is not vital issue in this research. (Studenmund, 1992).

Table 4 Discriminant Validity

	PV	PC	PCP	SR	IE	TL	PM	SMA	SMI
PV	**0.700**								
PC	-0.042	**0.685**							
PCP	-0.050	0.609	**0.720**						
SR	-0.021	0.584	0.635	**0.762**					
IE	0.424	-0.071	-0.068	-0.059	**0.858**				
TL	0.082	-0.125	-0.134	-0.103	0.072	**0.849**			
PM	0.521	-0.042	-0.004	-0.020	0.421	0.046	**0.685**		
SMA	0.462	-0.070	-0.042	-0.019	0.442	0.130	0.469	**0.701**	
SMI	0.559	-0.087	-0.036	-0.010	0.569	0.064	0.507	0.466	**0.684**

Table 5 Goodness of Fit for Measurement Model

Index	Acceptable Values	CFA Values	SEM Values
CMIN/DF	< 3.00 (Hair et al., 2006)	1.465	1.460
GFI	≥ 0.90 (Hair et al., 2006)	0.907	0.910
AGFI	≥ 0.85 (Schermelleh-Engal et al., 2003)	0.891	0.895
NFI	≥ 0.90 (Arbuckle, 1995)	0.901	0.901
CFI	≥ 0.90 (Hair et al., 2006)	0.966	0.966
TLI	≥ 0.90 (Hair et al., 2006)	0.962	0.963
RMSEA	< 0.05 (Browne & Cudeck, 1993)	0.031	0.030
RMR	< 0.05 (Hair et al., 2006)	0.022	0.027

Remark: CMIN/DF = The ratio of the chi-square value to degree of freedom, GFI = goodness- of-fit index, AGFI = adjusted goodness-of-fit index, NFI, normalized fit index, TLI = Tucker-Lewis index, CFI = comparative fit index, RMSEA = root mean square error of approximation, and RMR = root mean square residual

Source: Constructed by Author.

Structural Equation Model (SEM)

The data revealed SEM analysis on causal relationship among variables in the adoption model. It was demonstrated that Chi - Square = 1.460, consistent with the concept by Hair, Hollingsworth, Randolph & Chong (2017) at p-value = 0.05 (Bollen, 1989). Goodness-of-fit statistics (GFI) = 0.910, Adjusted Goodness-of-fit statistic (AGFI) = 0.895, Normed-fit index (NFI) = 0.901, Comparative Fit Index (CFI) = 0.966, Tucker-Lewis's index (TLI) = 0.963, Root Mean Square Error of Approximation (RMSEA) = 0.030, root mean square residual (RMR) = 0.027 (Per shown in Table 5).

The impacts of all independent variables on the dependent variable were also investigated using multiple regressions analysis. Table 6 summarizes factors that have impact on the SMDT adoption and implementation The research results which support hypotheses H1, H4, H5, H6, H7 and H8 with a p value less than 0.05 significance level. There were insignificances found in H2, H3 and H5.

Table 6 Hypotheses Result of the Structural Model

Hypothesis	Standardized path coefficient (β)	t-value	Test result
H1: PV => SMA	0.264	3.962*	Supported
H2: PC=> SMA	-0.212	-1.343	Not Supported
H3: PCP => SMA	0.163	0.926	Not Supported
H4: PM => SMA	0.305	4.306*	Supported
H5: SR => SMA	0.024	0.281	Not Supported
H6: TL => SMA	0.080	1.969*	Supported
H7: IE => SMA	0.283	5.367*	Supported
H8: SMA => SMI	0.642	10.377*	Supported

Note: *=p-value<0.05

Source: Constructed by Author

H1: The coefficient of determination (R^2) value shows that the relationship between perceived value (PV) and SMDT adoption was 0.264 (t-value =3.962*). Therefore, the results presented that perceived value of SMDT has a significant influence on smart manufacturing SMDT adoption. Consequently, H1 was supported.

H2: Perceived cost (PC) and SMDT adoption shows the coefficient of determination (R^2) value of -0.212 (t-value =-1.343). Hence, perceived cost of SMDT has shown no significant influence on smart manufacturing SMDT. Consequently, H2 was not supported.

H3: Prior digital transformation literature signified that the implementation costs as a major barrier to SMDT adoption. As the coefficient of determination (R^2) value presents 0.163 (t-value =0.926), perceived compatibility (PCP) and SMDT adoption has no significant influence. Consequently, H3 was not supported.

H4: The coefficient of determination (R^2) value presented that perceived market transparency (PM) associated with SMDT adoption (SMA) was 0.305 (t-value =4.306*). Thus, SMDT adoption was affected by perceived value. Consequently, H4 was supported.

H5: The linkage among strategic road mapping (SR) and SMDT adoption (SMA) was 0.024 (t-value =0.281) of the coefficient of determination (R^2) value. Additionally, strategic road mapping (SR) was found to insignificantly facilitate SMDT adoption (SMA), which is consistent with discoveries from other studies in the technological innovation literature. As a result, H5 was not supported.

H6: The coefficient of determination (R^2) shows the significant influence between transformational leadership (TL) and SMDT adoption (SMA) with the value of 0.080 (t-value =1.969*). Hence, transformational leadership has a significant influence on SMDT adoption (SMA). Subsequently, H6 was supported.

H7: The result confirmed that SMDT adoption is significantly influenced by the imposition from the environment, which implies that SMEs received pressure from their competitive environment to adopt manufacturing digitalization. The coefficient of determination (R^2) value verifies the correlation among them at 0.283 (t-value = 5.367*). Consequently, H7 was supported.

H8: In relation to SMDT adoption (SMA) and SMDT implementation (SMI), the relationship was proven with the coefficient of determination (R^2) value of 0.642 (t-value =10.377*). In addition, the result suggested that SMDT adoption (SMA) has the strongest significant influence on SMDT Implementation (SMI). Therefore, H8 was supported.

Discussion, Conclusions and Recommendations

Smart manufacturing integration of digital technology (SMDT) is one of the key factors which determine survival and growth of Myanmar firms in the digital industry 4.0 era. TOE framework was adapted with the tons of digital technology innovation literature review to evaluate the technological, organizational, and environmental factors that influence SMDT adoption and implementation in Myanmar food businesses.

The results indicated that most variables have significant influence on SMDT adoption. Firstly, perceived value of SMDT among employees can drive a successful SMDT adoption in food manufacturing (Ghobakhloo & Ching, 2019). Secondly, Prause (2019) confirmed that the higher the market transparency, the more likely advanced manufacturing technologies will be adopted. Thirdly, transformational leadership can inspire employees to adopt SMDT which was aligned with previous studies (Conger & Kanungo, 1988; Jaruwanakul, 2021; Sosik & Godshalk, 2005). Next, Ghobakhloo and Ching (2019) indicated that SMDT was significantly influenced by environmental imposition, which means the pressure on environment to produce digitalization can affect the decision to adopt SMDT. Lastly, successful implementation of technologies requires skilled employees to achieve new and higher efficiency of operation and machine maintenance to improve level of product quality commitment (Osterman, 1994; Phyu & Vongurai, 2020), which has an impact on SMDT adoption. Nevertheless, perceived costs, perceived compatibility and imposition by the environment had no significant on SMDT adoption in this study.

The recommendations are made from the concern with perceived value with the consideration of value-added innovation and the new marketing approach, perceived cost with financial support from government, perceived compatibility with company's infrastructure culture, values etc., perceived market transparency to reduce risk and the construction of public-private partnerships (PPP), strategic road mapping with the assortment of management support, transformational leadership with the promotion of innovation and encountering with imposition from the environment or pressure by competition to serve and satisfy customers better and faster. In addition, academic practitioners can consider significant factors in the results of this study based on technology adoption model in other business context.

This study is limited by its findings which holds a holistic perspective to evaluate the state of smart manufacturing within only three Myanmar food manufacturing enterprises. The conclusions have drawn about the fundamental relationship between variables using SEM techniques and limited cross-sectional studies that can explain cause and effect. Future research is guided to conduct in-depth case studies as time-series data, and analytical modelling techniques are required to assess Myanmar enterprises' maturity and smart manufacturing readiness as well as their impact on SMDT adoption.

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