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Predicting the antecedents of Digital Technology Adoption among Manufacturing firms: Artificial Neural Network (ANN) approach

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Abstract—**The concept of digital transformation offers a unique platform to gain competitive advantages both in the manufacturing and service sectors. Although the digitalization concept has gained popularity, there is a lack of studies on the antecedents of digital technology adoption. Therefore, the purpose of this study is to examine the antecedents of digital technology adoption (DTA) in manufacturing SMEs in Malaysia. To achieve the research aims, an Artificial Neural Network (ANN) technique has been adopted to examine and prioritize the antecedents for DTA. The outcomes of the ANN approach indicate that effective communication is the most important antecedent of DTA, followed by digital literacy, perceived ease of use, perceived cost effectiveness, and perceived usefulness. The examination of antecedents of DTA can serve as a starting point for further research into the idea of digital technology adoption in emerging economies.**

Index Terms—**Digital transformation, digital technology adoption, SMEs, manufacturing**

I. INTRODUCTION

The 21st century has seen widespread adoption of digital transformation (DT) in the manufacturing and service sectors, organizational management, and social sciences (Li et al., 2022). In general, it redefines how the organization functions. Organizations increasingly understand that realigning their strategic plans with digital transformation will give them a much better competitive advantage (Chawla and Goyal, 2021). As a result, digital technology and its applications are becoming an increasingly important component of organizational products, processes, and services. Digital transformation refers to the use of new digital technologies to enable major business improvements like enhancing customer experiences, creating new business models, and streamlining operations (Fitzgerald et a. 2013). According to Vial (2019), DT is the process that aims to enhance the firm by triggering significant changes to its operations through combinations of communications, information, computing, and connectivity technologies.

Recent COVID-19 pandemic outbreaks presented the DT with its toughest challenge. Almost all businesses changed their business models during the COVID-19 pandemic and implemented work-from-home or work-anywhere policies. As a result, the adoption of digital transformation is rapidly increasing and is still growing (Shi and Mai, 2022). The adoption of digital transformation has attracted wide attention during the COVID-19 outbreak, both in academia and industry. The research field has attracted an ample number of researchers from diverse areas of social and management sciences like economics (Chiemeke and Imafidor, 2020), marketing (Salo et al., 2021), operations (Ali & Johl, 2021), technology (Blichfeldt and Faullant, 2021), education (Yong et al., 2022), and society (Chakraborty et al., 2021). This has led to a widespread body of literature.

Regardless of the current state of the literature on this subject, technology adoption is a well-researched topic in the literature. Researchers adopted different approaches to studying digital technology adoption, especially in manufacturing. For instance, Mitra et al. (2022) studied the key antecedents of disruptive technology adoption in the digital supply chain perspective among Indian manufacturing firms. Lazar et al. (2020) develop and validate the antecedents of digital technology adoption. They categorized the antecedents into external, mediating, and internal factors. Sugandini et al. (2019) concluded that managerial support, time constraints, and user pressure are the antecedents of digital technology adoption in Indonesian manufacturing SMEs. Although past literature has evident that different factors are important for digital technology adoption. But there is a lack of studies regarding the importance of antecedents. Therefore, this study will address this gap. Based on the above discussion, the objective of this research is to investigate the important antecedents of digital technology adoption in E&E manufacturing SMEs.

The remainder of the article is structured as follows. First, the article outlines the research methodology. After that analysis and results are presented, and finally the discussion and conclusion are presented.

II. MATERIALS & METHODS

A. Data collection and sampling method

To achieve the study objectives, an online survey technique was used to collect data from Malaysian small and medium E&E manufacturing firms. The sampling frame of this study is based on the Federation of Malaysian

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Manufacturers (FMM) list 2018. Based on the FMM directory (2018), more than 3300 SME firms are operating across all states of Malaysia (Ali & Johl, 2022). In this study, the main focus industry was E&E SMEs manufacturing. According to SMECorp Malaysia (2008), a firm having a number of employees from 5 to 74 is categorized as small, and from 75 to not more than 200 is categorized as a medium firm. As recommended by Memon et al. (2020), the calculation of sample size through G*Power is more reliable as compared to other techniques. Thus, based on G*power the minimum sample size is 98 with a power of 0.80 and effect size of 0.15. The simple random sampling technique was employed to collect the data. The data was collected over two months period. Before the distribution of the questionnaire, the content of all items was validated by practitioners and academicians. A total of 125 completed questionnaires were collected and verified. However, 10 questionnaires were found to be incomplete, leaving a final of 115 usable samples. Based on G*Power, the study required a minimum of 92 respondents and since 115 completed questionnaires were obtained, the sample size is considered acceptable.

B. Operationalization of measurements items

In this study, the independent variables are perceived usefulness (PU), perceived ease of use (PEU), perceived cost effectiveness (PCE), perceived effective communication (EC), and digital literacy (DL). In this study, the dependent variable is digital technology adoption (DTA). All the study items are adapted from past studies.

The six items of PU and PEU were taken from Navimipour and Soltani (2016). The six items of perceived cost effectiveness were adapted from Gallardo-Echenique et al. (2015). The six items of effectiveness communication (EC) were adapted from Moreno et al. (2015), and six items of digital literacy were taken from Van Deursen et al. (2016). Finally, the six items of digital technology adoption (DTA) were adapted from Venkatesh et al. (2016). With the exception of demographic information, the measurement items were measured on a five-point Likert scale. Additionally, before the actual data collection, pilot testing was performed, and all the constructs achieved the minimum threshold of reliability and validity.

III. Analysis and Result

A. Demographic analysis

Table 1 contains a comprehensive demographic breakdown of the respondents. According to the gender breakdown, there were more males (66.09%) than females (33.91%). In terms of age distribution, 23.48 percent of respondents were under the age of 30, 28.70% were between the ages of 31 and 40, 39.15% were between the ages of 41 and 50, and 8.69% were over the age of 51. Finally, 18.26% of respondents have an intermediate qualification, 40.87% have a graduate degree, 32.17% have a master’s degree, and the remaining 8.70% have some other qualification.

Table 1. Demographic analysis

Variable	**Items**	**Frequency**	**Percentage (%)**
Gender	Male	76	66.09
	Female	39	33.91
Age	20-30	27	23.48
	31-40	33	28.70
	41-50	45	39.13
	≥51	10	08.69
Education	Intermediate	21	18.26
	Graduation	47	40.87
	Master/ Doctorate	37	32.17
	Other	10	08.70

B. Artificial Neural Network (ANN) Analysis

The artificial neural network technique is considered the most intelligent of the available analytical techniques. The ANN demonstrated a large but complex network that contains multiple neurons distributed into three layers; input, hidden and output layers (Hew et al., 2018). Models like multivariate regression analysis (MRA) and structural equation modeling (SEM) cannot represent the complexity of human decision-making since these analytical methods only find the liner relation (Cabanillas et al., 2017). Additionally, MRA and SEM are compensating models assuming that a decline in one variable may be compensated by an addition of another variable (Wong et al., 2020). In the research, the independent/exogenous variables are not compensable. This means that a drop in one independent variable cannot be substituted by an increase in another, because all constructs are distinct in terms of conceptualization and definitions, therefore these constructs are not identical. In addition, ANNs are inappropriate for testing and assessing causal relationships between exogenous and endogenous variables due to their "black-box" nature (Tan et al., 2014; Chan & Chong, 2012; Hew et al., 2016). Similar to Lim et al., (2021), the application of ANN in this research is utilized to evaluate each predictor variable's relative importance. This technique outperforms linear models in terms of multicollinearity, homoscedasticity, and non-normality of distribution (Hew et al., 2018; Wong et al., 2020). ANN models have surpassed traditional statistical techniques like MRA and SEM due to their high degree of prediction accuracy (Leong et al., 2015).

Prior research has attempted to provide a more detailed description of ANNs. Haykin (2001) stated that ANN is a massively parallel distributed processor composed of simple units with a neural propensity for accumulating & storing experimental knowledge and make available for use. Haykin (2001) stated that ANNs analysis is similar to the human brain performing a particular function or task. This technique is employed in a variety of research fields like supply chain quality management

(Lim et al., 2021), Blockchain in SMEs operations (Wong et al., 2020), m-commerce (Cabanillas et al., 2017), social media addiction (Leong et al., 2019) and e-learning (Sharma et al., 2017). However, its applicability to the digital technology adoption domain is limited. Therefore, by using ANN analysis to the predictive power of exogenous constructs to explain the endogenous construct, this work intends to make a significant methodological contribution.

An ANN model's architecture is made up of three layers; input, hidden, and output. The root means square errors (RMSE) and normalized significance of the input neurons were determined using the feed-forward-back-propagation technique and multilayer perceptron's (Hew et al., 2018). To address model fit, similar to Wong et al. (2020), the researcher assigned 90% of the data for training and 10% for testing. This study used a ten-fold cross-validation process to avoid the possibility of over-fitting and obtained the RMSE values (Wong et al., 2020). Table 2 shows the RMSE values of training and testing of digital technology adoption.

Table 2. RMSE values for the ANN of Digital Technology Adoption

Training		**Testing**		**Total**
N	**RMSE**	**N**	**RMSE**	**Samples**
99	0.321	16	0.307	115
107	0.307	8	0.311	115
104	0.383	11	0.225	115
99	0.370	16	0.253	115
107	0.382	8	0.255	115
102	0.312	13	0.305	115
102	0.328	13	0.282	115
104	0.355	11	0.305	115
102	0.332	13	0.201	115
102	0.303	13	0.452	115
Mean	0.340		0.290	
S.D	0.031		0.062	

Table 3 shows the sensitivity analysis of each predictor variable according to its relative importance to achieve digital technology adoption in E&E SME manufacturing firms. Based on the findings, effective communication (100%) is the most important factor to achieve DTA followed by DL (65%), PEU (61%), PCE (60%), and PU (57%).

Table 3. Sensitivity analysis of Digital Technology Adoption (DTA)

IV. Discussion

The purpose of this study is to examine the antecedences of digital technology adoption in E&E manufacturing SMEs. The study was performed in an emerging economy context such as Malaysia. To achieve the study objective, the artificial neural network (ANN) technique was adopted.

Neural Network (NN)	**PU**	**PEU**	**PCE**	**EC**	**DL**
1st	0.559	0.644	0.329	1.000	0.862
2nd	0.353	0.384	0.891	1.000	0.684
3rd	0.914	1.000	0.645	0.991	0.810
4th	1.000	0.513	0.410	0.853	0.507
5th	0.612	0.614	0.940	1.000	0.578
6th	0.384	0.801	0.520	1.000	0.703
7th	0.556	0.406	0.555	1.000	0.573
8th	0.422	0.495	0.469	1.000	0.452
9th	0.469	0.387	0.449	1.000	0.405
10th	0.353	0.735	0.687	1.000	0.844
Mean importance	0.562	0.598	0.590	0.984	0.642
Normalized importance	**57%**	**61%**	**60%**	**100%**	**65%**

Based on the analysis, effective communication is the most important factor followed by digital literacy, perceived ease of use, perceived cost-effectiveness, and perceived usefulness. The findings of this study are supported by the past literature. Perceived usefulness assessed intrinsic technological characteristics and was predicted to impact the intended utilization only for activities that are inherent to the technology. When the technology performs the fundamental task activity. Moreover, Cost-effectiveness is referred to as the degree to which an individual perceives that utilizing a particular device will incur additional costs. Cost-cutting solutions require the adoption of full-scale digital technology or the establishment of an information technology infrastructure in the hardware and software domains (Dale & Plunkett, 2017). Additionally, the study results indicated that effective communication is the most important factor for digital technology adoption in SME manufacturing. Dale and Plunkett (2017) described cost-effectiveness as an individual's belief that using a particular device would be costly. Cost-cutting measures demand the adoption of full-scale digital technology or the establishment of an information technology infrastructure in the hardware and software sectors. Finally, the results of this study support the relationship between digital literacy and DTA in SME manufacturing. The findings are consistent with the findings of past studies. For instance, List (2019) suggested that developing an individual's digital literacy enables them to be technology-driven or project-based.

V. Conclusion

In the digital era, digital transformation has gained significant importance in manufacturing and services.

Recently, the adoption of digital transformation has gained researchers' attention. Therefore, this study aims to investigate the most important antecedent of digital technology adoption in E&E Malaysian manufacturing SMEs. To achieve the study aims, the ANN approach was adopted. The analysis highlighted that effective communication is the most important factor for digital technology adoption. Conclusion

A conclusion section is not required. Although a conclusion may review the main points of the paper, do not replicate the abstract as the conclusion. A conclusion might elaborate on the importance of the work or suggest applications and extensions.

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