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Structural Relationship of Technology Adoption and Performance Factors in UAE Manufacturing Industry

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Abstract: The world is rapidly changing as a result of technology, which has played an important role in organisational development by improving operations and reducing obstacles. Businesses are constantly investing in technology in order to improve their performance and gain a competitive advantage over their competitors. Technological advancements assist businesses in automating their systems and management, providing them with the impetus to efficiently target customers through low-cost business solutions. As a result, this paper examined the relationship between technology adoption and the performance of business organisations involved in manufacturing. This study was conducted quantitatively, with data collected via questionnaire survey. The collected data was used to develop the model of structural relationship between the factors using PLS-SEM approach. Based on the validated PLS-SEM model, it was found that performance expectancy, effort expectancy, social influence, and facilitating condition all have a positive relationship with technology adoption. One of the most significant benefits of increased technological use in manufacturing firms is increased revenue through improved performance. The evaluation of the mediation effects of firm size and training on the relationship between technology adoption and manufacturing firm performance in the UAE revealed that the hypotheses' outcomes were positive, indicating that firm size and training do play a role in manufacturing performance. When using technology in manufacturing, the training and firm size have a significant impact on manufacturing performance.

Keywords: Technology adoption, manufacturing industry, firm size, training, PLS-SEM, UAE

1. Introduction

Businesses worldwide are established to maximize revenue and profits and minimize losses. To achieve this fiat, businesses always evolve and adapt to the changing requirements to remain competitive and efficient. Technology plays a significant function in leveraging productivity and efficiency in firms. Remarkable results of technology has been reported in different industries such as education (Mohammad AlHamad, 2020), health (Alrahbi et al., 2019), agriculture (Nakano et al., 2018), banking (Aboelmaged & Gebba, 2013), governance (Ahmad & Khalid, 2017; Almuraqab, 2016), manufacturing (Kristianto et al., 2012; Yadegaridehkordi et al., 2018), (Nuseir&Aljumah, 2020).

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The manufacturing industry is both labour and capital intensive requiring great investment in human capital and technologies (Igwe et al., 2020; Kristianto et al., 2012; Yadegaridehkordi et al., 2018). Most of the positive results of technology in firms are mostly in the developed nations with evidence of replication in developing nations. For instance, there are numerous literature reports indicating the penetration in many developing countries including the UAE (Ahmad et al., 2019; Ahmad & Khalid, 2017; Almuraqab, 2016; Ameen et al., 2018; Ameen & Willis, 2018; Mohammad AlHamad, 2020). The increasing presence of technology adoption in the UAE may be because of its concern with technology and innovation, as investment in innovations and interventions will have a positive impact on achieving the strategies and goals of the UAE government and companies and enhancing firm performance (Mohamed et al., 2019). The UAE depends on innovations to maximize profits and returns and achieve economic purposes (Al Hallami et al., 2013).

Technology is critical in contemporary firms. It fuels the effectiveness of firms through technological activities. World is rapidly changing due to the technology that has played an important role in organizational development to improve operations and reduce obstructions. Innovations in technology that are produced widely can change the quality of any sectors' activities. Firms are continuously investing more on technologies to leverage on their performance and have competitive advantage over others (Ahmad et al., 2019; Boothby et al., 2010; Clohessy& Acton, 2019; Papadopoulos et al., 2020). The technological advances help in the firms to automate their systems and management and give them the impetus to efficiently target customers through low-cost business solutions (Nuseir & Aljumah, 2020).

Technology adoption has various definitions. It is defined as the "determination to fully exploit an innovation as the most effective course of action available" (Ameen, 2017). Individuals or organisations' acceptance of a newly developed technology is also known as technology adoption (Rad et al., 2018). Sharma & Mishra (2015), on the other hand, defined technology adoption as the “stage of selecting a technology for use by an individual or an organization”. Oliveira & Martins (2009) considers technology adoption as the organisation’s readiness to use technology infrastructure and IT human resources. Abdallah (2016) considers technology adoption as the extent of technology use by individuals or organisation. This research tilts towards the definition of Abdallah (2016) and considers technology adoption as the firm’s readiness to acquire and the extent of novel technology or system usage for their activities. Due to dynamic business environment and continuous changes in human and material needs, technologies are always evolving to meet the growing demands. Consequently, technology adoption has become a growing research field in various fields including ICT, banking, marketing, business management, manufacturing and others (Ahmad & Khalid, 2017). The level of technology adoption by individuals, firms, organizations, and governments vary from one to another.

Over the years, several models have been created to determine the causes or determinants of technology adoption. The Theory of Reasoned Action is the source of the majority of these models. Later, the idea was renamed the Theory of Planned Behaviour (Ajzen, 1991). Since then, various methods for studying technology uptake have emerged. TAM (Technology Acceptance Model) and IDM (Innovation Diffusion Model) are two examples (IDM). In the literature on technology adoption, these theories and models have been widely used empirically. These theories explain why people want to use new systems and technology (Aboelmaged & Gebba, 2013; Almuraqab & Jasimuddin, 2017; Lou & Li, 2017; Salloum et al., 2019). Social Cognitive Theory (SCT), Combined TAM & TPB (C-TAM-TPB), Motivational Model (MM), and Model of PC Utilisation (MPCU) are some of the other models that incorporate technology adoption models (Ameen, 2017; Ameen et al., 2018; Ameen & Willis, 2018; Rodrigues et al., 2016). Venkatesh et al. (2003) later developed the Unified Theory of Acceptance and Use of Technology, which combined the ideas and models (UTAUT). Performance expectations, social influences, effort expectations, and conductive factors are proposed as antecedents of technology adoption in the theory. These factors have been demonstrated to explain more variance in technology adoption than other constructs from various theories and models (Ameen et al., 2018; Rodrigues et al., 2016). As a result, the highlighted factors can be considered to influence technology adoption.

Technology adoption does not always lead to improved firm performance. Technology may be adopted but the firm or its employees may not have the requisite skills and training to achieve the required impact. There may be a tendency that training may significantly mediate the relationship between technology adoption and firm performance (Brandon-Jones & Kauppi, 2018; Nakano et al., 2018). Similarly, the value of technology in any organization depends on its infrastructure which is a set of shared tangible and intangible resources composed of computers, network and communication, technologies and data. Thus, the firm size and capability may play a vital role in achieving the required performance (Che & Zhang, 2016; de Vass et al., 2018). Thus, firm size may moderate the relationship between technology adoption and firm performance.

This research work developed a framework of technology adoption toward firm performance through firm size and training in the UAE manufacturing industry. The framework extended the UTAUT model, which provided the basic theoretical foundation of this research, by assessing the original constructs of the UTAUT and testing the mediation effect of training between technology adoption and firm performance. The proposed framework will determine the moderation effect of the firm size on the relationship between technology adoption and firm performance as well as the mediation effect of training on such relationship. The research also covers firm performance, firm size and training, serving as the endogenous, moderating and mediating constructs respectively.

2. Literature Review

2.1 Productivity in Firms

Productivity is arguably an important factor for businesses. As a result, the ultimate goal of technology adoption is to maximise productivity (Iqbal et al., 2018). However, the majority of previous studies have failed to empirically test whether technology adoption improves firm performance. The studies mostly concentrate on the factors that influence technology adoption and do not go beyond that. Several researchers have found a link between technological adoption and firm performance (Ahmad et al., 2019; Boothby et al., 2010; Chae et al., 2018; Che & Zhang, 2016; Igwe et al., 2020; Marsh, 2018; Müller et al., 2018; Nakano et al., 2018; Yadegaridehkordi et al., 2018). However, very few studies in the UAE have been conducted to determine the impact of technology adoption on firm performance. Thus, researching the impact of technology adoption on firm performance in the UAE will contribute to the literature on firm performance.

The Theory of Reasoned Action (TORA), Theory of Planned Behavior (TPB), Technology Acceptance Model (TAM), The Innovation Diffusion Model (IDM), Social Cognitive Theory (SCT), Combined TAM & TPB (C-TAM-TPB), Motivational Model (MM), and Model of PC Usage (MPCU) are a few examples (Ameen, 2017; Ameen et al., 2018; Ameen & Willis, 2018; Rodrigues et al., 2016). Venkatesh et al. (2003) developed the Unified Theory of Acceptance and Use of Technology, which incorporated the previous studies' ideas and models (UTAUT). The UTAUT has been shown to explain more variation in technology adoption than the defined antecedents (Ameen et al., 2018; Rodrigues et al., 2016; Venkatesh et al., 2003). As a result, UTAUT is thought to be a better fit for modelling technology adoption (Ameen et al., 2019). In contrast, the methodology disregards the firms' technology adoption results. As a result, the UTAUT was updated to include the variable of interest, making it more adaptable to a wide range of settings and situations (Isaac et al., 2019; Viswanath Venkatesh et al., 2016). Similarly, previous research examined a single technology using a variety of models. Looking at only one aspect of technology in the adoption model may not be enough to generalise (Ameen, 2017; Ameen et al., 2018; Ameen & Willis, 2018). As a result, this study will examine a broad range of technology adoption by manufacturing firms across their value chains.

2.2 Unified Theory of Acceptance and Use of Technology

The Unified Theory of Acceptance and Use of Technology (UTAUT) aim to unite disparate but related theories about technology adoption into a single unified theory. Venkatesh et al. (2003) proposed UTAUT to describe technology consumption behaviour. The concept has received significant support and has been validated as a reliable predictor of system usage and acceptance in various empirical studies (Ameen et al., 2019). UTAUT has compiled eight models and theories, as well as their concepts and theoretical foundations. TAM (Davis, 1989), SCT (Bandura, 1986), and DOI (Diffusion of Innovation Theory) (Rogers, 2003).

UTAUT is a newer unified model that forecasted technological acceptance and adoption by drawing empirical, theoretical, and conceptual parallels between the eight theories described previously (Rodrigues, Sarabdeen, & Balasubramanian, 2016). It was concluded by Venkatesh et al. (2003) that it would make sense to map and integrate the various constructs of existing theories in order to arrive at a unified theoretical model, as many of these constructs are related in nature. Since its inception in 2003, the UTAUT has gained widespread popularity and recognition in the academic literature addressing the topic of how people adopt and use new technologies (Schaupp, Carter, & McBride, 2010). The model's versatility, validity, and dependability in predicting technological adoption have all been extensively examined. The UTAUT model is considered to be the best is because it can explain a larger percentage of individual differences in usage intent (R^2) (Venkatesh et al. 2003; Al-Shafi and Weerakkody 2009).

UTAUT has four main ideas that it conveys: performance expectancy, effort expectancy, social effects, and enabling conditions (Venkatesh et al. 2003). Performance expectancy is an individual's belief that using a new innovation will lead to enhanced productivity. A person's belief in the ease of the innovation's implementation is based on their effort expectation. Similarities exist between these two structures and those in TAM. Social influence refers to the extent to which an individual is convinced that a significant other thinks he or she should implement the innovation. Last but not least, enabling conditions evaluate how confident an individual is in the system's underlying organisational and technological infrastructure.

The UTAUT model is a gold standard in the literature on technology acceptance and adoption, according to Rosen (2005), because it captures user acceptance more thoroughly and realistically than any other model. The subsections depicted in figure 1 below outline the constructs of the unified theory of acceptance and use of technology, performance expectancy, effort expectancy, social influence, facilitating condition, and actual usage of technology.

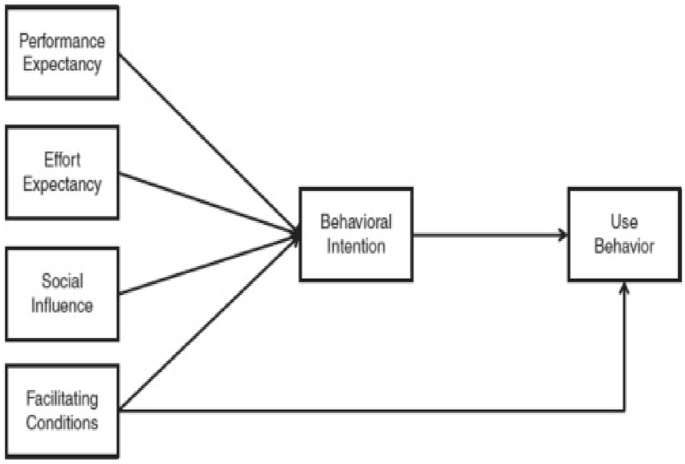

Fig. 1 - Unified theory of acceptance and use of technology (Venkatesh et al., 2003)

Figure 1 depicts that there are four basic parameters as performance expectancy, effort expectancy, social influence and facilitating conditions as discussed below:

2.2.1 Performance Expectancy (PE)

The degree to which an organisation or firm considers the assistance of technology usage in achieving performance and productivity improvements is referred to as performance expectancy (Ameen et al., 2019; Viswanath Venkatesh, Thong, Statistics, Xu, & Acceptance, 2016). This is the firm's belief that implementing a specific technology will boost its performance and productivity. Thus, if a firm believes that adopting a specific technology will improve its performance, it is highly likely that the firm will adopt the technology; however, if the firm believes that adopting the technology will not improve its performance, the likelihood of adopting the technology is low. Several studies have used performance expectancy constructs to explain technology adoption by individuals and firms (Ameen et al., 2019; Ameen, 2017; Viswanath Venkatesh, Thong, Statistics, et al., 2016).

2.2.2 Effort Expectancy (EE)

Effort expectancy refers to the ease and simplicity with which the technology is used. This is analogous to the perceived ease of use concept in the technology adoption model. According to this construct, a company is more likely to adopt a technology if it is simple and easy to use. A company may be hesitant to implement a complex technology due to the time, effort, and training required. A company may be more willing to accept a less sophisticated technology than a sophisticated technology that requires extensive training. The expectation of effort is an important factor in technological acceptance and use. Several studies have examined the construct in various contexts and discovered it to be a significant predictor of technology adoption (Ameen et al., 2019; Ameen, 2017; Ameen et al., 2018; Ameen & Willis, 2018; Rodrigues et al., 2016; Venkatesh et al., 2016).

2.2.3 Social Influence (SI)

The degree to which a firm or individual believes that key stakeholders expect them to use novel technology is referred to as social influence. This construct is related to the subjective norm construct in the theory of planned behaviour, which assumes that people are influenced by others to perform a specific behaviour. Policymakers, customers, shareholders, and competitors are all examples of firm stakeholders. When a company believes that all of its key stakeholders expect it to use new technologies, it is more likely to do so. Such social influence includes rival firm competition. Firms may succumb to this influence in order to gain an advantage over competitors in order to remain competitive. Social influence is a critical concept in technology adoption. Several previous studies found it to be extremely important in explaining technology adoption decisions (Ameen et al., 2019; Isaac et al. 2019; El-Masri & Tarhini, 2017).

2.2.4 Facilitating Conditions (FC)

The degree to which firms believe they have the technical and organisational resources to afford technology use and adoption is referred to as the facilitating condition. The facilitating condition construct is related to the theory of planned behavior's perceived behavioural control, which is defined as an individual's or firm's perceived ability and capability to perform a given behaviour. A firm with vast technical, organisational, and financial resources is more likely to adopt a technology than a firm with limited resources. Facilitating conditions are critical for individuals and businesses to adopt and use technology. Several previous studies discovered a significant relationship between enabling conditions and a firm's decision to adopt technology (Ameen et al., 2019; Ameen, 2017; Isaac et al., 2019; Viswanath et al., 2016).

2.2.5 Actual Usage (USE)

The use of technology is the ultimate requirement for technology adoption. Thus, actual usage refers to the extent and manner in which firms use a technology's capabilities. The firm's readiness to acquire and use novel technology or systems for its activities is referred to as technology adoption. It is the extent to which firms use technology. Adoption or use of technology is defined as the extent and context in which users make use of a technology's capabilities (firms in this context). It is related to the appropriateness, frequency, nature, amount, purpose, and extent of technology use (A. Ameen et al., 2019). Rogers (2003) defines technology adoption as "a decision to fully utilise an innovation as the best course of action available." Technology adoption and use are also related to the amount of time and frequency with which technology is used. In other words, it is the extent to which firms use technology to achieve their output. Actual usage is the foundation upon which all other constructs are built.

2.3 Framework and Hypothesis Development

The review of literature discusses relevant topics for the research, such as firm performance, technology adoption, and relevant theories that will be used to develop the research's theoretical framework. Figure 2 depicts the proposed research framework from which the hypothesis emerges.

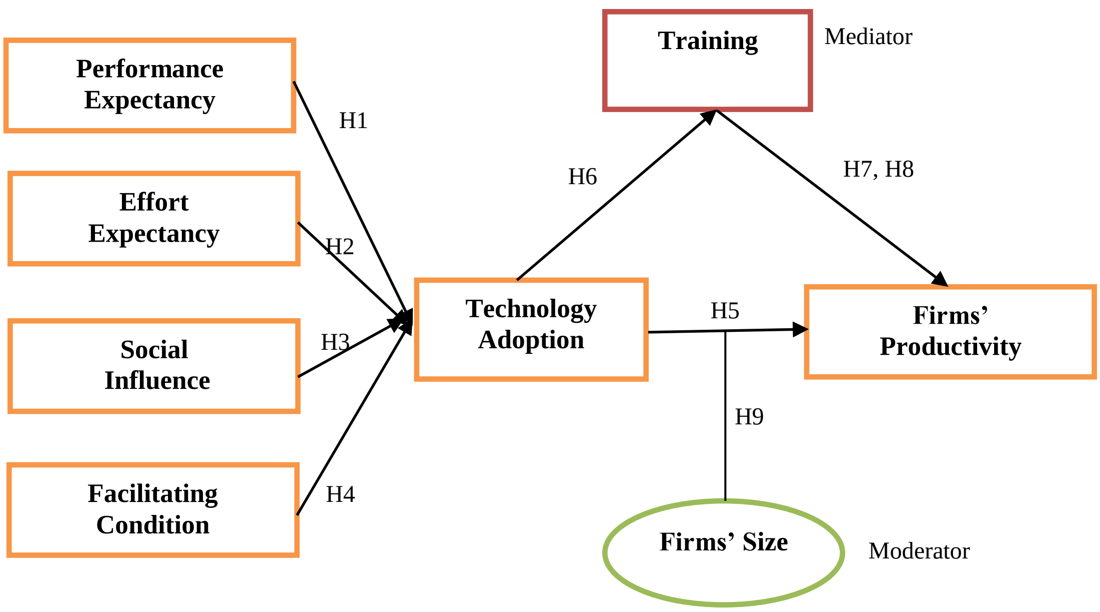

Fig. 2 - Theoretical framework

Figure 2 depicts the proposed theoretical framework for the research. The method demonstrates that the UTAUT dimensions of performance expectancy, effort expectancy, social impact, and facilitating condition all contribute to technology adoption. Technology adoption has an impact on firm performance. In contrast, the impact of technology adoption on company performance is influenced by firm size and mediated by training. These relationships are hypothesised in the subsections that follow.

2.3.1 Performance Expectancy and Technology Adoption

According to the UTAUT theory, performance expectations lead to technology adoption. The extent to which firms believe that using a particular technology will help them improve their performance is referred to as performance expectancy (Ameen et al., 2019). Several studies have discovered a strong link between performance expectations and technology adoption (Ameen, 2017; Isaac et al., 2019; Viswanath et al., 2016). Firms are likely to base their technology adoption decisions on expected performance. They are more likely to adopt a new technology if they believe it will improve their performance, and vice versa. As a result, firms with higher performance expectations will likely adopt more technology, while firms with lower performance expectations will likely adopt less technology. As a result, it is proposed.

H1: *Performance expectancy is a significant positive determinant of technology adoption*.

2.3.2 Effort Expectancy and Technology Adoption

Another important aspect of technology adoption is the expectation of effort. The ease and simplicity with which a firm's technology is used is referred to as effort expectancy. It means that a company is more likely to adopt a technology if it perceives it to be simple and easy to implement. Given the time, effort, and training required to implement a complex technology, a company is unlikely to adopt it. The expectation of effort is a significant determinant of technology adoption and use. Several previous studies have discovered a significant positive relationship between effort expectation and technology adoption (Ameen et al., 2019; Ameen, 2017; Ameen et al., 2018; Ameen & Willis, 2018; Rodrigues et al., 2016; Venkatesh et al., 2016). It implies that firms with higher levels of effort expectancy will adopt more technology, whereas firms with lower levels of effort expectancy will adopt less technology. As a result, it is hypothesized.

H2: *Effort expectancy is a significant positive determinant of technology adoption*.

2.3.3 Social Influence and Technology Adoption

Others' social pressure on someone to do something is referred to as social influence. Social influence refers to how much a company believes its stakeholders expect it to do something. The degree to which a firm believes that important stakeholders expect it to adopt and use new technology is referred to as social influence. Policymakers, customers, shareholders, and even competitors are among the firm's stakeholders. When a company believes that all of its key stakeholders expect it to use new technologies, it is more likely to do so. Social influence is a critical concept in technology adoption. Several studies have found it to be extremely important in explaining technology adoption decisions (Ameen et al., 2019; Isaac et al. 2019; El-Masri & Tarhini, 2017). According to these studies, greater social influence is associated with higher technology adoption, whereas lower social influence is associated with lower technology adoption by firms. As a result, it is hypothesised.

H3: *Social Influence is a significant positive determinant of technology adoption.*

2.3.4 Facilitating Conditions and Technology Adoption

The resources available to a company to adopt a technology are known as facilitating conditions. In this context, the facilitating condition refers to the extent to which a company believes it has the human, technical, organisational, and financial resources to adopt and use a specific technology (Ameen et al., 2019). A firm with vast technical, human, organisational, and financial resources is more likely to adopt a technology than a firm with limited resources. Firms must have favourable conditions in order to adopt and use technology. Several previous studies discovered a significant relationship between enabling conditions and a firm's decision to adopt technology (Ameen et al., 2019; Ameen, 2017; Isaac et al., 2019; Viswanath et al., 2016). As a result, higher facilitating conditions are more likely to lead to a firm's adoption and use of technology, whereas lower facilitating conditions will lead to a firm's lower adoption and use of technology. As a result, it is proposed:

H4: *Facilitating condition is a significant positive determinant of technology adoption*.

2.3.5 Technology Adoption and Firms Productivity

The primary goal of any company or organisation is to increase productivity. Previous research suggests that there is a link between technology adoption and firm productivity. According to a study that examined the impact of technology adoption on productivity, increasing technology adoption plays a significant role in increasing manufacturing productivity (Boothby et al., 2010b). It should also be noted that the use of technology in a company has a significant impact on its productivity (Chege et al. 2020). This is because the use of these technologies, such as ICT, strengthens the information and network system, opening up new business markets. Product and process technology innovation patterns have been discovered to be the result of numerous factors, including a desire for increased company productivity (Mihalic & Bousinakis, 2013; Novac-ududec, Enache, & Sbughea, 2011). These methodologies take a wide range of factors into account at all stages of company development, with the goal of determining the duration and process of a technology's development (Churchill & Lewis, 1983). Access to reliable information on time is critical to increasing company productivity, and ICT plays an important role in this (Grguri-Rashiti et al., 2017; Yunis et al., 2018). Ahmad et al. (2019) highlighted that the adoption of technology increases information dissemination and cost reduction, thereby increasing firm productivity. They noted that, despite evidence of such a link, there is a scarcity of empirical studies that investigate the relationship between technology adoption and firm productivity. As a result, increased technology adoption is expected to increase firm productivity and vice versa. As a result, it is hypothesized:

H5: *Technology adoption has significant positive effect on manufacturing firm performance.*

2.3.6 Technology Adoption, Training and Firm Productivity

As previously stated, the path from technology adoption to firm productivity may not be straightforward. It could be influenced by the amount of training employees receive on how to use technology. Training is the process of improving employees' skills in order to improve job performance. Training is viewed as an essential component of employee satisfaction, which leads to increased employee commitment (Muhammad et al., 2020). Despite the positive effects, some researchers argue that training has no effect on commitment and those other factors, such as HR practices are more important (Meyer & Smith, 2000). Employees respond differently to training. Some argue that it improves employees' ability to learn new skills (Vasudevan, 2014). Training improves workers' abilities, ultimately leading to increased work engagement and employee motivation. In this day and age of technological advancement, where corporations are becoming more complex and organized, training advances employee job-related knowledge and skills, which aids in the resolution of complex problems (Elnaga and Imran, 2013; Mital et al., 1999).

It is claimed that when technology adoption is combined with employee development through training, firm productivity rises (Emeka et al., 2015). Firms must invest in technical innovation and staff development on a regular basis to keep up with evolving technology. Any company that wants to stay afloat in today's global economy must be creative and invest heavily in employee training and technology (Szell, 1992). Firms that want to be creative, according to Gupta and Singhal (1993), must ensure that their human resources are well-cared for, and that people, not just things, are important sources of innovation. Employee development is a continuous effort on the part of an employee and the company for which he or she works to improve the employee's knowledge, skills, and talents.

The appropriate combination of skilled labour and technology is a determinant of improved firm performance (Boothby et al. 2010). Employee development and continuous training in the use of new technologies are the only ways to obtain skilled labour. Similarly, there is an expanding body of knowledge demonstrating that simply acquiring new technologies does not automatically translate into full benefit of the technology inform of increasing productivity unless they are used in conjunction with and supplemented by new workplace organizations, including training (Boothby et al., 2010b). Brandon-Jones and Kauppi (2018) observed that even with widespread adoption of technologies, the performance outcomes can be disappointing. Employee engagement in new technologies was attributed to a lack of effective trainings. Marsh (2018) also stated that employee skill with the adopted technology is an important factor to consider for firm performance improvement. As a result, employee training is an important determinant of firm performance and may play a role in the relationship between technology adoption and firm performance. As a result, it is proposed:

H6: *Technology adoption has significant effect on training*.

H7: *Training has significant effect on manufacturing firms' productivity.*

H8: *Training significantly mediates the relationship between technology adoption and manufacturing firms' productivity*.

2.3.7 Technology Adoption, Firm Size and Firm Productivity

There is a possible link between technology adoption and firm productivity (Abdallah, 2016; S. Z. Ahmad et al., 2019; Kibiya et al., 2019; Nuseir & Aljumah, 2020; Papadopoulos, Baltas, & Balta, 2020b). However, the link between technology adoption and firm productivity is not always clear. It has been proposed that technology adoption only leads to firm productivity when combined with organizational strength (Emeka et al., 2015). The impact of technology adoption on firm productivity varies due to moderating factors such as organisational capacity (Chege et al., 2020). After reviewing the application of their UTAUT model across various fields and locations, Viswanath Venkatesh et al. (2016) lamented the lack of moderating effects in previous studies using the model and recommended that the model be extended to include moderating effects. This is due to the fact that adoption may differ depending on the characteristics of the firms. Firms range in size and capability. According to the organizational capability theory, a firm's productivity improvement is dependent on its capabilities and resources, which are an integral part of its size (de Vass et al., 2018). Thus, the value of technology in any organisation is determined by its infrastructure, which is a collection of shared tangible and intangible resources that includes computers, networks and communication, technologies, and data. As a result, the firm's size and capability may be critical in achieving the required productivity (Che & Zhang, 2016; de Vass et al., 2018). Thus, firm size matters because it can change the relationship between technology adoption and firm performance. In other words, the impact of technology adoption on firm productivity may differ depending on firm size. As a result, it is hypothesized that:

H9: *Firm size significantly moderates the relationship between technology adoption and firm performance*.

3. Research Methodology

A quantitative methodology was used in this study. Quantitative research seeks to investigate and test theories, as well as explain phenomena by demonstrating that they are founded on theoretical premises (Oberiri, 2017). The quantitative methods in the humanities are built on the deductive interpretation model. Quantitative research seeks outcomes that can be used to quantify the problem and comprehend its prevalence in a larger population. Structured data collection methods or survey methods, such as online surveys, paper surveys, polls taken on mobile devices, in-person interviews, and phone interviews, are commonly used to collect quantitative data. Because surveys are among the best and most widely used data collection tools, this study used self-administered questionnaires to collect data. Self-administered questionnaires can be mailed or delivered in person to respondents. Questionnaire used 5-points Likert scale to collect data. A total 330 completed questionnaire forms were gathered. Data was analyzed using the Statistical Package for the Social Sciences (SPSS) and Partial Least Squares-Structural Equation Modelling (PLS-SEM) was used. PLS is a structural equation modelling method based on variance that combines regression analysis and factor analysis. It is employed to forecast the connection between the exogenous and endogenous latent variables. PLS-SEM mitigates the drawbacks of classic multivariate analysis approaches while reducing the covariance-based SEM's tight assumptions. It addresses the shortcomings of traditional multivariate analysis techniques, such as the multicollinearity problem, non-heteroscedastic error, and the assumption that variables are measured without error, as well as the proposal of a basic model structure. The strict suppositions of covariance-based SEM of sample size and normality are lessened by the PLS-SEM (Haenlein& Kaplan, 2004; Wong, 2013). The use of PLS-SEM in this study was motivated by the fact that research constructs are multi-dimensional and latent, making Structural Equation Modelling (SEM) the most appropriate technique (Arshad, Goh, & Rasli, 2014; Bawuro et al. 2019). PLS-SEM is evaluated in two stages. In the first phase, the measurement model (the outside) is assessed, while in the second phase, the structural model (the inside) is assessed. Composite reliability, item factor loadings, and the average variance extracted (AVE) are used to assess the measurement model's convergent validity; the Fornel and Larcker (1981) criterion, cross-loadings, and the Hetro-Trait-Mono-Trait (HTMT) criterion are used to assess the measurement model's discriminant validity (Hair et al., 2011, Memon & Rahman, 2013; Wong, 2013). The indicator variables in the construct are verified to be measuring the correct things with this level of evaluation.

4. Evaluation of Measurement Models

Prior to assessing the structural model, PLS-SEM requires the measurement models to meet certain quality criteria. These quality criteria include the evaluation of measurement model reliability via composite reliability, convergent validity, and discriminant validity.

4.1.1 Reliability Assessment

The degree to which a scale yields consistent and stable measures over time is referred to as reliability. It also shows that how the scale is free of random error (Pallant, 2011; Creswell, 2014). Although Cronbach's alpha is the most commonly used measure of reliability (Awang, 2012), composite reliability is preferable when dealing with PLS-SEM (Joe F Hair, Sarstedt, et al., 2011; Memon & Rahman, 2013; Wong, 2016).

For the measurement model to be reliable, the composite reliability must be at least 0.7 (Wong, 2013). However, a composite reliability of 0.6 is also considered adequate for achieving reliability, particularly for newly developed scales (Chin, 1998, Hair et al., 2011, Bagozzi& Yi, 1988). Table 1 shows the reliability of the measurement models.

Table 1 - Measurement models reliability

Constructs	Cronbach's Alpha	rho_A	Composite Reliability
Technology adoption	0.884	0.890	0.905
Effect of firm size	0.898	0.912	0.917
Effect of training	0.895	0.906	0.914
Manufacturing performance	0.863	0.888	0.892

Table 1 displays the measurement model reliability results. The minimum values of Cronbach's alpha, rho A, and composite reliability are 0.884, 0.888, and 0.892, respectively, all of which are greater than the recommended threshold of 0.7. As a result, all measurement models met the reliability requirement.

4.1.2 Technology Adoption, Firm Size and Firm Productivity

Convergent validity requires that the measurement models provide an explanation for the variation in the observables. The predictive or explanatory power of the measurement model for the observed variables is assessed (Wong, 2016). Convergent Validity is the extent to which one apparent attribute is associated to others in the same dependent latent (Hair, Hult, Ringle, & Sarstedt, 2014). To evaluate the level of explanation for the variance in the manifest variables, we calculate the average variance extracted (AVE) and examine the item factor loadings and their significance (Memon & Rahman, 2013; Wong, 2016). The AVE of the measurement models should be greater than 0.5. (Hair et al., 2014; Hair et al., 2014; Hair, Ringle, et al., 2011; Vinzi et al., 2010; Wong, 2016). This implies that the manifest variables should explain at least 50% of the variance in the outer model (Memon & Rahman, 2013).

Also, the factor loadings for manifest variables must be higher than on others. To achieve convergent validity, the loadings must be at least 0.7 (Hair et al., 2014). The factor loadings of 0.6 to 0.7 are considered acceptable in exploratory research (Hair, Ringle, & Sarstedt, 2011). Manifest variables with factor loadings less than 0.4 must be excluded from the measurement model. Items with lower loadings should also be removed from the measurement model in order to improve the Average Variance Extracted (AVE) (Hair et al., 2014). The factor loadings must be significant and converge after a few iterations less than the maximum 300 iterations (Wong, 2016).

Table 2 - Convergent validity

Items	ATA	ET	EF	MP
AVE	***0.850***	***0.874***	***0.766***	***0.844***
ATA1	0.891			
ATA2	0.939			
ATA3	0.927			
ATA4	0.931			
ATA5	0.930			
ATA6	0.928			
ATA7	0.927			
ATA8	0.925			
ATA9	0.924			
ATA10	0.922			
ET1		0.934		
ET2		0.947		
ET3		0.924		
ET4		0.934		
ET5		0.933		
ET6		0.922		
ET7		0.912		
ET8		0.911		
ET9		0.908		
ET10		0.904		
EF1			0.872	
EF2			0.866	
EF3			0.881	
EF4			0.874	
EF5			0.882	
EF6			0.878	
EF7			0.860	
EF8			0.855	
EF9			0.844	
EF10			0.835	
MP1				0.906
MP3				0.945
MP4				0.900
MP5				0.922
MP6				0.911
MP7				0.896
MP8				0.928
MP9				0.889
MP10				0.868

Table 2 displays that the measurement models of DM, GIS, ST, TR, and TT had AVE values of 0.850, 0.874, 0.766, 0.844, and 0.821, which were all greater than the recommended minimum of 0.5. Likewise, all manifest variables had factor loadings greater than 0.8, indicating significant loadings. As a result, all of the measurement models met the convergent validity requirements.

4.1.3 Discriminant Validity

Discriminant validity assesses how distinct measurement models are from other research constructs. It assesses how a specific measurement model differs from other models in the structural model (Memon & Rahman, 2013). Historically, discriminant validity has been evaluated using two criteria: the Fornell and Larker criterion and the Cross-loading criterion. Recently, both theoretical and empirical support has been gained for the use of the Heterotrait-Monotrait (HTMT) criterion in assessing discriminant validity (Henseler, Ringle, & Sarstedt, 2015).

A heterotrait-monotrait ratio (HTMT) is the ratio of correlations between indicators across constructs measuring different phenomena (heterotraits) to correlations between indicators across constructs measuring the same phenomenon (monotraits) (i.e., correlations of indicators within the same construct). If the Heterotrait-Monotrait (HTMT) ratio with other measurements is less than 0.85, or more generally less than 0.9, we have achieved discriminant validity between models of measurement. "(Henseler et al., 2015)" The HTMT ratio criteria values for the measurement model variables are shown in Table 3.

Table 3 - Discriminant validity using HTMT ratio criterion

Items	ATA	EF	ET	MP
Antecedent of technology adoption	0.701			
Effect of firm size	0.853	0.729		
Effect of training	0.945	0.807	0.705	
Manufacturing performance	0.881	0.973	0.848	0.680

The assessment of discriminant validity using the HTMT criterion as shown in Table 3 reveals that the highest HTMT ratio value of 0.973 is found between MP and ET, which was equal to the most liberal value of 0.9. (Henseler et al., 2015). The HTMT value of 0.680 between ATA and MP was also less than the maximum liberal value of 0.9. The remaining HTMT ratios were less than the 0.85 maximum conservative values (Henseler et al., 2015). As a result of the HTMT criterion, the measurement models achieved discriminant validity. According to Fornell and Larcker (1981), the square root of the AVE of each measurement model must be greater than the correlation of the model with any other model in the structural model. As a result, the square root of each outer model's AVE should be greater than its correlation with any other construct (Jeo F Hair et al., 2014). The results of discriminant validity using Fornell and Larcker Criterion are presented in table 4.

Table 4 - Discriminant validity using Fornell and Larcker Criterion

Construct	ATA	MP	ET	EF
ATA	***0.922***			
MP	0.821	***0.935***		
ET	0.761	0.729	***0.875***	
EF	0.845	0.775	0.690	***0.919***

In the table 4, the diagonally italicised and bolded values represent the square roots of the measurement models' AVEs. Correlations between measurement models are represented by the values beneath the diagonal. The results revealed that no measurement model has a greater correlation with any other measurement model than the square root of its AVE. As a result, the measurement models met the Fornell and Larcker criterion for discriminant validity.

5. Evaluation of Structural Models

PLS-SEM evaluation criteria assess the quality of the structural (inner) model (Hair et al., 2014). Cause-and-effect relationships among the structural model's measurement models are determined by it (Hair et al., 2014). The outlined connections are meant to help researchers find solutions to their problems and put their hypotheses to the test. For the most part, structural model assessment is used to rank models based on how well they predict endogenous constructs. Path coefficients and significance, R-squared for the endogenous construct, f-scores for the exogenous measurement model, Q-scores for predictive relevance, and global goodness-of-fit are all used to assess the structural model (GoF) (Goh, Ali, & Rasli, 2014; Hair et al., 2014; Hair et al., 2011; Memon & Rahman, 2013; Vinzi et al., 2010; Wong, 2016). The structural model is presented in figure 12 while the results obtained from bootstrapping for t-values and hypothesis tests are presented in figure 3.

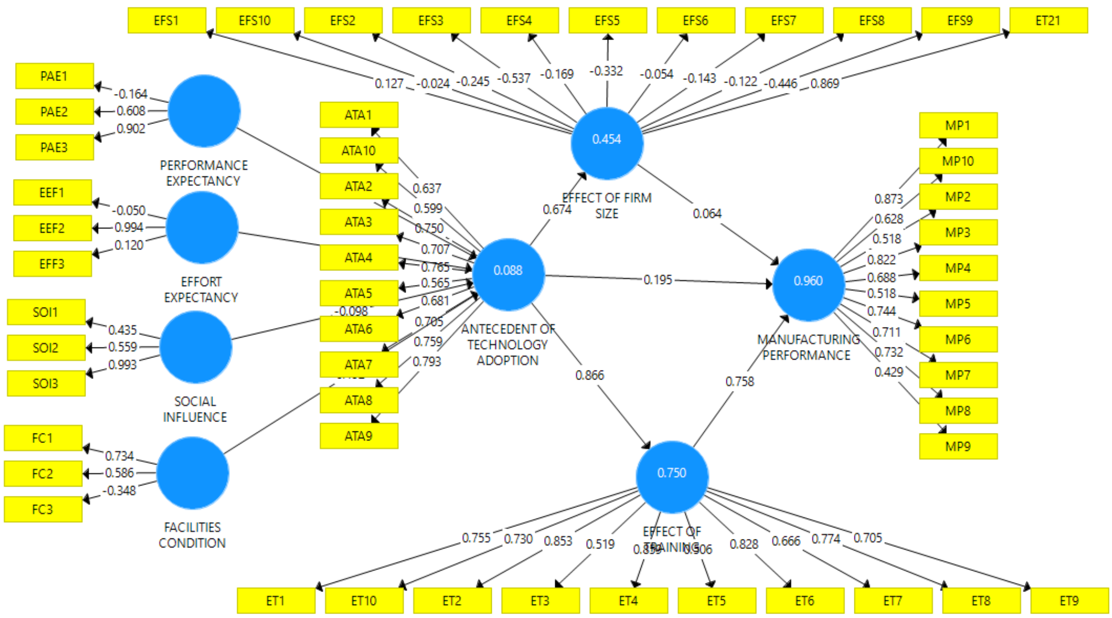

Fig. 3 - Final model

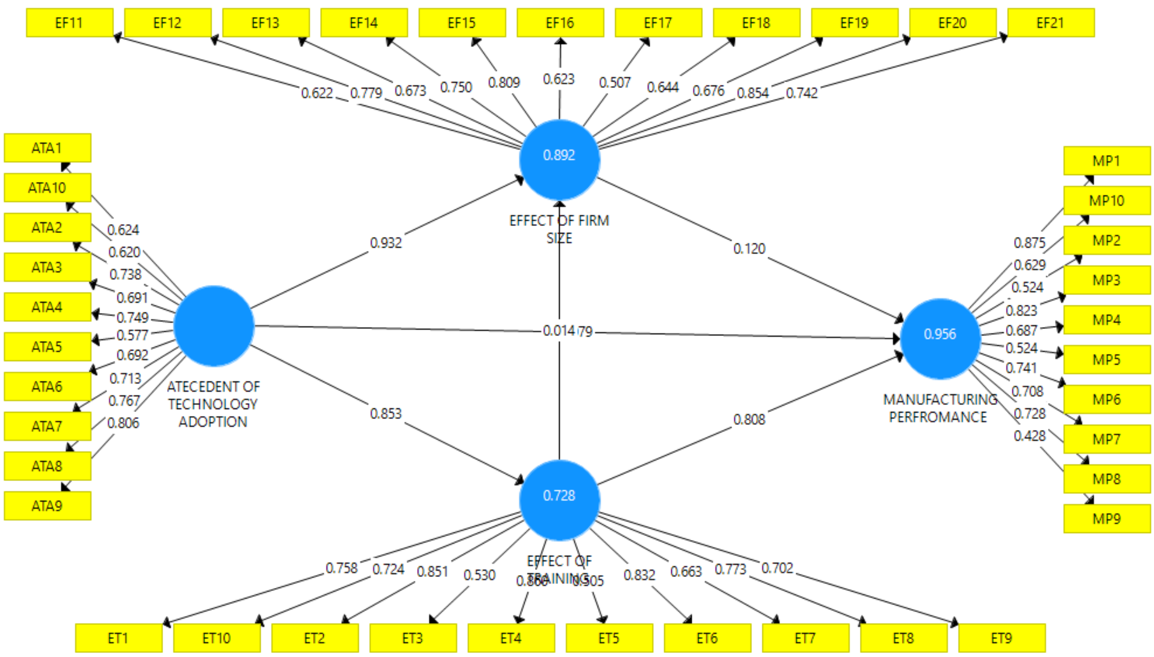

Fig. 4 - Final model t-statistics

The coefficients of the model paths and their significance provide the necessary information for testing the stated research hypothesis. The results are presented in Table 5.

Table 5 - Hypothesis testing

Paths	Hypothesis	Path Coefficient	T Statistics	P Values	Remark
PAE -> ATA	H1	0.203	4.297	0.000	Supported
EFE -> ATA	H2	0.160	2.887	0.005	Supported
SOI -> ATA	H3	0.252	3.299	0.000	Supported
FC-> ATA	H4	0.386	5.106	0.000	Supported
ATA> MP	H5	0.171	3.551	0.001	Supported
ET -> MP	H6	0.396	5.244	0.000	Supported
ET -> ATA ->MP	H7	0.347	4.720	0.000	Supported

EFS -> ATA ->MP	H8	0.485	3.896	0.000	Supported

There were multiple paths in the structural model, some of which represented the previously formulated hypotheses of the research. Table 5 demonstrated that all hypotheses were supported. The results showed a significant causal relationship between performance expectancy and antecedent of technology adoption, effort expectancy and antecedent of technology adoption, social influence and antecedent of technology adoption, and facility condition and antecedent of technology adoption, as indicated by the path coefficients 0.203, 0.160, 0.252, 0.386, 0.171, 0.396, 0.347, and 0.485 with T-statistics values of 4.297, 2.887, 3.299, 5.106, Thus, the following hypotheses are supported: H1, H2, H3, H4, H5, H6, H7, H8, and H9. Thus, the findings support the following hypotheses: performance expectancy is a significant positive determinant of technology adoption; effort expectancy is a significant positive determinant of technology adoption; social influence is a significant positive determinant of technology adoption; facilitating condition is a significant positive determinant of technology adoption; and technology adoption has a significant positive effect on manufacturing firm performance.

The role of training and firm size in mediating the relationship between the antecedent of technology adoption and manufacturing performance is modelled. The findings revealed that technology adoption was significantly related to manufacturing performance (= 0.347, t-value = 4.720, p-value = 0.000), and (= 0.485, t-value = 3.896, p-value = 0.000). According to the coefficient of determination (R^2) value of 0.874, training and firm size explained approximately 81.4 percent of the variance in technology adoption in the UAE. Assessment of the structural model is discussed in following sub-sections.

5.1.1 Path Coefficients Evaluation

One of the primary goals of PLS-SEM is to predict the causal relationship between endogenous and exogenous constructs, as specified in research hypotheses. Path coefficients are used to assess the strength of the linkages between the researches constructs in the structural model. The coefficients indicate the strength of a relationship, with values near 1 indicating a very positive link (Hair et al., 2014). The importance of the path is assessed using the t-statistics during the bootstrapping process (Kock, 2014). The path coefficients and their level of significance provide evidence of the model's internal quality (Joe F Hair, Sarstedt, et al., 2011). The route coefficients must be significant in order to ensure the inner model's validity (Wong, 2016). The route coefficients for the study are shown in Table 6 below.

Table 6 - Path coefficients

Paths	Hypothesis	Path Coefficient	T Statistics	P Values	Remark
PAE -> ATA	H1	0.203	4.297	0.000	Significant
EFE -> ATA	H2	0.160	2.887	0.005	Significant
SOI -> ATA	H3	0.252	3.299	0.000	Significant
FC-> ATA	H4	0.386	5.106	0.000	Significant
ATA> MP	H5	0.171	3.551	0.001	Significant
ET -> MP	H6	0.396	5.244	0.000	Significant
ET -> ATA ->MP	H7	0.347	4.720	0.000	Significant
EFS -> ATA ->MP	H8	0.485	3.896	0.000	Significant

The structural model's 9 paths all had significant coefficients. It is possible to conclude that the research structural model is of sufficient quality because all of the path coefficients are significant.

5.1.2 Coefficient of Determination (R^2) Assessment

Coefficient of determination R^2 evaluates how much variance the model can explain. It measures the quality of the structural model. The R^2 demonstrates how much the exogenous constructions contributed to the structural model's ability to predict or explain the variance of the endogenous construct overall. The model's quality grows in proportion to how well it can explain or predict variation, and vice versa (Hair et al., 2014; Hair, Sarstedt, et al., 2011; Memon & Rahman, 2013; Wong, 2016). For example, an R^2 value of 0.25 is considered weak, 0.50 is considered moderate, and 0.75 is considered significant (Hair et al., 2014; Wong, 2016). According to Hair et al. (2014), an R^2 score of 0.2 is considered high in the field of consumer behaviour. These general guidelines were used to evaluate the study's R^2 levels. Table 7 displays the R^2s for the final model.

Table 7 - R^2 evaluation

Constructs	R Square
ATA	0.894
ET	0.695
EFS	0.689

Table 7 displays the coefficients of determination (R^2) for mediator variable, effect of Training (ET) is 0.695, while the primary endogenous construct, Technology Adoption (DM) has an R^2 value of 0.894. Using the rule of thumb, the level of the study R^2 could be described as substantial. According to the data presented above, all endogenous constructs had R^2 values greater than 0.5. This demonstrates that the values were above average, indicating that the models predicted accurately (Hair et al., 2014).

5.1.3 Effect Size (F2) Evaluation

R^2 analysis does not reveal the specific impact of external factors. Although route coefficients and R^2 represent the individual influence of each path in the structural model and, respectively, the total contribution of all exogenous constructs to variance prediction, they do not show the relative contribution of a single exogenous construct to R^2. The effect size (f^2) is used to assess an exogenous component's individual contribution to the R^2 (Hair, Sarstedt, et al., 2011).

Chin (1998)'s effect size demonstrates the relative impact of several exogenous constructions on the endogenous construct by measuring changes in R-squared (s). The effect size of each construct in the structural model is calculated using Cohen's f^2. Cohen (1988) proposed a criterion for evaluating effect sizes, according to which the size is considered small if f^2 is 0.02, medium if f2 is 0.15, and large if f^2 is 0.35. The effect sizes of these research constructs were evaluated using the criteria listed above, as shown in Table 8.

Table 8 - Effect sizes (F^2)

Construct	MP
ATA	0.990
EF	0.930
EFS	0.844

Table 8 shows that firm size and training had a large effect on manufacturing performance, as indicated by f2 values of 0.990, 0.930, and 0.844, respectively.

5.1.4 Predictive Relevance (Q^2) Assessment

Cross-validated redundancy is used to assess the predictive significance of the structural model. The accuracy of prediction of all data points for all indicators in the outer model of endogenous constructs is examined using Stone-predictive Geisser's relevance (Q^2) (Wong, 2016). A portion of the data matrix is left out in this method, the model's parameters are estimated, and the remaining portion is predicted using the estimations (Hair et al., 2011; Hair et al., 2014). The cross-validated redundancy (Q^2) value had to be a positive integer greater than zero for this quality evaluation criterion to have effective predictive relevance (Chin, 1998).

The study's final models were evaluated using SmartPLS3 software based on the submission to determine cross-validated redundancy (Q^2) (Ringle, Wende & Becker, 2015). The results of the blindfolding technique are shown in Table 9.

Table 9 - Predictive relevance

Constructs	SSO	SSE	Q^2 (=1-SSE/SSO)
ATA	1316.000	414.227	0.685
MP	1316.000	1316.000	
ET	1645.000	1645.000	
EFS	1316.000	554.337	0.579

The structural model's cross-validated redundancy is shown in Table 9. Q^2 values greater than 0 were found in all endogenous constructs. This indicated that the research model was predicatively relevant (Chin, 1998).

5.1.5 Goodness-of-Fit (GoF) Assessment

Unlike covariance-based structural equation modelling, PLS-SEM lacks a widely accepted global goodness of fit metric (Vinzi et al., 2010). Tenenhaus et al. (2004) made an attempt, proposing the "GoF" index as a global criterion of goodness of fit. The index is the geometric mean of the average communality (AVE) index and the coefficient of determination average (R2). The GoF index is intended to explain the performance of the PLS model at both the measurement and structural levels, with a focus on the model's overall prediction performance (Memon & Rahman, 2013). The R2 in the formula represents the structural model, whereas the AVE (communality) addresses the quality of the index's measurement models. If the GoF index is 0.1, 0.25, or 0.36, it is considered small, medium, or large (Akter, 2011). The model produced a GoF of 0.7916. According to Akter's (2011) proposal, the GoF of the research models was high, indicating their high calibre.

6. Discussion and Conclusion

One of the most important factors influencing manufacturing performance is technology adoption. Users can access the services at any time and from any location, and their transactions are entirely confidential. This could explain the study's high mean value of AI security solutions, which is consistent with previous research demonstrating the security and privacy of users' personal information, which is difficult for outsiders to access (Fukuda, 2020; Chiang, &Trimi, 2020). Even though the current study used multiple dimensions to investigate the effect of firm size, training, and other factors on firm performance from various perspectives, the participants were enthusiastic. The dimensions outlined above are used to test the study's four hypotheses. The first hypothesis confirmed that performance expectancy is significantly related to technology adoption. This is consistent with the findings of Fragoso et al. (2017) that technology adoption affects manufacturing performance in terms of training and firm size. In other words, users' readiness to use technology is influenced by their training and firm size. Similarly, the second hypothesis found that Effect expectancy has a significant and substantial relationship with technology adoption. Similarly to social influence and facility condition, the other hypothesis revealed that technology adoption has a positive relationship with manufacturing performance. This finding is consistent with Almarashdeh (2018) and Rehman and Shaikh (2020), who discovered that many people, are unwilling to adopt technology because it is difficult or does not improve job performance. As a result of such negative experiences, people may be hesitant to use technology.

Because technology improves manufacturing performance for manufacturing firms in various aspects. One of the most significant advantages of increased technological use in manufacturing firms is that the firms increase their revenue through improved performance. One key point is that the function of technology in improving performance leads to user pleasure, which encourages UAE manufacturing firms to adopt new technologies in their operations. The third goal of the study is to use mediation analysis to evaluate the mediation effect of firm size and the mediation effect of training on the relationship between technology adoption and manufacturing firm performance in the UAE.

This study also developed and tested a mediation relationship model of the effect of firm size and the effect of training on the relationship between technology adoption and manufacturing firm performance in the United Arab Emirates. The study's nine hypotheses examined the relationship between the effect of firm size and the effect of training on the relationship between technology adoption and manufacturing firm performance in the UAE, with the necessity for basic firm size and training acting as a mediator. When it comes to employing technology in manufacturing, the study hypotheses' outcomes were positive, indicating that firm size and training play a role in manufacturing performance. Training and firm size have a significant relationship with manufacturing performance when using technology in manufacturing. Firm size and training have a significant relationship with technology adoption in the workplace. Furthermore, firm size and training have a mediating effect on the relationship between technology adoption and manufacturing performance in the employment of technology in manufacturing. Based on these findings, the study proposed a SmartPLS model for determining the relationship between technology adoptions and manufacturing performance.

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