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Exploring and Developing an Industrial Automation Acceptance Model in the Manufacturing Sector Towards Adoption of Industry4.0

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Technological progress in the 21st century has catalysed the industrial revolution (Industry 4.0) following the development of multiple new industrial automation technologies in the manufacturing sector. Regardless, past research indicated the unsuccessful attempts in adopting Industry 4.0 technologies among manufacturing organisations. Undoubtedly, the operationalisation of Industry 4.0 in manufacturing proved challenging as organisations were required to evaluate various aspects for effective implementation. Thus, a sound understanding of constructs concerning employees' acceptance and readiness levels towards novel automation technologies was required. Hence, this study aims to explore, develop, and validate the suggested conceptual framework by integrating the Technology Acceptance Model (TAM) and Technology Readiness Index (TRI) with Exploratory Factor Analysis (EFA). The EFA process was the first crucial step in ensuring the internal consistency and stability of the instrument across the sampling population. Consequently, the research outcome potentially enabled the manufacturing sector to identify and comprehend the key determinants in designing industrial automation technologies. This study also contributed to knowledge on technology acceptance by synthesizing TAM 3 and TRI 2.0 theories, thus constructing a new TAM in manufacturing.

Keywords: Industrial automation, Manufacturing, TAM, TRI, EFA

1 Introduction

The past three industrial revolutions have transformed the manufacturing sector by incorporating mechanisation, electricity, and information technology (IT) [1]. Specifically, technological progress and futuristic manufacturing systems led to the conception of Industry 4.0 [2, 3]. The term was first coined by German researchers in 2015 and has since drawn academicians' and industry players' interest over the past decades. Industry 4.0 was catalysed by the astute digitalisation of efficient manufacturing systems with four focal drivers: the Internet of Things, Industry Internet of Things (IIoT), smart manufacturing, and cloud-based manufacturing [4, 5]. Additionally, the industrial revolution would convert production facilities into a fully-integrated, mechanised, and optimised production flow following the nine Industry 4.0 pillars [6]. One of the pillars included 'autonomous robotic' or 'industrial automation'. Industrial automation employed flexible control systems to perform complex tasks autonomously, effectively, and accurately in production lines [3] daily through systemised self-learning [6].

Industry 4.0 also integrated new equipment, knowledge, concepts [7], standards, interconnections, technical aid, information transparency, and decentralised decision-making [8] within the organisation. The primary challenges in manufacturing companies concerned organisational flexibility and agility in line with the dynamic market trends [9] and the timely need to adapt to technological innovations and boost technological efficiency [10]. Furthermore, the manufacturing industry must demonstrate more integration and agility in responding to industrial changes and adopting novel technologies in line with industrial requirements. The recent trends in manufacturing involved mass customisation, personalised products, and versatile product designs [11] that needed advanced equipment and technologies. Regardless, the occurrence of any technological shifts in manufacturing organisations was complex and potentially risked the operationalisation of the entire business model.

Business model characteristics required serious consideration in innovating new technologies. It was highly challenging for the manufacturing industry to simultaneously change both the business model and relevant technologies [12]. Overall, the technological advancements in manufacturing significantly affected the organisations involved. Thus, employees' perceptions of the industrial changes should also be regarded in planning organisational strategies for structural changes in the operative design of organisational systems [13]. A timely response to the technological shifts through Industry 4.0 ensured organisational sustenance and established a strategy for the future needs of manufacturing organisations [14]. Nevertheless, Industry 4.0 remains a novel phenomenon at the preliminary stage and is yet to be widely acknowledged except by a few experts. Unsurprisingly, research on the current adoption of Industry 4.0 technologies remains lacking.

The relationship between industrial characteristics and the adoption of Industry 4.0 is still relatively unknown [15]. Thus, manufacturers needed to comprehend the adoption factors in designing and constructing appropriate decision-making processes to analyse the adoption strategies and understand the acceptance and resistance factors involved. Industrial adoption at both individual and organisational levels was vital for the successful operationalisation of Industry 4.0. Government bodies should also be cognizant of the acceptance process outcomes in decision-making, the implementation of Industry 4.0, and incentive adjustments. The rapid technological development of Industry 4.0 simultaneously accelerated the mechanised pace in manufacturing and improved the industrial automation level, thus resulting in a closed-loop information flow at the factory level [16].

Undoubtedly, a holistic implementation of Industry 4.0 in the manufacturing industry was challenging owing to the various organisational aspects [6]. Past studies indicated that the primary barriers in actualising Industry 4.0 involved advanced automation, virtualisation, and flexibilisation. Nonetheless, the manufacturing organisations that succeeded in operating highly complex technologies achieved a better competitive advantage [17]. Furthermore, the lack of digitalisation and knowledge on the benefits of implementing Industry 4.0 tools at the organisational level hindered the manufacturing industry from initiating technological adoptions [18, 61]. Another obstacle faced by the manufacturing industry, particularly for Small and Medium Enterprises (SMEs), involved big-scale financial investments and expenditure to computerise the manufacturing process through new software and equipment installations [18]. Organisations would also need to provide adequate staff training to efficiently operate the tools and deliver optimal usage corresponding to the Industry 4.0 pillars [1].

Following the scepticism in combining new technologies in organisations, the crucial components involving employees' and other parties' acceptance and readiness levels in integrating new automation technologies required serious consideration. Multiple studies in recent years gauged and elaborated on the factors influencing technological usage and acceptance [19, 21]. For example, TAM proved to be a vital model for scholars to identify and predict human behaviour towards the possible acceptance or rejection of novel technologies [20], whereas TRI emphasised individuals' positive and negative readiness towards technological usage. As such, this study recommended a conceptual model that integrated technological readiness and acceptance constructs in manufacturing, specifically regarding the implementation of automation technology under TAM and TRI. Moreover, the model empirically contributed to a sound understanding of technology acceptance in Industry 4.0 among manufacturing organisations.

2 Theoretical Analysis

2.1 Industrial Automation

Manufacturing processes could be optimised with the congruent integration of industrial robots and human operators. For example, industrial robots were capable of managing high payloads in a faster and more efficient manner without fatigue. Although the physical human capacity and cognitive reasoning required in multiple production activities were irreplaceable by robots, the stamina and repeatability required in less-skilled and hazardous tasks could still be provided through artificial intelligence. Hence, the integration of employees' deductive and cognitive abilities with the speed, accuracy, and strength of industrial robots was deemed logical.

Employees could execute tasks requiring judgment and versatility, whereas industrial robots could conduct tasks, particularly hazardous activities, that require accuracy, speed, and strength. In this vein, the human-robot collaboration (HRC) was established in the manufacturing context. Additionally, recent technological progress has led to the adoption of more comprehensive health and safety standards that allowed humans to safely engage with robots [22]. The industrial HRC concept is gaining importance to increase productivity and efficiency in manufacturing. Nevertheless, safety features are vital in HRC and require complex planning and strategizing following industrial health and safety standards. Hence, the organisational factors affecting individuals in manufacturing needed to be explored to consider the advantages of industrial HRC. For example, Charalambous, Fletcher and Webb attempted to identify the core human factors in organisations to successfully implement industrial HRC using an industrial exploratory case study [23].

Past studies outlined the complexity and reliability of human-automation interactions in the cognitive engineering field. Given the lack of focus on human-automation decision-making compatibilities, incongruencies between human and automation problem-solving styles (in adopting industrial automation at the factory level) could become a critical issue in the Industry 4.0 context. Research on automation acceptance primarily emphasised the identification and prevention of inappropriate automation usage, often categorised as the misuse (overreliance) or disuse (under reliance) of automation [24].

Relevant works of literature generally regarded the incorporation of human capacities and autonomous technologies in high-risk, evolving, and intricate ecosystems [18, 25], such as aircraft carriers, nuclear power plants, space shuttle operations, firefighting, and heavy manufacturing such as automotive industry [26, 27, 62, 63]. Several influential elements concerning the choice of automation used in manufacturing involved automation trust, self-confidence in manual performance, perceived risk, and fatigue. In contrast, the human elements included innovation, efficient communication, competency, software-based training, collaboration, and continuous digital awareness (specifically automation attitude, trust, workload, and complexities, the perceived risk of automation use, and perceived automation reliability) [18, 28, 31].

In transforming Industry 4.0, manufacturing organisations were required to gauge the employees' views on a revolutionised system: organisational reforms were highly risky, did not guarantee success, and significantly impacted manufacturing companies. The high-risk factors inevitably led to employees' anxiety and confusion and indicated serious morale issues within the organisation. Employee morale was inextricably linked to organisational trust and highly affected the chances of success following organisational changes or innovations [32]. Therefore, the top management in organisations needed to actively address employees' concerns on the Industry 4.0 benefits. In this regard, employees' training and development should complement Industry 4.0-oriented competencies and skills, such as data analytics, IT, software, and the intricacies of human-machine interactions [33]. Besides, employees' commitment to systemic changes following a new operational paradigm was enhanced by duly addressing the transition and preparation phases without undermining communication and training prerequisites. Consequently, the communicating issues and potential misunderstandings from incomplete project implementations and over-expectations in organisations could be minimised [34].

2.2 The TAM

The development of TAM in enabling individuals to predict acceptance and technological levels [35] has gained importance over the past two decades. Specifically, the widely-adopted theory was extensively used to explain and gauge systemic usage in several recently-developed TAM-oriented models. As an influential study model, TAM was developed by Davis [36] to examine the determinants of technological acceptance and predict individuals' intentions and acceptance of technological use. For example, TAM consisted of two determinants: perceived ease of use (PEoU) and perceived usefulness (PU). Specifically, PU denoted the extent to which an individual believed that employing a particular information system or technology elevated work performance. In contrast, PEoU denoted the extent to which an individual believed that utilising a particular information system or technology waived human effort. Hence, PEoU and PU could positively influence users' attitudes, intentions and acceptance levels towards information systems. In this vein, PEoU could positively influence PU, whereas both PEoU and PU were influenced by external variables [36].

The TAM 3 is an extension of TAM established by Venkatesh and Bala [35] to measure individuals' technological acceptance and adoption using specific constructs. For example, TAM 3 theorised novel relationships between (i) PU and PEoU, (ii) computer anxiety (CA) and PEoU, and (iii) PEoU and behavioural intentions (BI). The theoretical foundation in TAM3 outlined four primary factors that explicitly affected technology acceptance: social influences, individual differences, system characteristics, and facilitating conditions. Following Venkatesh and Bala [35], the four factors had varying impacts on both PU and PEoU constructs.

Based on the aforementioned factors, TAM determinants were categorised in groups as no cross-overs among the determinants were deemed possible. The separation denoted that the determinants influencing PU could not influence PEoU and vice versa. Besides, social influence factors demonstrated the importance of an individual's belief in system usage. Specifically, system characteristics were demonstrated through cognitive instrumental processes and reflected individuals' beliefs on the advantages of technological usage. The individual difference generally illustrated individuals' beliefs towards computers and computer utilisation. Meanwhile, facilitating conditions indicated the perception of external control (PEC) determinants regarding access to technical support and resources [35].

Venkatesh and Bala [35] also inserted 'Experience' and 'Voluntariness' as the moderators potentially influencing PU, PEoU, and BI (see Figure 1). To date, TAM has been modelled by many researchers to hold more superiority than other models, such as the Theory of Reasoned Action and Theory of Planned Behaviour in explaining people's novel technological adoption intentions [20, 37, 38].

2.3 The TRI

In Parasuraman[39], technology played a significant role at organisational and individual levels. Specifically, technology readiness defined people's eagerness to accept, adopt, and incorporate technological changes on a personal and professional basis. In this vein, TRI measured people's tendency to accept and utilise modern technologies[39]. The four TRI dimensions are listed as follows [39, 40]:

- Optimism (OP): positive approaches at individual and organisational levels following new technological usage;
- Innovativeness (IN): the IN levels accepted by individuals and organisations in developing cutting-edge technology;
- Discomfort (DS): a negative response to technological changes. Some people experienced DS due to the complications and immediacy of technological changes. The dimension was a negative factor for companies, particularly small-scale companies with limited funds. Organisational management could also face high DS levels in adopting or implementing novel technologies;
- Insecurity (IS): scepticism or distrust towards technology, thus resulting in people's IS. Organisations could also observe IS in new technological implementation owing to high cost and ambiguities in long-term technological sustenance.

Following Parasuraman [39, 40], OP and IN were the two most positive technological drivers in introducing a new model at individual and organisational levels. Meanwhile, DS and IS were negative elements that may hinder the overall acceptance rate of advanced technologies among individuals and organisations. Consequently, TRI was often selected based on the aforementioned factors to suit the psychological assessment of individuals and companies in rejecting or accepting new technologies. Initially, TRI was employed to measure customers' technological readiness towards technology-based services (financial and online services) [39, 40].

2.4 The TRAM

The integration of TRI and TAM resulted in the Technology Readiness and Acceptance Model (TRAM) with resounding popularity in the past decade. Notably, Lin et al. [41] indicated high correlations between TRI attributes towards the PU and PEoU of TAM. Similar studies by Hallikainen and Laukkanen[42], Shin and Le [43], Larasati et al. [44], and Yi et al. [45] supported TRAM. Furthermore, TRAM emphasised the mapped attributes of the personality-specific TRI construct and the system-specific TAM construct. Past studies revealed that personality construct could affect people's technological interactions, experiences, and usage. For example, Yi's et al. study implied that both TRI and TAM were designed to outline individual technology acceptance. Specifically, TRI emphasised individuals' general technological perspective, whereas TAM entailed people's system-specific perception of technological acceptance[36].

Although the original TAM was established in 1989 and TRI was established in 2000, both theories are still valid and recently there are still numerous researchers are using TAM and TRI models to measure the user acceptance and readiness of new emerging technologies on various applications such as acceptance of Airbnb sharing accommodation [64], online learning system [65], facial recognition payment [66], e-learning adoption [67], students' use of Zoom application [68], online food delivering ordering services [69], adoption of self-service technology [70] and virtual reality in fashion retailing [71].

It should be emphasized that even though the TAM, TRI and TRAM models used are similar in term of the constructs, there was still a lack of researches in the area of the manufacturing sector. Hence in this paper, our novelty is to study the industrial automation technology level of acceptance and readiness in the manufacturing sector. The scope of the study and target respondents are the employees that have experience in adopting new technology in the manufacturing facilities. With this model, we are expecting to contribute to the new knowledge of the level of acceptance of Industry4.0's technology adoption in the manufacturing sector.

3 Proposed Conceptual Model and Hypothesis

Based on the literature review, this research proposed the incorporation of TAM 3 constructs and TRI 2.0 into the Automation Acceptance Model as the research conceptual framework (see Figure 1). The TAM 3 constructs included Job Relevance (JR) for System Characteristic, Computer Self-Efficacy (CSE) and CA for Individual Difference, and PEC for Facilitating Conditions. The JR construct was selected to indicate an individual's trust level towards automation technology in increasing work improvement and positively influencing PU [35].

Meanwhile, CSE denoted computer-based competencies to demonstrate how the employees' competencies influenced the acceptance and readiness of automation technology. The CA construct was included to examine how individuals perceived technological usage, particularly automation technology. The PEC construct was also examined. Before implementing automation technology, undivided organisational support was vital to ensure employees' technological acceptance and readiness. The attributes were then mapped to PEoU as it was proven to significantly influence behaviour [35].

Although TAM 3 and TRI 2.0 could be utilised to predict technological adoption, the core distinction between both theories indicated that TAM 3 employed system-specific observations to gauge technological adoption. On the other hand, TRI 2.0 emphasised individuals' overall dispositions that influenced the intentions to use a product. Thus, this study integrated both TAM3 and TRI 2.0 to examine employees' psychological and cognitive traits, such as PU in gauging acceptance intentions regarding Industry 4.0. Despite the TRI-TAM integration into one model in past studies, very few combined the latest versions of both theories in recommending a new technology adoption model.

Regarding TRI 2.0, the OP, IN, DS, and IS constructs were mapped to both PU and PEoU as emotions potentially influenced usage behaviour Yi et al. [42], [44, 45]. Figure 2 presents the mapping of TAM and TRI construct details and the development of the Automation TAM. The study data would then be collected to identify the acceptance and readiness levels towards the operationalisation of automation technology following the study hypotheses. Several study hypotheses were constructed in line with the conceptual framework to understand the relationships between variables.

For example, JR provided insights into users' technology familiarity levels concerning task performance. Owing to various working environments, users developed multiple expectations following technological usage. Several studies affirmed that JR was a significant PU predictor [46, 48]. Hence, the study hypothesis was developed as follows:

H1:JR has a positive and significant effect on PU.

The OP construct measured individuals' perception of specific technologies [42]. A technology optimist would expect more benefits from technological adoptions, such as flexibility, increased control, and more productivity [39]. Hence, innovation visionaries were more inclined to be optimistic regarding novel technologies and less inclined to be sceptical, consequently adopting new technologies in advance. As such, the following hypotheses were developed:

H2:OP has a positive and significant effect on PU.
H3:OP has a positive and significant effect on PEoU.

Essentially, IN was described as the pioneer in technological use and a contributing factor in technological adoption. Hence, individuals with higher IN traits possessed fundamental motives in utilising or trying new technologies [45]. Consequently, IN affected both PU and PEoU [49]. Following the discussion above, the following hypotheses were developed:

H4:IN has a positive and significant effect on PU.
H5:IN has a positive and significant effect on PEoU.

The DS construct was described as a sense of inundation following the lack of control in utilising unknown technology [50]. Individuals overwhelmed by novel technologies worried that the tools or innovations were inappropriate and risky [50]. The construct was relevant to anxieties caused by new technologies and negatively influenced PEoU [51] and PU [52]. Hence, the following hypotheses were developed:

H6:DS has no significant effect on PU.
H7:DS has a negative and significant effect on PEoU.

The IS construct denoted individuals' scepticism or cynicism in the accurate functioning of novel ideas or technologies [39]. Individuals with high IS levels generally possessed little confidence in the security features of new technologies and were concerned with the potential risks involved [39]. Previous findings affirmed that risk-oriented perceptions would affect PU and PEoU [53]. As such, the following hypotheses were developed:

H8:IS has a negative and significant effect on PU.
H9: IS has a negative and significant effect on PEoU.

Fundamentally, CSE enabled individuals to comprehend a novel idea or technology and the success levels in technological assessment [35]. It was observed that CSE positively influenced the usage of new technology [35]. Based on the discussion above, the following hypothesis was developed:

H10: CSE has a positive and significant effect on PEoU.

The apprehensions and fears arising from the complications in technology-human interactions could trigger various destructive emotions, such as technological usage anxiety [35]. Consequently, technological ambiguities and fear of failure would lead to a negative perception of novel ideas and influence individual decisions [35]. Hence, the following hypothesis was developed:

H11: CA has a negative and significant effect on PEoU.

The PEC construct was defined as individuals' perception of accessibility concerning technology and knowledge, sufficient resources, and skills proficiency in implementing new technologies [35]. Consequently, adequately-skilled individuals with access to relevant resources found it easier to accept ambiguous tasks and was willing to accept new ideas. Thus, the following hypothesis was developed:

H12: PEC has a positive and significant effect on PEoU.

Past research indicated that individuals who adapted to a system experienced enhanced work performance and individual lifestyles. Hence, PU was found to be a significant determinant in new technological adoptions [35]. In this vein, individuals observed that a system could potentially improve the overall performance of routine tasks.

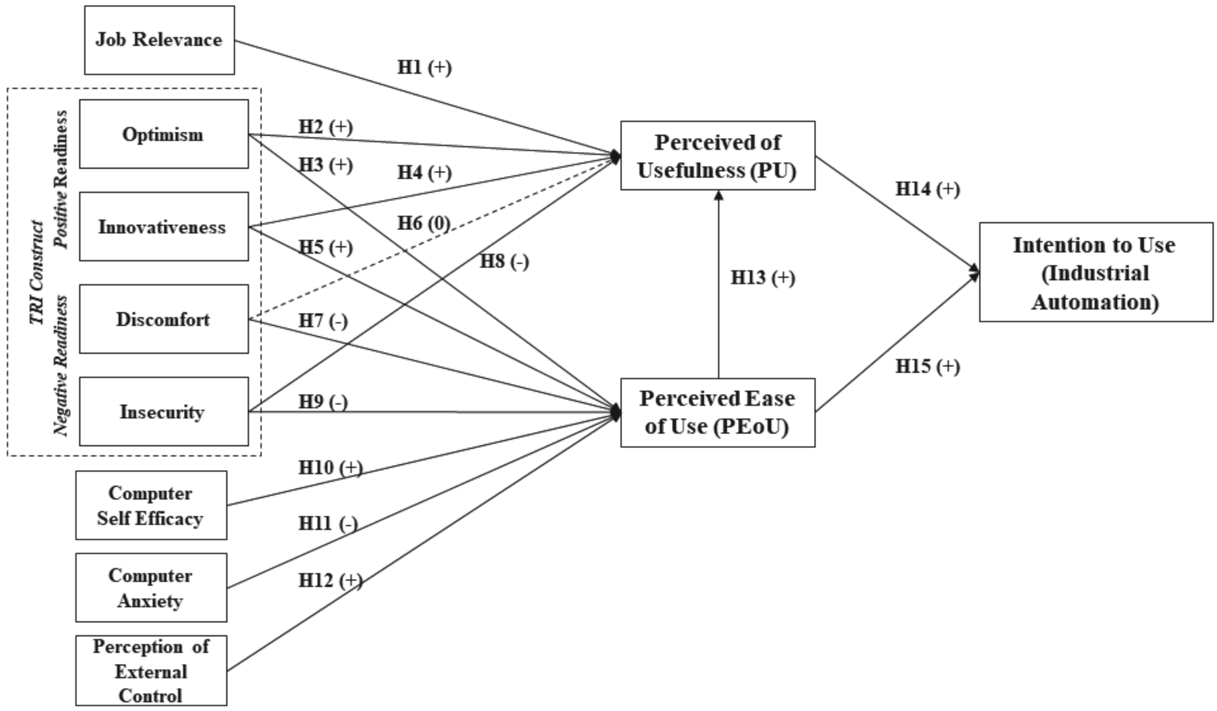

Fig. 1 *Conceptual Model of Industrial Automation TRAM with Hypotheses*

The PEoU construct denoted the degree to which users observed the effortless usage of systems or technologies [35] and the importance of trust-building among customers [35]. For example, past researchers indicated that the PEoU of IIoT inventions increased user satisfaction and positively influenced the intention to use [35]. Both PU and PEoU significantly influenced the adoption of Industry 4.0. Hence, the following hypotheses were developed:

H13: PEoU has a positive and significant effect on PU.

H14: PU has a positive and significant effect on the Intention to Use

H15: PEoU has a positive and significant effect on the Intention to Use

4 Methodology

This study employed the survey technique for data collection, particularly in the context of manufacturing organisations. A pilot test was initially conducted to validate the suggested model constructs. The study data were then obtained through a structured survey questionnaire adapted from the previous studies of Venkatesh and Bala [35] (TAM 3) and Parasuraman and Colby [40] (TRI 2.0) and was developed accordingly to complement this research. The structured questionnaire involved 42 items using a 10-point Likert scale to provide respondents with more comprehensive response options that reflected individual perspectives. The questionnaire was then distributed to 110 respondents in the target population (manufacturing company employees in Kuala Lumpur, Malaysia). Table 1 below presents the respondents' demographic criteria.

This study aimed to validate the recommended conceptual framework of TAM and TRI constructs using EFA. In Hoque et al. [54, 55], researchers who modified previously-established instruments and items to fit the current research must perform a pilot study using the EFA procedure. In the study context, The pilot study was necessary owing to the socio-economic, racial, and cultural differences of the current study population as opposed to past studies. Hence, some items may no longer be appropriate for this study. On another note, the EFA procedure was implemented on the notion that measurable variables were reduced into fewer latent variables that shared a common variance and were unobservable [56].

Tab. 1 *Respondents' Profile*

Demographic Criteria	Frequency	%
Gender		
Male	82	74.5
Female	28	25.5
Age		
18 – 25	24	21.8
26 – 35	34	30.9
36 – 45	35	31.8
46 – 55	16	14.5
Over 55	1	0.90
Level of Education		
Below High School	3	2.7
High School Diploma	29	26.4
Vocational/Technical degree	34	30.9
Bachelor's Degree	39	35.5
Master's Degree	5	4.5
Doctorate Degree	-	-
Work Experience (related to Industrial Automation)		
Less than three years	8	7.3
3 - 5 years	28	25.5
6 - 10 years	32	29.1
10 - 15 years	27	24.5
Over 15 years	15	13.6

5 Results and Findings

This study employed EFA to examine the structural elements of all the study measures. Furthermore, EFA was the most common assessment method to measure internal reliability [56]. On the other hand, the principal component analysis (PCA) was the most-utilised method to indicate variations and detect strong dataset patterns by reducing the dataset dimensionality while maintaining the highest variability [56]. Two distinct EFA procedures employed the PCA extraction method using Varimax Rotation. The first procedure was tested on the 26 items measuring TAM constructs, whereas the second procedure assessed the16 items measuring TRI constructs.

The EFA procedures were expected to produce the study results for i) the Kaiser-Meijer-Olkin measure of sampling adequacy (KMO), ii) the total variance for each construct, iii) the factor loading for every item, and iv) the internal consistency score of the construct through Cronbach's Alpha [54]. The KMO test investigated data adequacy for factor analysis [57] and evaluated the sampling fit for all variables and the variance proportion among variables in the suggested model. A KMO higher than 0.5 indicated acceptable data adequacy for factor analysis [57].

5.1 The KMO and Bartlett's Test of Sphericity (Bartlett's Test)

Tables 2a and 2b indicate Bartlett's significant test result (P-Value < 0.05), whereas the KMO results were 0.518 and 0.578, thus indicating a higher value than the required 0.5. Overall, both test values (significant Bartlett's Test and KMO > 0.5) reflected data adequacy [57].

Tab. 2(a) *KMO and Bartlett's Test (TAM constructs)*

KMO and Bartlett's Test		
KMO		.518
Bartlett's Test	Approx. Chi-Square	2778.696
	df	325
	Sig.	.000

Tab. 2(b) *KMO and Bartlett's Test (TRI constructs)*

KMO and Bartlett's Test		
KMO		.578
Bartlett's Test	Approx. Chi-Square	1143.520
	df	120
	Sig.	.000

5.2 Total Variance Explained

The total variance explained was an extraction process of questionnaire items to be reduced into a manageable number before further analysis. Specifically, the components with eigenvalues exceeding 1.0 were extracted to different components [54, 55]. Table 3 reveals that EFA extracted seven components from TAM constructs and four components from TRI constructs with the eigenvalue presented in Tables 3(a) and (b) below. The results demonstrated that the items were categorised into 11 components for further analysis.

Tab. 3(a) *Total Variance Explained (TAM constructs)*

Total Variance Explained						
Component	Initial Eigenvalues			Rotation Sums of Squared Loadings		
	Total	% of variance	Cumulative %	Total	% of variance	Cumulative %
1	5.602	21.546	21.546	3.441	13.236	13.236
2	3.411	13.118	34.664	3.201	12.310	25.546
3	3.047	11.720	46.385	3.129	12.033	37.580
4	2.580	9.923	56.307	2.859	10.995	48.575
5	2.310	8.885	65.193	2.852	10.968	59.543
6	1.972	7.586	72.778	2.392	9.201	68.744
7	1.253	4.820	77.599	2.302	8.855	77.599

Tab. 3(b) *Total Variance Explained (TRI constructs)*

Total Variance Explained						
Component	Initial Eigenvalues			Rotation Sums of Squared Loadings		
	Total	% of variance	Cumulative %	Total	% of variance	Cumulative %
1	3.771	23.571	23.571	3.109	19.433	19.433
2	3.099	19.368	42.939	2.913	18.207	37.640
3	2.888	18.052	60.992	2.829	17.681	55.322
4	1.803	11.266	72.258	2.710	16.936	72.258

Tables 3(a) and (b) also reveal that the total variance explained was 77.599% (TAM construct) and 72.258% (TRI construct). Overall, the total variance explained for the study constructs were acceptable (above the minimum requirement of 60%) [54, 55]. In contrast, values below 60% indicated item inadequacy in construct measurement.

5.3 Factor Loading

Tab. 4(a) *Rotated Component Matrix (TAM constructs)*

Rotated Component Matrix[a]							
	Component						
	1	2	3	4	5	6	7
JR1							.911
JR2							.885
JR3							.792
CSE1				.893			
CSE2				.898			
CSE3				.722			
CSE4				.825			
CA1	Item to be removed						
CA2						.724	
CA3						.803	
CA4						.765	
PEC1					.824		
PEC2					.857		
PEC3					.829		
PEC4					.841		
PU1	.742						
PU2	.785						
PU3	.865						
PU4	.730						
PEoU1		.928					
PEoU2		.709					
PEoU3		.942					
PEoU4		.898					
BI1			.853				
BI2			.834				
BI3			.878				
Extraction Method: PCA. Rotation Method: Varimax with Kaiser Normalisation.							
a. Rotation converged in 6 iterations.							

Job Relevance (JR), Computer Self-Efficacy (CSE), Computer Anxiety (CA), Perceptions of External Control (PEC), Perceived Usefulness (PU), Perceived Ease of Use (PEoU), Behavioral Intention (BI)

Tables 4 (a) and (b) present the factor loading for every item and component, thus indicating the importance of the specific item in construct measurement. As the acceptable value of factor loading was 0.6, items with a factor loading of less than 0.6 should be removed from the study [54, 55]. Resultantly, items CA1 and DS1 (with values below 0.6) was omitted from the questionnaire. The remaining items with factor loadings above 0.6 were retained.

Tab. 4(b) *Rotated Component Matrix (TRI constructs)*

Rotated Component Matrix[a]				
	Component			
	1	2	3	4
OP1	.898			
OP2	.911			
OP3	.888			
OP4	.742			
IN1			.836	
IN2			.876	
IN3			.825	
IN4			.771	
DS1	Item to be removed			
DS2				.865
DS3				.879
DS4				.863
IS1		.879		
IS2		.853		
IS3		.844		
IS4		.806		
Extraction Method: PCA. Rotation Method: Varimax with Kaiser Normalisation.				
a. Rotation converged in 5 iterations.				

Optimism (OP), Innovativeness (IN), Discomfort (DS), Insecurity (IS)

5.4 Internal Consistency Score (Cronbach's Alpha)

Finally, this study employed Cronbach's Alpha to assess the internal reliability of the survey items in construct measurement. The reliability analysis was employed to measure the study items under each construct and evaluate the extent to which the items were error-free. Some authors had varying perceptions concerning the acceptance value of Cronbach's Alpha as an indicator of the internal consistency of items. Nevertheless, it was commonly agreed that a Cronbach's

Alpha of 0.6 and above provided a reliable measure of internal consistency. Furthermore, a score of 0.70 and above indicated that the instrument possessed an excellent reliability standard [58, 59]. Tables 5 (a) and (b) present the Cronbach's Alpha value for every component. All 11 components demonstrated the Cronbach's Alpha value to be higher than 0.7, thus reflecting high reliability and suitability regarding the selected study items.

Tab. 5(a) *Internal Reliability (TAM constructs)*

Reliability Statistics		
Component	N of Items	Cronbach's Alpha
1	4	0.928
2	4	0.870
3	3	0.953
4	4	0.858
5	4	0.854
6	3	0.840
7	3	0.834
Total	25	

Tab. 5(b) *Internal Reliability (TRI constructs)*

Reliability Statistics		
Component	N of Items	Cronbach's Alpha
1	4	0.894
2	4	0.861
3	4	0.853
4	3	0.867
Total	15	

Based on the results, the instrument measuring the suggested Industrial Automation Acceptance Model construct involving a combination of 11 components with a specific number of items in every component (40 items in total) was ready to be used. Upon obtaining the study data, a Confirmatory Factor Analysis (CFA) procedure was performed to validate the latent construct. This study then designed the structural model and performed the Structural Equation Modelling (SEM) procedure to assess and verify the study hypotheses and goodness-of-fit in the conceptual model.

6 Conclusion and Future Work

This study discussed the technological characteristics implemented in the manufacturing industry, particularly in automation technology, by addressing the current industrial issues. Additionally, a new TAM was developed by augmenting the TAM 3 constructs and TAMs to predict the acceptance of Industry 4.0 among manufacturing employees. Following the EFA result, Bartlett's Test was statistically significant (P-Value < 0.05), KMO was above the minimum value (> 0.5), the factor loadings exceeded the minimum threshold of 0.6, and a high Cronbach's Alpha value (> 0.7) was achieved. The development and validation of EFA procedures were crucial steps in ensuring that the new instrument was internally consistent and stable across samples. Regarding the study data collection, the recommended minimum sample size followed a 10-to-one ratio of the questionnaire items [60]. Consequently, 40 questionnaire items were designed. A minimum sample size of $40 \times 10 = 400$ respondents was required from the target population. Upon data collection, an empirical study for the CFA procedure to verify the latent construct before employing SEM was suggested to test the study hypotheses and goodness-of-fit model.

7 Implications and Suggestions

Several study implications were indicated following the study results. Theoretically, this study contributed to existing works of literature on technology acceptance by synthesising TAM 3 and TRI 2.0 theories, thus developing a novel TAM in manufacturing. This study also incorporated past studies on technological acceptance with significant insights into adopting Industry 4.0 under TAM 3 and TAMs. Furthermore, the reliability of variables in the suggested model was empirically examined using EFA and Cronbach's Alpha. The KMO test was employed to analyse data adequacy for factor analysis.

Conclusively, this study could become the groundwork in enhancing the adoption of Industry 4.0, particularly in the use of industrial automation technologies. Hence, the study outcome enabled the manufacturing sector to identify and understand the key determinants in designing industrial automation technology processes. The study results could also be considered as valuable input for relevant government bodies in drafting new Industry 4.0 policies, particularly on the industrial automation policy. Following the input, policymakers would be able to formulate better incentives or grants that met the industrial requirements in adopting industrial automation technologies.

Regardless, some study limitations were encountered in this study. As the current study sample was collected from several factory workers in Kuala lumper, Malaysia, the generalisability of the study results might have been compromised. Additionally, this study adopted a cross-sectional research design. Therefore, future studies should consider a longitudinal approach to add value to the recommended conceptual model. Lastly, the current research only emphasised manufacturing employees in the context of Industry 4.0 adoption. Thus, future research may also investigate different staff members, such as the board of directors and CEOs to obtain a sound understanding of the decision-making processes in technological implementation.

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