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Effect of internet of things on manufacturing performance: A hybrid multi-criteria decision-making and neuro-fuzzy approach

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A R T I C L E I N F O

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A B S T R A C T

We have entered a new technological paradigm with the emergence of Internet-embedded software and hardware, so-called the Internet of Things (IoT). Although IoT offers pan-industry business opportunities, most industries are only just beginning to employ it. We thus determine and prioritize the most important factors that influence IoT adoption, and reveal how IoT adoption affects the performance of manufacturing companies. We use a hybrid method that integrates the adaptive neuro-fuzzy inference system with the decision-making trial and evaluation laboratory, a novelty of the study. The literature on this subject informs our selection of the critical adoption factors, namely, technological, environmental, and organizational. The data are acquired from industrial managers involved in the decision-making process of information technology procurement in manufacturing companies in Malaysia. Our results can support IoT adoption guidelines geared to yield maximum efficiency in manufacturing industries, service providers, and governments.

1. Introduction

Organizations could not guarantee success by simply responding to customer needs, but in the twenty-first century, success is more complex and elusive. Organizations must now monitor current trends and predict future ones; their supply chains should be agile, while their capabilities should include high adaptability, alignment, efficient decision-making, flexibility, and product and process innovation; the market expects them to collaborate with supply chain partners and develop trust as well (Bustinza et al., 2021). The most recent technology to grace the industry, Internet of Things (IoT), offers these capabilities by generating large-scale, real-time, linked data from myriad sources (Brous et al., 2020). IoT can connect any entity with another entity at any point, in any location, through any path, network, or service (Lu et al., 2018), (Baldini et al., 2018). It essentially allows for "smart" manufacturing that has immense economic prospects (Dai et al., 2020) by connecting manufacturing systems, services, and "things." This makes it an enabling technology for a cyber–physical system (Yang et al., 2019). In manufacturing, such smart machines can interact with each other and transmit data across the Internet (Tekade, 2015). Smart machines make business more efficient; they can forecast maintenance and reduce downtime. These benefits make smart technology a cost-saving investment (Ammirato et al., 1108). IoT also improves system performances in international and distributed settings within the manufacturing industry (Bi et al., 2014). Yang (Yang et al., 2019) for example, list the benefits of energy efficiency management, safety and ergonomics, operation management, integration of cloud computing, and cyber–physical manufacturing with respect to IoT in manufacturing. Despite these established gains, the literature in the information systems domain has hitherto not sufficiently assessed how manufacturing companies have adopted IoT or its effect on performance. To promote IoT in manufacturing means to unveil the factors that aid its adoption. These factors will enable policymakers, IoT vendors, and manufacturer managers to make better investment decisions in order to efficiently adopt

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and promote IoT. We determine these factors in our study and how they affect organizational performance. The literature on this subject informs our selection of the critical adoption factors, namely, technological, environmental, and organizational. We assessed these factors, how they are linked, and their degree of significance for IoT adoption and organizational performance.

1.1. The statement of the problem and contributions of the study

The literature on IoT mainly deals with enabling technologies and applications thereof, technical difficulties, standardization activities, and privacy and security (Lu et al., 2018; Xu et al., 2014), the drivers of IoT adoption in manufacturing, where IoT adoption is still in its nascency and organizations are often indecisive (He et al., 2020).

We thus extracted 20 factors from studies on IoT adoption and divided them into technological, environmental, and organizational (TOE) factors (see Table 1). Although there is substantial literature on the potential benefits of IoT in manufacturing (Kiel et al., 2017; Sestino et al., 2020), the extent to which TOE factors, through IoT, influence performance in manufacturing is yet to be determined. Although soft computing approaches and multi-criteria decision making (MCDM) can assess and prioritize enablers in technology acceptance research (Yadegaridehkordi et al., 2018; Shen et al., 2011; Asadi et al., Nazir), few studies exist on the use of those techniques to examine IoT adoption.

Table 1
Dimensions and criterion affecting the IoT adoption.

Main factors	Criteria	References
Technology	Technology Infrastructure	(Hsu and Yeh, 2017), (Ogidiaka et al., 1314)
	Compatibility	(Karahoca et al., 2018), (Arnold and Voigt, 1142), (Wang et al., 2010), (Cicibas and Internet, 2018), (Lin et al., 2016), (HWA)
	Complexity	(Lin et al., 2016), (Wang et al., 2010)
	Technology Competence	(Wang et al., 2010), (Van Leemput)
	Security Concern	(Hsu and Yeh, 2017), (Karahoca et al., 2018), (Cicibas and Internet, 2018)
	Perceived Benefits	(Lin et al., 2016), (Hsu and Yeh, 2017), (Karahoca et al., 2018), (Tu, 2018)
	Technology Integration	(Hsu and Yeh, 2017), (Whitmore et al., 2015)
Organization	Top management support	(Cicibas and Internet, 2018), (Sezgin, 2018), (Lin et al., 2016), (Oliveira et al., 2014b)
	Organizational readiness	(Hsu and Yeh, 2017), (Zaidi and Faizal, 2017), (van de Weerd et al., 2016)
	Technical Knowledge	(Lin et al., 2016), (Janssen et al., 2017), (Brown, 2017)
	Executive Support	(Wang et al., 2010), (Lin et al., 2016), (Arnold and Voigt, 1142)
	Firm size	(Wang et al., 2010), (Arnold and Voigt, 1142), (Cicibas and Internet, 2018), (van de Weerd et al., 2016)
	Financial resource	(Tang and Ho, 2018), (Kodogiannis and Petrounias, 2011)
	Perceived Cost	(Lin et al., 2016), (Karahoca et al., 2018), (HWA), (Tu, 2018), (Cicibas and Internet, 2018)
	Prior IT experience	(Mokhtar et al., 2017), (Al-Isma'ili et al., 2016), (Hsu and Lin, 2016)
Environmental	Competitive pressure	(van de Weerd et al., 2016), (Al-Isma'ili et al., 2016), (Oliveira et al., 2014c)
	Government support	(Lin et al., 2016), (van de Weerd et al., 2016)
	Government policy	(Hsu and Yeh, 2017), (Cicibas and Internet, 2018), (Hsu and Lin, 2016)
	Trading partner pressure	(Lin et al., 2016), (Hsu and Yeh, 2017), (HWA), (Wang et al., 2010), (van de Weerd et al., 2016)
	External ICT support	(Ramdani et al., 2013), (AlBar and Hoque, 2017)

To accomplish our complicated evaluation of factors, we employ a hybrid technique that combines the decision-making trial and evaluation laboratory (DEMATEL) with the adaptive neuro-fuzzy inference systems (ANFIS). This tool is robust in ranking variables and for modeling and forecasting outputs based on inputs. DEMATEL is particularly used to demonstrate the cause and effect relationship among variables (Awasthi and Grzybowska, 1007). It is identical to mind mapping in that the responses from experts for selecting variables are structured as a visual impact map, which is useful for identifying the direction of actions in practical problem-solving (Kaur et al., 2018). DEMATEL reveals relationships among variables, and then ranks them based on their degree of mutual influence and the type of their relationships (Kaur et al., 2018). This technique is used to prioritize and assess the relationship among variables of a system in order to solve problems that emerge from technology and human activity growth (Tseng, 2010; Chen and Chi, 2013).

ANFIS is one of the most robust neural network systems (Chan et al., 2011). Petković et al. (2014) states that “ANFIS is about taking an initial fuzzy inference (FIS) system and tuning it with a back-propagation algorithm based on the collection of input and output data.” It can handle complicated and nonlinear associations between input and output data using hybrid learning (Ho and Tsai, 2011). It is powerful in selecting a subset of variables related to the output, yielding very high system performance. ANFIS uses very complex mathematical basis that allows an appropriately organized output representation (Ho and Tsai, 2011). The literature includes many studies that have employed ANFIS to predict system performance (Esen et al., 2008; Mohandes et al., 2011); it has been found to be a powerful tool in the statistical pattern recognition algorithm and for developing an identical framework because of its ability to approximate and categorize function (Esen et al., 2008).

DEMATEL and ANFIS have rarely been assessed together in terms of acceptance and use of technology. To the best of our knowledge, such a hybrid method has never been used for assessing IoT adoption and organizational performance. We can resolve decision-making problems that have different effects among criteria using this integrated structure. Our DEMATEL–ANFIS model can reveal the inter-relationships among IoT adoption factors and their role in predicting performance. We thus summarize our research aim:

1. To determine the TOE factors that affect IoT adoption in manufacturing firms; and
2. To determine which TOE factors, because of IoT, affect performance. We employ DEMATEL to uncover the relationship between the factors of IoT adoption, and ANFIS to find and rank the degree of significance of these factors in predicting performance based on expert opinions.

The study makes the following contributions:

1. As explained earlier, IoT in manufacturing is still in its nascency, yet its benefits are transformational. Our study could provide useful insights on strategies for promoting IoT adoption in manufacturing, thus making investments in this technology truly profitable.
2. To the best of our knowledge, we are the first to combine DEMATEL and ANFIS within the scope our objective—establishing the factors of IoT adoption and interdependencies thereof and ranking them via their importance in effectively forecasting performance.

2. Literature review

2.1. IoT in manufacturing firms

Manufacturing is critical to all economies. To keep up with the digital age, manufacturing must converge the physical with the cyber, and thus achieve lower production costs and higher quality and productivity. There is already a transformation to data-driven smart manufacturing

(Ghobakhloo, 2020), and the extant of "smartness" depends on the extent of data available to an organization (Dai et al., 2020; Tao et al., 2018). IoT is especially useful here because of its ability to generate and communicate large amounts of data, known as Big Data (Caputo et al., 2016). Thus, the new Industry 4.0 aims to generate smart solutions in manufacturing through digital technologies, such as cloud computing, cyber–physical systems, and IoT (Singh et al., 2020).

As noted earlier, IoT enables predictive, cloud-based, cyber–physical manufacturing systems as well as energy efficient manufacturing operations and supply chain management (Yang et al., 2019). For example, it increases inter-device transparency, especially of performance. This way, IoT transforms the existing reactive operation into an anticipatory one (Singh and Bhanot, 2020). IoT-enabled cloud computing facilitates plant-to-customer traceability, helps manage inventories, and improves productivity (Yang et al., 2019). IoT influences adaptive production control, anticipative maintenance strategy, and adaptive scheduling in production planning by connecting virtual and physical systems, earlier known as "cyber–physical" manufacturing (Monostori et al., 2016). Indeed, there are benefits to energy management when IoT is embedded into the workings of an organization (Tan et al., 2017). In operations management, IoT allows manufactures to provide the best service to customers through efficient feedback and communication systems (Rymaszewska et al., 2017). It also helps in the effective and efficient management of the supply chain owing to better tractability, adaptability, transparency, and flexibility (Singh and Bhanot, 2020).

2.2. IoT adoption intention

There are three broad streams of research in the corpus of IoT literature: One group of studies examines the benefits of IoT in different sectors, such as healthcare (Onasanya and Elshakankiri, 1007), manufacturing (Yang et al., 2019), smart cities (Singh et al., 2020), and logistics (Wang et al., 2020). These works consider IoT a simple game-changer rooted in heightened connectivity to solve problems and increase competitive advantages (Li et al., 2021). The second group explains the relationship of IoT with other Industry 4.0 technologies, such as block-chain, artificial intelligence, and cloud computing (Singh et al., 1016; Kumar et al., 2020), and how these technologies should be integrated for competitive advantages. The final group investigates the barriers and drivers of IoT adoption and implementation, especially in manufacturing, where its growth is lagged (Kamble et al., 2019; Sharma et al., 2020). The literature on adoption, diffusion, and acceptance of technologies is an established avenue of research within information systems research (Carcary et al., 2018). Indeed, numerous theoretical models exist within the management, education, economics, and sociology subjects to assess the adoption and diffusion of technologies (Carcary et al., 2018; Asadi et al., 2017; Qasem et al., 1014). Some of these theories include the technology acceptance and the diffusion of innovation models; the former has been used to assess the concept of information systems innovation at individual levels (Tsou and Hsu, 2015), (Yadegaridehkordi et al., 2019), while the latter has been used to examine technological innovation at the market level. However, the diffusion of innovation model ignores environmental factors because of its overly technical orientation (Lian et al., 2014).

There also exist studies on technology adoption at the organizational level that use the TOE model, discovering it to be a powerful tool to explain the decision to adopt new technology (Maroufkhani et al., 2020; Oliveira et al., 2014a). This framework identifies three contexts that may influence the organizational usage of an innovation: technological, organizational, and environmental (Tsou and Hsu, 2015), (Lian et al., 2014). Information systems scholars have successfully used the TOE model to understand the main factors affecting the acceptance and use of the latest information systems. In summary, the TOE model is more extensive, includes more organizational features, and is appropriate for our study. We thus present the key and already established determinants of IoT adoption in Table 1.

3. Methodology

As noted in section 1, we use the DEMATEL–ANFIS combination approach to investigate the interdependencies among the factors and rank them and demonstrate the nonlinear relationships between inputs and outputs (Awasthi and Grzybowska, 1007), respectively. Here, the former provides the input for the latter, while ignoring the inter-dependencies may lead to a bias in measuring the degree of significance of factors in a complex problem (Ho and Tsai, 2011).

3.1. DEMATEL technique

DEMATEL is a sophisticated tool to develop a structural framework that can present the causal associations among intricate factors (Awasthi and Grzybowska, 1007). DEMATEL is a group decision-making technique that uses matrices and diagrams to visualize the structure of intricate causal associations (Fontela and Gabus, 1976). DEMATEL employs matrices and other relevant mathematical theories to compute the "cause and effect" of every factor. There are myriad intricate problems this technique can solve; it can thus effectively comprehend intricate structures and offer feasible alternative resolutions (Chen and Chi, 2013). In our study, DEMATEL assesses the relationships between among factors of IoT adoption in manufacturing in Malaysia. Without interpreting this relationship, we cannot determine their degree of significance. Tseng (2010) and Chen and Chi (2013) present the computational flow of the DEMATEL approach. The methodology is explained below:

Phase1 A questionnaire is developed for each expert in the preliminary phase. This may be a $m \times m$ matrix comprising the factors being examined. The answer matrix is noted as $\widehat{\mathrm{M}}^{a} = \left[rx_{ij}^{a}\right]$, whit $a = \{1, \ldots, n\}$ where n signifies the number of experts. In matrix $\widehat{M}$, rx_{ij}^{a} signifies the experts answer outcome, which can be noted as $rx = \{0, 1, 2, 3, 4\}$ where 0 indicates the (No influence) factor and 4 indicates the (Very high influence) factor.

$$\widehat{M} = \begin{pmatrix} 0 & rx_{12} & . & . & . & rx_{1n} \\ rx_{21} & 0 & . & . & . & rx_{2n} \\ rx_{31} & rx_{32} & 0 & . & . & rx_{3n} \\ . & . & . & 0 & . & . \\ . & . & . & . & 0 & . \\ rx_{n1} & rx_{n2} & . & . & . & 0 \end{pmatrix}; \quad (1)$$

Phase2 The average matrix, $A_v = [av_{ij}]$ is developed in this phase, which is calculated using the average influence level $av_{ij=}\frac{1}{n}\sum_{a=1}^{n} rx_{ij}^{a}$. The initial direct relation matrix is represented by the matrix A.

Phase3 The normalized direction relation matrix D is computed in this phase using the average matrix A, from the preceding step. When the normalization factor

$$\alpha = \frac{1}{\underset{1 \le i \le n}{Max}\left(\sum_{j=1}^{n} rx_{ij}\right)} \quad (2)$$

is calculated in this step, the normalized direct relation matrix $\mathrm{D} = \alpha A$ can be computed.

Phase4 The total relation matrix (T) is computed in this step as follows:

$$I_n = \begin{pmatrix} 1 & 0 & \cdots & 0 \\ 0 & 1 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & 1 \end{pmatrix} \quad (3)$$

$$\lim_{k\to\infty}\left(\mathrm{I} + \mathrm{D} + \mathrm{D}^2 + \cdots + \mathrm{D}^k\right) = (\mathrm{I} - \mathrm{D})^{-1} \Longrightarrow T = D(I - D)^{-1}$$

Phase5 We compute the r_i and c_i in this phase, which are the direct and indirect influences on the factors the. The sum of rows and the sum of columns are distinctly signified as i and j, within the total-relation matrix T through the formulas.

$$\begin{pmatrix} r_1 \\ \vdots \\ r_n \end{pmatrix} \mapsto r_i = \sum_{j=1}^{n} t_{ij} \quad \text{where} \quad (i = 1, 2, \ldots, n)$$
$$(c_1 \ldots c_n) \mapsto \mathcal{C}_j = \sum_{i=1}^{n} t_{ij} \quad \text{where} \quad (j = 1, 2, \ldots, n) \tag{4}$$

Phase6 The extent to which the factor i is significant in the overall system is determined in this step using the equation given below:

$$\begin{aligned} im_i &= (r_i + c_i) = \sum_{j=1}^{n} t_{ij} + \sum_{k=1}^{n} t_{ki} \\ ef_i &= (r_i - c_i) = \sum_{j=1}^{n} t_{ij} - \sum_{k=1}^{n} t_{ki} \end{aligned} \tag{5}$$

3.2. ANFIS technique

Jang (Jang, 1301), developed the ANFIS as a soft computing method based on the neural network and fuzzy logic, and it caters to implicit and explicit knowledge. ANFIS formulates a fuzzy inference system (FIS) by using training samples to develop the fuzzy laws of If/Then Rules. ANFIS includes two major steps in decision-making: fuzzification and defuzzification (Kumar et al., 2012). ANFIS has been used mostly to investigate the associations among input variables ("technology infrastructure, compatibility, complexity, technology competence, security concern, perceived benefits, technology integration, top management support, organizational readiness, technical knowledge, executive support, firm size, financial resource, perceived cost, prior it experience, competitive pressure, government support, government policy, trading partner pressure, external ICT support") and TOE dimensions ("technological, organizational, environmental").

Takagi-Sugeno fuzzy model that is of first-order involves the following standard rule set that has "two fuzzy if-then rules" having "two inputs" $x1$, $x2$ and a single "output variable f":

Rule 1 If $x1$ is $A1$ and $x2$ is $B1$, then $f1 = p1x + q1y + r1$
Rule 2 If $x1$ is $A2$ and $x2$ is $B2$, then $f2 = p2x + q2y + r2$

Here $p1$, $q1$, $r1$ and $p2$, $q2$, $r2$ specify the consequent parameters of the model and $A1$, $B1$ and $A2$, $B2$ refer to the linguistic labels. As depicted in Fig. 1 the five layers in ANFIS are applied in an inference system. In Layer 1, each node is considered an adaptive node. Hence, the group accomplishes the fuzzification task. As far as this layer is concerned, on behalf of every node and with μ_{A_i} as a Gaussian membership function, we can point out the node function for the output of the ith node $(O_{1,i})$ as:

$$O_{1,i} = \mu_{A_i}(x) \tag{6}$$

The following equation presented the Gaussian membership function:

$$\mu_{A_i}(x) = \exp\left[- \left(\left(\frac{x - c_i}{a_i} \right)^2 \right)^{b_i} \right], i = 1, 2 \tag{7}$$

where the parameters a, b, and c transform the shape of the membership function. Each node is associated with a fixed node label in the second layer, and the product of all the incoming signals is the output. Hence, $O_{2,i}$, which is the output of Layer 2 is that is acquired by:

$$O_{2,i} = w_i = \mu_{A_i}(x) \times \mu_{B_i}(x), i = 1, 2 \tag{8}$$

where w_i indicates the firing strength of the i_{th} rule.

The normalization layer is basically the layer no 3. Therefore, the given below equation determines the output of this layer $O_{3,i}$:

$$O_{3,i} = \overline{w_i} = \frac{w_i}{w_1 + w_2} \tag{9}$$

where, the normalized firing strength is denoted by 'w'. The defuzzification layer is specified in layer 4 and every node is described as an adaptive node in this layer. Each node subsequently perceives a node function. The following equation calculates the output of this layer:

$$O_{4,i} = \overline{w_i} f_i = \overline{w_i}(p_i x + q_i x + r_i), i = 1, 2 \tag{10}$$

The output layer is basically the layer no 5. The given below equation computes the output:

$$O_{5,i} = \sum_i \overline{w_i} f_i = \frac{\sum_i w_i f_i}{\sum_i w_i}, i = 1, 2 \tag{11}$$

3.3. Data collection procedure

A number of Malaysian manufacturing companies were considered for data collection. Manufacturing makes an enormous contribution to

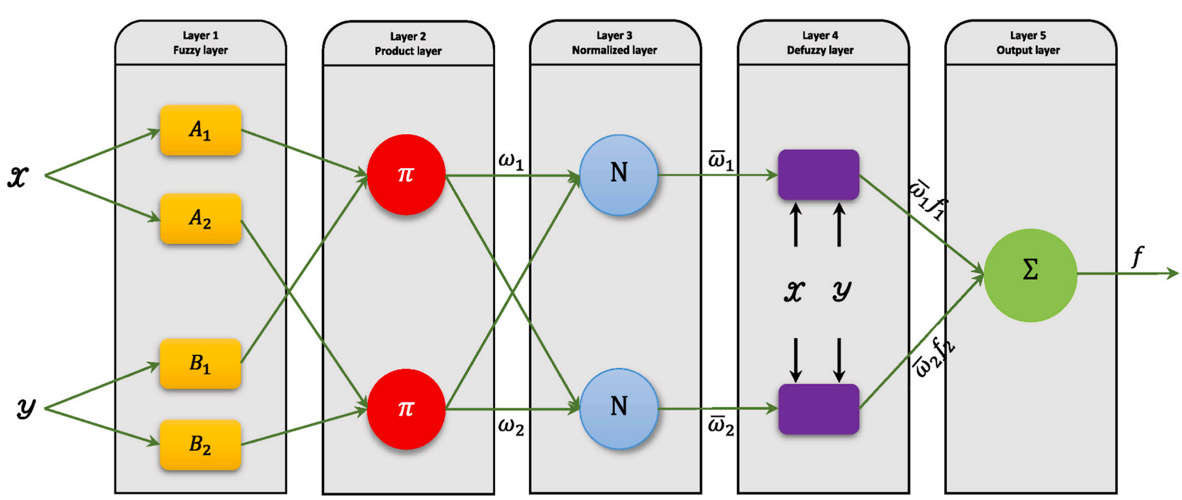

Fig. 1. Five layers in ANFIS.

Malaysia's gross domestic product (GDP), particularly in employment creation and exports (Nordin et al., 2014). According to the Malaysian Industry Development Authority, Malaysia is growing economy and is dependent on manufacturing. By 2020, Malaysia aimed to improve its manufacturing industry and evolve into an industrialized nation (Jabar et al., 2010).

The sampling frame was from the Federation of Malaysian Manufacturers directory. Various senior managers were among the target population, as they are associated with the decision-making process in organizations. We contacted organizations to (i) explain the purpose of the study, (ii) seek their intention to participate, and (iii) collect the email address of a manager with enough information to answer the questionnaire. Seven hundred and thirty e-mails were sent to the corresponding respondents, and we received 211 completed questionnaires after two months. After thorough analysis, 189 questionnaires were found valid for further analysis. As noted earlier, organizational, technological, and environmental factors formed a section each in the designed questionnaire. IoT adoption and organizational performance items were covered in another section. Table 2 presents the sample characteristics.

4. Results

Table 3 presents the effect scale employed to register the degree of significance. This is an extensively used data collection scale in DEMATEL, and ranges from "Very high influence" to "No influence." The data were gathered from 20 responders that included professional academic scholars and industrial experts in manufacturing. The DEMATEL-based questionnaire survey was used for data acquisition, and it compromised sections each for organizational, technological, and environmental factors, respectively.

Table 4 presents the three dimensions and the criteria for IoT adoption. The technological dimensions include compatibility, technology infrastructure, technology competence, complexity, perceived benefits, and security concern and technology integration. The organizational dimension includes organizational readiness, top management support, executive support, technical knowledge, financial resource, organizational size, prior information technology experiences, and perceived cost. The environmental dimensions include government support, competitive pressure, trading partner pressure, government policy and external information and communication technology (ICT) support. To investigate the interdependencies among the factors, besides identifying the significance levels thereof, for predicting IoT adoption, the acquired data from the target responders were employed in the DEMATEL approach.

TDEMATEL produces the initial direct relation matrix in the first step. As depicted in Table 5 the direct effects of a factor on other factors were initially uncovered by the researchers. Subsequently, the equations in Phases 2 and 3 are explained the calculation of the "normalized initial direct relation matrix D." Thus, in Phase 6, the (T) matrix or total relation matrix is determined. Table 6 presents the outcomes of the total relation matrix (T). Further, the influence of the technological factor on other related factors was in the range of (1.04) to (1.68). The outcomes expose a large effect of the technological factor on the environmental factor. Thus, the former greatly influences the latter. The findings further show a strong effect of the organizational factor on the environmental factor as well (1.58). Fig. 2 illustrates the total influence map.

In Table 7, presents the outcomes of "r", "$r - j$" and "$r + j$". The results depict the ranks of the factors by their given effect and received effect for each criterion. Technological factors have the strongest effect on organizational and environmental factors. Environmental factors are the most affected; they are indirectly or directly influenced by other factors. Astonishingly, technological factors (7.30) have the strongest effect on performance, followed by organizational factors (7.20).

Table 2
Sample characteristics.

Variables	Categories	Frequency/percentage
By industry	Textile and leather	29 (15.34%)
	Chemicals	39 (20.63%)
	Machines	62 (32.80%)
	Metal products	33 (17.47%)
	Others	26 (13.76%)
Job Title	Manager	43 (22.75%)
	Chief executive officer	21 (11.11%)
	IT manager	32 (16.93%)
	Senior manager	14 (7.41%)
	Mid-level manager	67 (35.45%)
	Other decision makers	12 (6.35%)
Age	30 and below	20 (10.58%)
	31–45	78 (41.27%)
	45 and above	91 (48.15%)
Working experience	3 and below	18 (9.52%)
	3–5 years	24 (12.70%)
	6–8 years	79 (41.80%)
	8 years and above	68 (35.98%)

Table 3
Defined Linguistic scale in DEMATEL.

Values	Linguistic definition
4	"Very high influence"
3	"High influence"
2	"Medium influence"
1	"Low influence"
0	"No influence"

Table 4
IoT adoption factors and criteria.

Main factors	Criteria
Technology	Technology Infrastructure
	Compatibility
	Complexity
	Technology competence
	Security Concern
	Perceived Benefits
	Technology Integration
Organization	Top management support
	Organizational readiness
	Technical Knowledge
	Executive Support
	Firm size
	Financial resource
	Perceived Cost
	Prior IT experience
Environmental	Competitive pressure
	Government support
	Government policy
	Trading partner pressure
	External ICT support

Table 5
Matrix A

	Technology	Organization	Environmental
Technology	0	3.4	3.5
Organization	3.2	0	3.1
Environmental	1.6	1.7	0

Table 6
Matrix T.

	Technology	Organization	Environmental
Technology	1.04	1.42	1.68
Organization	1.30	1.03	1.58
Environmental	0.8	0.83	0.77

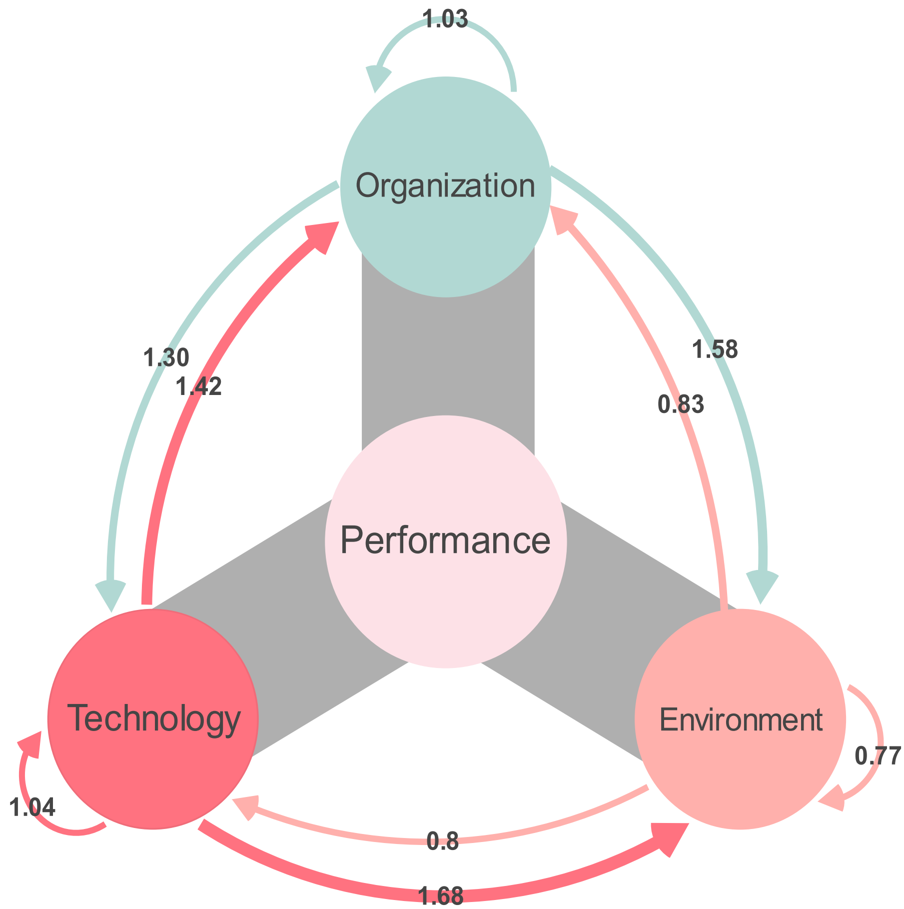

Fig. 2. Total influence map.

Table 7
Total impacts of each factors by given and received on others factors.

	R	J	$im_i = (r_i + c_i)$	$ef_i = (r_i - c_i)$	Rank
Technology	4.15	3.15	7.30	0.99	1
Organization	3.92	3.28	7.20	0.63	2
Environment	2.4	4.03	6.44	−1.62	3

Technological factors also strongly affect business performance during IoT adoption. The second group of factors shows that the highest negative effect on business performance is from environmental factors.

Table 8 classifies all the factors in each group. The key criteria in the technological dimension are perceived benefits, technology competence, technology infrastructure, and compatibility. The most important criteria in the organizational dimension are prior information technology experience, executive support, organizational readiness, and organizational size. For the environmental dimension, they are government support and external ICT support. Further, decision-makers are primarily concerned with executive support, technology competence, and external ICT support during IoT implementation for improving business.

Next, we used ANFIS to identify the significance degree of the adoption factors chosen with the DEMATEL approach for organizational performance. ANFIS helps us discover the relationship between performance and the adoption factors. We apply it to each dimension. The DEMATEL approach selected 12 factors, four each in the organizational, technological, and environmental dimensions. Uniquely, we used the ANFIS-based subtractive clustering technique to investigate the relationships between the nominated factors and performance. This approach has two benefits: besides simplifying the fuzzy network, it

Table 8
The results of the DEMATEL technique for ranking of defined factors.

Criteria and extracted factors	R	J	$im_i = (r_i + c_i)$	$ef_i = (r_i - c_i)$	Rank
● Technology factor	4.15	3.15	7.30	0.99	1
1 Technology competence	3.89	3.05	6.95	0.84	1
2 Perceived Benefits	3.41	2.950	6.36	0.46	2
3 Compatibility	2.91	3.06	5.98	−0.15	3
4 Technology Infrastructure	2.88	3.02	5.91	−0.14	4
5 Complexity	2.93	2.94	5.87	−0.006	5
6 Technology Integration	2.64	3.16	5.81	−0.51	6
7 Security Concern	2.64	3.13	5.78	−0.48	7
● Organization factor	3.92	3.28	7.20	0.63	2
1 Executive Support	15.35	15.58	30.93	−0.22	1
2 Prior IT experience	15.14	14.34	29.49	0.79	2
3 Firm size	14.75	14.65	29.41	0.10	3
4 Organizational readiness	14.32	14.59	28.91	−0.26	4
5 Financial resource	14.17	14.36	28.53	−0.19	5
6 Technical Knowledge	13.67	14.50	28.17	−0.82	6
7 Perceived Cost	14.49	13.53	28.02	0.95	7
8 Top management support	13.77	14.10	27.87	−0.33	8
● Environment factor	2.4	4.03	6.44	−1.62	3
1 External ICT support	11.30	12.26	23.57	−0.95	1
2 Government support	10.45	11.64	22.09	−1.18	2
3 Competitive pressure	10.64	11.10	21.75	−0.45	3
4 Trading partner pressure	11.83	9.248	21.08	2.589	4

enhances the performance and accuracy of fuzzy rules. For factors evaluation, a general framework of ANFIS based applications is presented in Fig. 4. Four ANFIS models were developed in the two steps to evaluate the effects of the adoption factors on performance. The effects of the nominated criteria in the organizational, technological, and environmental dimensions were evaluated in the first stage. Subsequently, an association among the affirmation and performance in the second stage was found and the influence of these dimensions, with their allied criteria, on performance was identified.

In MATLAB, the fuzzy logic toolbox helps us implement the ANFIS model. Thus, the Takagi-Sugeno FIS was developed using the hybrid optimization technique. The combination of back propagation algorithm and least-squares was used. As far as each ANFIS model is concerned, 200 training epochs were used for constructing the prediction model. For each input factor, the defined linguistic variables, namely, “High,” “Moderate,” and “Low,” as well as three membership functions were employed. Using ANFIS, the data were analyzed. The results are presented in Figs. 3 and 4. For each factor, the membership functions yield the results and the data to produce the fuzzy rules. The associations among the TOE factors can be revealed by these figures. They help us ascertain the effect of the three types of factors on performance. According to Fig. 3, organizational, technological, and environmental factors and business performance are strongly correlated with IoT implementation in manufacturing. According to the charts, technological factors strongly influence business performance. These results will allow decision-makers to better understand the types of factors and their influence on IoT adoption for improved efficiency in manufacturing.

5. Discussion and implications

Heretofore, scholars have offered important insights on successful IoT adoption in manufacturing (Lu and Cecil, 2016), (Rymaszewska et al., 2017). To extend this exciting enquiry, we employed a new hybrid approach that combines the DEMATEL and ANFIS techniques in order to rank the factors of IoT adoption and, thus, illustrate the nonlinear effects of TOE factors on business performance. Our findings illustrate the inter-relationships between TOE factors and their role in shaping organizational performance. TOE factors are mutually dependent and influential. Our DEMATEL analysis shows that technological factors strongly influence environmental and organizational factors, while environmental factors are strongly influenced by technological and organizational factors. The total influence exerted by organizational factors is higher than the one received by these factors. Organizational and technological factors have high mutual influence. Managers should prioritize both technological and organizational factors for successful IoT adoption. To simplify, IoT compatibility with the current structure of an organization cannot lead to successful IoT adoption without

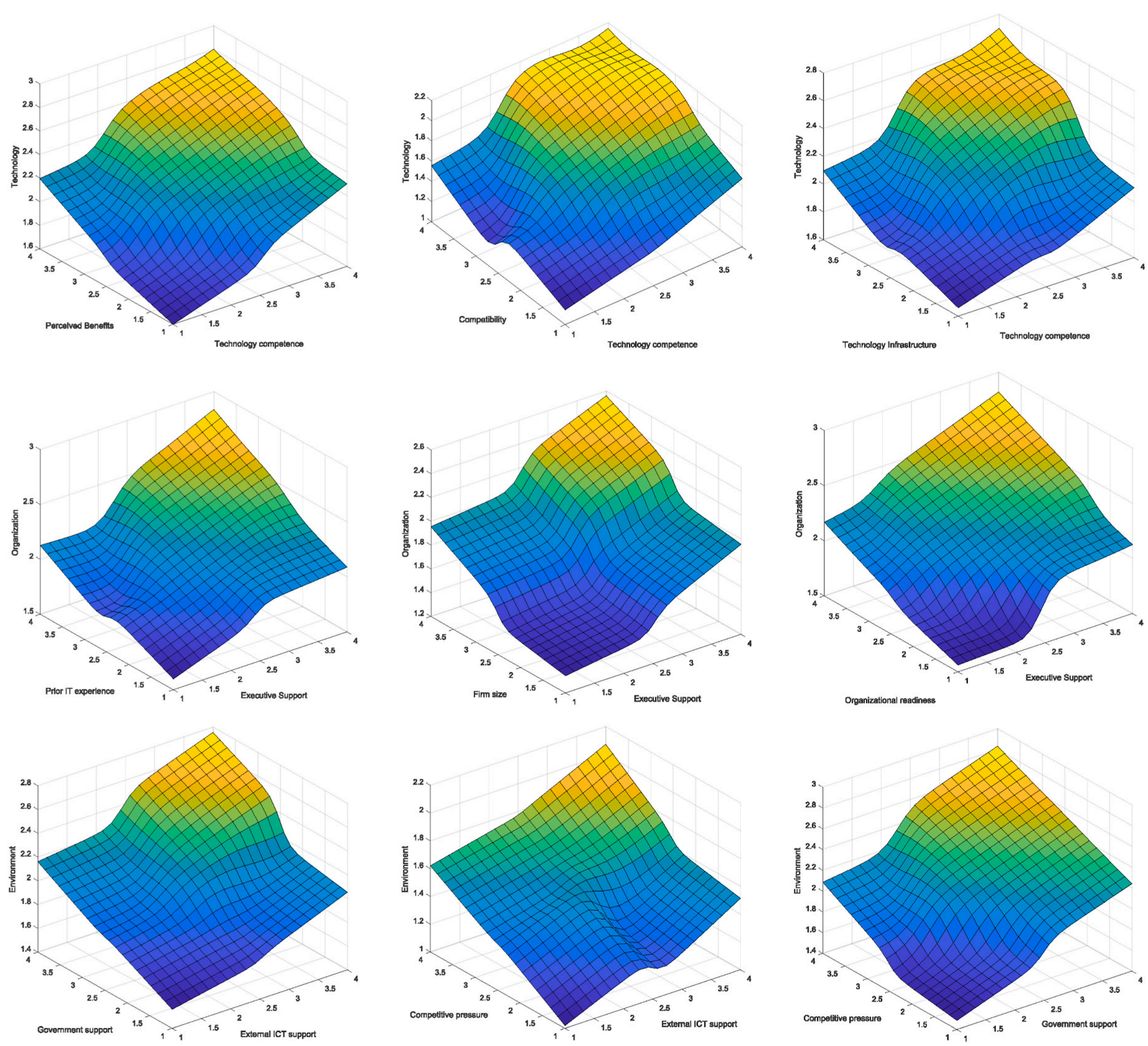

Fig. 3. The relationship between technology, organization and environment factors with their criteria.

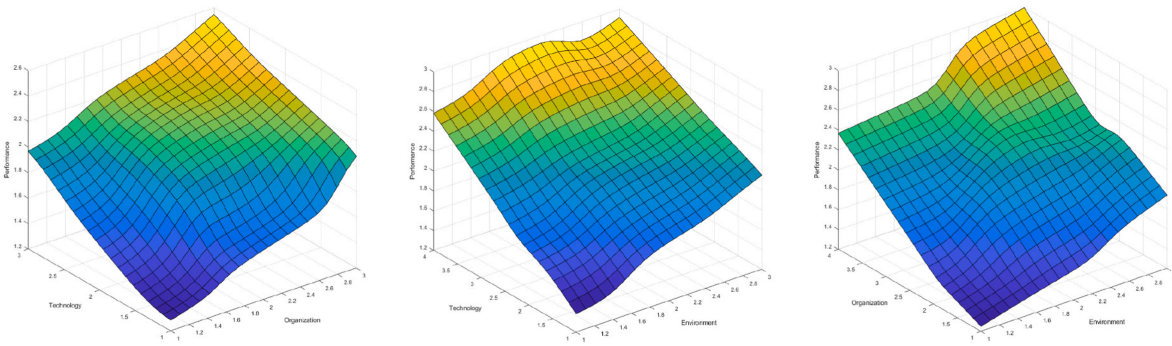

Fig. 4. The relation within the TOE dimensions and the performance".

executive support and adequate organizational readiness. A balance between technological and organizational factors can guarantee successful adoption. Further, environmental factors are strongly influenced by organizational and technological factors for IoT adoption. Indeed, importance of external ICT support, government support, and competitive pressure depend on the degree of technological and organizational factors. Policymakers and IoT vendors should clearly understand the status of technological and organizational factors when designing services based on organizational needs. For instance, if an organization lacks skilled employees who can implement IoT, vendors and the government can offer training or support programs. The effectiveness of their actions depends on the current organizational and technological status. Hence, they should recognize which organizations are lacking in these factors and develop strategies and action plans accordingly. We also used DEMATEL to rank the factors of the TOE dimensions, whereas the ANFIS approach illustrated the interdependencies among factors of each dimension and predicted the total performance based on the TOE dimensions. Our findings confirmed that the effects of the TOE factors on business performance are not linear. High business performance through IoT is possible by balancing the TOE factors. Our findings have both theoretical and practical implications. First, we extend the literature through our hybrid approach. This approach enables us to consider the interrelationships among the TOE factors, and to measure their influence more accurately on performance. So far, most methods for predicting technology adoption have been simple linear and nonlinear multiple correlations (Asadi et al., Nazir; Dalvi-Esfahani et al., 1016). To the best of our knowledge, our choice of methodology and our finding stated above contribute to the novelty of the research. Second, we show that technology competence, perceived benefits, compatibility, and technology infrastructure are the most important technological factors. This result offers insights to policymakers, IoT vendors, and managers on investment and IoT support decisions. They can thus more effectively communicate the benefits and prior successes of IoT and mitigate technological barriers; develop infrastructure for IoT implementation; and increase compatibility between industry and IoT applications with respect to each organization's structure, systems, and needs. Our ranking of factors enables managers to understand which factors should be targeted for investment. Further, we successfully show that executive support, prior information technology experience, organizational size, and organizational readiness are important drivers of successful IoT adoption. Governments and vendors should provide training to current employees of organizations and prepare information technology professionals to mitigate related IT knowledge and skills barriers. They should consider the organizational size when developing an effective plan. Maroufkhani et al. (Sezgin, 2018) showed that the drivers of technology adoption are different for small to medium-sized enterprises and large companies. Compatibility can be a more important factor for large companies, as making adjustment in organizational structure is easier for SMEs. Finally, among environmental factors, external ICT support has the strongest influence on IoT adoption, followed by government support, competitive pressure, and trading partner pressure. Thus, governments and vendors should provide ICT support to facilitate IoT adoption. The interrelationship between TOE factors and their influence on the effect of other factors in gaining better business performance through IoT implies that a good balance of factors is needed for success.

6. Concluding remarks

IoT has the potential to deliver favorable solutions through which the role and operation of industrial systems, such as in manufacturing, can be reshaped. We thus determined and prioritized the most important factors that influence IoT adoption and revealed how IoT adoption affects the performance of manufacturing companies. We used a hybrid method combining DEMATEL and ANFIS, a novelty of the study. Our study provides some directions for future research. First, future studies can use other MCDM techniques such as fuzzy analytic hierarchy process and the Vlsekriterijumska Optimizacija I Kompromisno Resenje integrated with soft computing techniques to realize remarkable outcomes and make good comparisons among the results of different techniques. Second, our findings can be used for wide-ranging exploratory studies using structural equation modeling, and also for developing theoretical research models. Third, by evaluating different views of customers, suppliers, and employees, more exhaustive studies can be conducted. Fourth, testing the justifications of this study and interviewing experts to explore other potential reasons for the strong influence of technological factors on organizational and environmental factors are other possible avenues of research. Finally, future forecasting studies can employ our novel research methodology.

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