Prioritizing the Barriers to the Adoption of Cyber-Physical Systems in Manufacturing Organizations Using Fuzzy AHP

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Abstract. In the near future, cyber-physical systems (CPSs) and the Internet of Things will be ubiquitous. These technologies will be deeply integrated with manufacturing strategies, processes, and systems to assist manufacturing organizations in carrying out routine operations while achieving the organizational objectives. However, to realise this vision, several barriers and obstacles need to be conquered. Therefore, the aim of this research is to identify and prioritize the barriers to the adoption of CPSs in manufacturing organizations. To this end, the study employs a two-phase approach. In the first phase, an exhaustive literature review and semi-structured interview of experts from industry and academia have been conducted to identify the barriers and categorize them into different groups. In the second phase, the barriers are ranked using the fuzzy analytical hierarchy process (AHP) technique. The findings of this study offer a roadmap that could be helpful to the practitioners in deciding how to proceed towards the adoption of CPSs.

Keywords: Cyber-physical systems (CPSs) · Fuzzy AHP · Barriers

1 Introduction

Due to the rapid technological advancements, nowadays, a new era of manufacturing, commonly known as industry 4.0, has come into existence. Industry 4.0 is making significant changes in every aspect of businesses, starting from product design to process implementations, and helping businesses to stay competitive by providing innovative and creative solutions for various industrial problems [1, 2]. Industry 4.0 refers to a set of advanced technologies, which are implemented to develop intelligent production systems capable of producing and delivering high quality products with high efficiency and responsiveness, cyber-physical system (CPS) being one of them [3]. The term CPS can be defined as a hardware-software system that uses sensors, actuators, and the internet to connect various physical elements to the virtual world [4]. These are network embedded systems that take data from physical entities and create virtual twins that are updated in real-time based on the data collected from the physical world. As a result, the interaction

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between the physical and virtual worlds is established, with physical entities following the instructions from the virtual world [5, 6]. By combining product and process data with machine data, CPS enables easier automation, data exchange, and machine-to-machine communication, resulting in significant improvements in operational activities [7, 8]. The benefits of CPS are extensively discussed in the literature; nevertheless, the implementation of CPSs is difficult since it necessitates merging old systems with digital systems in order to build smart products and processes [3–8]. Despite numerous benefits, the implementation of CPSs in manufacturing industries are rather low, necessitating further research to identify the barriers affecting the rate of adoption so that appropriate action plans to mitigate the barriers may be devised and executed [2, 9]. To this end, the present study makes an effort to identify and analyze the barriers to the adoption of CPS in manufacturing organizations. The study uses fuzzy analytical hierarchy process (AHP) to rank the identified portfolio of barriers and highlight the most significant barriers.

2 Literature Review: A Brief Introduction to the Barriers

By performing a comprehensive assessment of the available literature and semi-structured interviews of experts, this study was able to identify 29 barriers, which has been classified into four different categories namely (i) technological barriers, (ii) management barriers, (iii) operational barriers, and (iv) economic barriers (Table 1). A brief description of these categories of barriers are provided in the following sub-sections.

2.1 Technological Barriers

Several technologies barriers exist, which significantly affect the CPS adoption decisions of manufacturing organizations [4, 6]. For example, CPS intends to integrate operational technologies and information technologies to create a smart embedded system having enhanced control capabilities, however, to achieve the above, a large number of devices, platforms, models, systems, and communication networks must be coupled together that leads to the development of a complex and heterogeneous system [4]. Since there is a lack of standard solutions, reference architecture, metrics and tools for CPS verification and validation, the development, maintenance, and performance measurement of such a complex system is extremely difficult [10, 11]. Furthermore, many organizations rely on legacy-based systems, and the integration of these systems with advanced technologies causes interoperability and compositionality issues, making monitoring and control of these integrated systems extremely difficult [11]. Another significant barrier is data security and management [12, 23]. As evident, CPS needs to collect and analyse a vast amount of data at a very high speed in order to ensure high efficiency and effectiveness in production operations. Therefore, CPS must be capable of adapting the physical environment and sustaining both cyber and physical attacks while maintaining data integrity and reliability in order to be reliable, safe, and secure [13–15]. Because the technologies are mostly in their infancy and convincing service providers are rarely available, manufacturing organizations are hesitant to adopt CPS in order to avoid the risks [9].

Table 1 List of barriers to the adoption of CPS

Criteria	Code	Sub-criteria	References
Technological barriers (TB)	T1	Complex and heterogeneous system of devices	[4, 10, 11]
	T2	Metrics and tools for CPS verification, and validation	[4, 6, 10]
	T3	Systems integration, interoperability and compositionality	[4, 11, 15]
	T4	Data security and management	[11–13, 23]
	T5	Lack of standard solutions and reference architecture	[2–4]
	T6	Lack of clear ownership of performance interfaces	[2–4, 14]
	T7	Immaturity of available technologies	[4, 6, 17]
	T8	Lack of convincing service providers	[4, 9, 16, 17]
Operational barriers (OB)	O1	Limited knowledge of available technology solutions for various operational issues	[9, 15, 17]
	O2	Improper communication channel	[1, 9, 17]
	O3	Scarcity of industrial technologists to lead the transformation initiatives	[4, 13, 17]
	O4	Poor in-house technological infrastructure	[1, 9, 13]
	O5	Difficulties in reconfiguring the existing workflow	[9, 17, 23]
	O6	Complex transactions at the human and machine interfaces	[4, 16, 23]
	O7	Connectivity issues	[9, 17]
Economic barriers (EB)	E1	High costs of adoption	[1, 9, 17]
	E2	High costs of maintenance	[17, 20–22]
	E3	High energy usages	[17, 20–22]
	E4	Financial constraints	[9, 17, 20–22]
	E5	Lack of comprehensive view towards ROI	[9, 17, 20–22]

(*continued*)

Table 1 (*continued*)

Criteria	Code	Sub-criteria	References
	E6	Focus on achieving short-term economic benefits	[9, 17, 20–22]
	E7	Higher wages of skilled personnel	[9, 17, 20–22]
	E8	High costs of conduction of training programme for workers	[9, 17, 20–22]
Management barriers (MB)	M1	Lack of enthusiasm among senior management	[1, 9, 17]
	M2	Inadequate strategic planning for CPS adoption	[9, 14, 16]
	M3	Limited knowledge and understanding of advanced technologies	[1, 4, 9, 17]
	M4	Dubiousness regarding the benefits of CPS	[18, 20, 21]
	M5	Organizational inertia	[1, 9, 17]
	M6	Scarcity of key performance indicators	[4, 9, 16, 17]

2.2 Management Barriers

The literature reports that one of the more prominent reasons for low adoption rate of CPS is lack of interest among the top management due to limited knowledge and understanding of advanced technologies, uncertainty regarding the potential benefits of CPS adoption, inadequate strategic planning, inability to manage organizational inertia, and satisfaction with the current organizational performance [1, 9, 14, 16]. The top management's reluctance to adopt CPS is understandable given the abundance of failure stories and fewer success stories. Due to a lack of knowledge, the senior management is unable to foresee the future benefits of CPS, and their concerns are limited to the disruption of present organizational ecosystem that would occur during the CPS implementation, and also, they believe that they will not be able to enforce change initiatives throughout the value chain. Furthermore, owing to the lack of key performance indicators for strategies processes, and systems, the senior management is not being able to understand the need for the modification of existing system [16].

2.3 Operational Barriers

To stay competitive, it is critical to integrate advanced technologies with the existing systems and operational practices. However, the majority of organizations have inadequate technological infrastructure as well as a lack of knowledge and expertise about the available technological solutions for resolving various operational issues [9, 15, 17]. Furthermore, the implementation of CPS necessitates the reconfiguration of existing workflow, which could be difficult in the absence of a proper communication channel and Internet connectivity. Thus, there is a need for industrial experts to steer the organizational transformation initiative in the right direction. However, such experts are currently scarce, which impedes the adoption of CPS [4, 17]. Another important issue is the establishment of an effective interface between human workers and hardware and software of CPS [9]. As evident, the workers have the authority to decide what CPS can do or not do, the issue arises when the capability and autonomy of CPS systems increases. In such a case, transactions at the human–CPS interface become extremely complex and difficult. Due to a high level of precision with minimal variability is required during decision making, a decision clash between the CPS and human could occur due to the lack of trust between the human and machine [18, 19].

2.4 Economic Barriers

In addition to the aforementioned barriers, the high investment and expenses associated with CPS installation and maintenance pose a significant impediment to their widespread adoption [9, 20]. The majority of organizations have a limited cash flow, resulting in a lack of finance, which becomes a major barrier to digital transformation, especially in the absence of external funding from financial institutions [17]. Furthermore, high energy consumption, training of worker, and higher wages of skilled professionals all add to the financial burden on organizations [21, 22]. As a result, instead of taking a holistic approach to return on investments, organizations prioritize short-term profits and economic gains [4, 9, 17].

3 Research Methodology

In the present study, a two-phase approach has been adopted to identify and rank the barriers (Fig. 1). During the first phase, a literature review and expert opinions are used to identify the barriers to the adoption of CPS in manufacturing organizations. A total of 50 barriers has been identified from the available literature. Further, five experts, 2 from industry and 3 from academia, were approached to check the relevance of these barriers and perform screening. Finally, a total of 29 barriers were selected for the study.

The second phase entailed the use of fuzzy AHP approach to analyze and prioritize the barriers according to their importance. AHP is one of the most widely used multi-criteria decision making (MCDM) technique [23]. AHP helps managers in making effective decisions while solving problems by breaking them into individual components, assigning the components into different categories, and then arranging them in a prioritized manner [24]. In this method, the variables under consideration are compared together using a predetermined measurement scale to rank the variables according to their relevance. To achieve the above, the perception and judgement of the experts plays the main role, thus, there is subjectivity factor in decision making [25]. Moreover, AHP lack the ability to handle the uncertainty and ambiguity that arises while comparing the variables and converting the expert's judgement into numbers [26].

To take care of the above issues, AHP technique is integrated with fuzzy set theory [24, 25]. In fuzzy AHP methodology, triangular fuzzy numbers (TFNs) are employed to

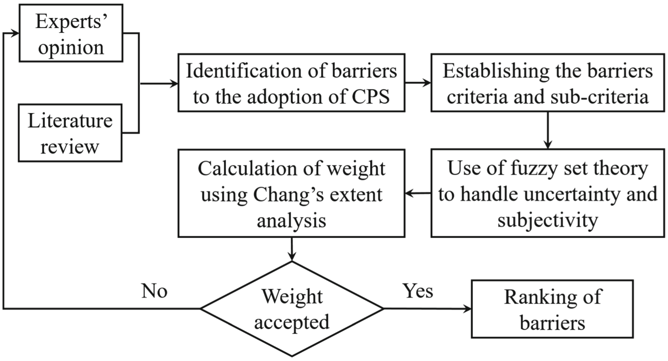

Fig. 1 Research methodology

make pair-wise comparisons between variables, and the extent analysis method, proposed by [27], is used to generate the synthetic extent values of the aforementioned comparison. The steps involved in the extent analysis method are presented below.

Let $M_{g_i}^1, M_{g_i}^2, M_{g_i}^3, \ldots\ldots\ldots, M_{g_i}^m$ be the TFNs, with g_i representing the set of goals (i = 1, 2, 3, 4, 5,…, n), and $M_{g_i}^j$ representing the TFNs (j = 1, 2, 3, 4, 5,…, n) shown in Table 2.

Table 2 TFN scale for linguistics variables

Fuzzy number	Linguistic variable	Triangular fuzzy number
$\tilde{1}$	Equal importance	(1, 1, 1)
$\tilde{2}$	Equal to moderate importance	(1, 2, 3)
$\tilde{3}$	Moderate importance	(2, 3, 4)
$\tilde{4}$	Moderate to strong importance	(3, 4, 5)
$\tilde{5}$	Strong importance	(4, 5, 6)
$\tilde{6}$	Strong to very strong importance	(5, 6, 7)
$\tilde{7}$	Very strong importance	(6, 7, 8)
$\tilde{8}$	Very strong to extreme importance	(7, 8, 9)
$\tilde{9}$	Extreme importance	(8, 9, 10)

Step 1. First, experts' judgement is used to create a fuzzy matrix $\tilde{Z}$ (z_{ij}) of order $n \times n$ containing the fuzzy numbers z_{ij}.

$$\tilde{Z}_{ij} = \begin{cases} 1 & i = j, \\ 1, 3, 5, 7, 9 \text{ or } \cdots \frac{1}{1}, \frac{1}{3}, \frac{1}{5}, \frac{1}{7}, \frac{1}{9} & i \neq j. \end{cases} \quad (1)$$

Step 2. The following equation is used to calculate the values of the fuzzy synthetic extent (S_i) for the i-th criterion:

$$
\begin{aligned}
& \mathrm{S}_i = \sum_{j=1}^{m} M_{\mathrm{g}_i}^{j} \times \left[\sum_{i=1}^{n} \sum_{j=1}^{m} M_{g_i}^{j} \right]^{-1} \\
& \sum_{j=1}^{m} M_{g_i}^{j} = \left(\sum_{j=1}^{m} l_{ij}, \sum_{j=1}^{m} m_{ij}, \sum_{j=1}^{m} u_{ij} \right) \\
& \left[\sum_{i=1}^{n} \sum_{j=1}^{m} M_{g_i}^{j} \right]^{-1} = \left(\frac{1}{\sum_{i=1}^{n} \sum_{j=1}^{m} u_{ij}}, \frac{1}{\sum_{i=1}^{n} \sum_{j=1}^{m} m_{ij}}, \frac{1}{\sum_{i=1}^{n} \sum_{j=1}^{m} l_{ij}} \right)
\end{aligned}
\tag{2}
$$

where l, m, and u denote the lower, most promising, and upper limit values, respectively.

Step 3. The degree of possibility for $\tilde{S}_2 = (l_2, m_2, u_2) \geq \tilde{S}_1 = (l_1, m_1, u_1)$ is performed as follows:

$V\ (S_2 \geq S_1) = \text{hgt}\ (S_2 \cap S_1) = \mu(d)$

$$
\mu(d) = \begin{cases} 1, & \text{if } m_2 \geq m_1 \\ 0, & \text{if } l_1 \geq u_2 \\ \frac{(l_1 - u_2)}{(m_2 - u_2) - (m_1 - l_1)}, & \text{otherwise} \end{cases}
\tag{3}
$$

where $\mu(d)$ denotes the highest intersection of two fuzzy numbers, as shown in Fig. 2.

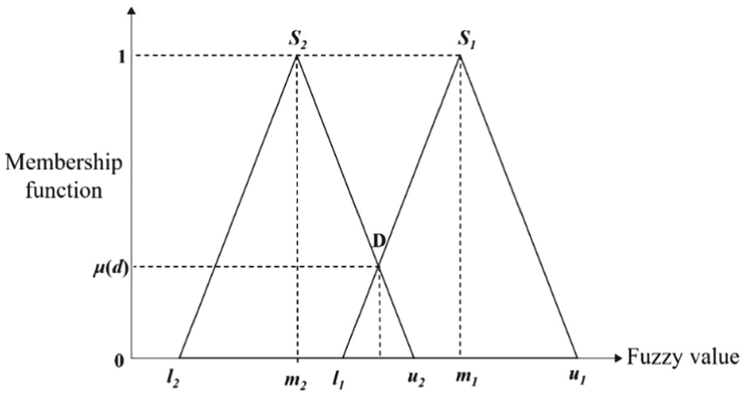

Fig. 2 Intersection of two fuzzy numbers

To compare S_1 and S_2, the calculation of both $V\ (S_2 \geq S_1)$ and $V\ (S_1 \geq S_2)$ is imperative. The procedure of calculating the degree of possibility for a convex fuzzy number being bigger than k involves:

$$
\begin{aligned}
& V(S \geq S_1, S_2, S_3, \ldots, S_k) = V[(S \geq S_1), (S \geq S_1), \ldots\ldots\ldots, \\
& (S \geq S_k)] = \min V(S \geq S_i), i = 1, 2, 3, \ldots, k
\end{aligned}
\tag{4}
$$

Suppose $d'(A_i) = \min V (S_i \geq S_k)$, where $k = 1, 2, 3, 4, \ldots\ldots, n$; and $k \neq i$, then the weight vectors can be represented as

$$W' = \left(d'(A_1), d'(A_2), d'(A_3), \ldots, d'(A_m)\right)^{\mathrm{T}} \tag{5}$$

Step 4. After performing the normalization, the normalized weight vectors can be expressed as

$$W = (d(A_1), d(A_2), d(A_3), \ldots, d(A_m))^{\mathrm{T}} \tag{6}$$

where W is a non-fuzzy number.

4 Application of Proposed Methodology to Rank the Barriers

Following the selection and categorization of the barriers into four different categories, fuzzy decision matrices were constructed through pair-wise assessment of the main barriers as well as their sub-categories. These matrices were developed with the assistance of five experts and the TFN scale. The above matrices were then combined to create the aggregate fuzzy decision matrices for barriers and sub-barriers (see Tables 3, 4, 5, 6, 7).

Table 3 Fuzzy pairwise comparison matrix for main barriers

	TB	MB	OB	EB	Weight	Rank
TB	(1, 1, 1)	(0.13, 0.14, 0.17)	(0.2, 0.25, 0.33)	(2, 3, 4)	0.2507	2
MB	(6, 7, 8)	(1, 1, 1)	(4, 5, 6)	(3, 4, 5)	0.4215	1
OB	(3, 4, 5)	(0.17, 0.2, 0.25)	(1, 1, 1)	(0.25, 0.33, 0.5)	0.1051	4
EB	(0.25, 0.33, 0.5)	(0.2, 0.25, 0.33)	(2, 3, 4)	(1, 1, 1)	0.2227	3

The fuzzy synthetic extent has been calculated using Eq. (2) as follows:
$S(\mathrm{TB}) = (3.33, 4.39, 5.5) \otimes (25.2, 31.5, 38.08)^{-1} = (0.097, 0.14, 0.22)$;
$S(\mathrm{MB}) = (14, 17, 20) \otimes (25.2, 31.5, 38.08)^{-1} = (0.37, 0.54, 0.79)$;
$S(\mathrm{OB}) = (4.42, 5.53, 6.75) \otimes (25.2, 31.5, 38.08)^{-1} = (0.12, 0.18, 0.27)$;
$S(\mathrm{EB}) = (3.45, 4.58, 5.83) \otimes (25.2, 31.5, 38.08)^{-1} = (0.09, 0.15, 0.23)$.

The degree of possibility has been calculated using Eq. (3), and the minimum values of the degree of possibility were determined using Eq. (4) as follows:
$d'(\mathrm{TB}) = \min V (S_1 \geq S_k) = \min (0.595, 0.738, 0.955) = 0.595$.
A similar procedure was carried out for other barriers, and the values are.
$d'(\mathrm{MB}) = 1$, $d'(\mathrm{OB}) = 0.249$, and $d'(\mathrm{EB}) = 0.528$.
The weight vector was determined as $W' = (0.595, 1, 0.249, 0.528)^{\mathrm{T}}$.
Following nominalization, the final weight vector was found as $W = (0.251, 0.421, 0.105, 0.223)$.

Table 4 Fuzzy pairwise comparison matrix for sub-barriers of TB

	T1	T2	T3	T4	T5	T6	T7	T8
T1	(1, 1, 1)	(1, 2, 3)	(2, 3, 4)	(0.17, 0.2, 0.25)	(1, 1, 1)	(1, 1, 1)	(0.25, 0.33, 0.5)	(0.11, 0.13, 0.14)
T2	(0.33, 0.5, 1)	(1, 1, 1)	(0.17, 0.2, 0.25)	(0.25, 0.33, 0.5)	(0.2, 0.25, 0.33)	(1, 1, 1)	(0.33, 0.5, 1)	(0.13, 0.14, 0.17)
T3	(0.25, 0.33, 0.5)	(4, 5, 6)	(1, 1, 1)	(1, 1, 1)	(0.17, 0.2, 0.25)	(1, 1, 1)	(3, 4, 5)	(0.14, 0.17, 0.2)
T4	(4, 5, 6)	(2, 3, 4)	(1, 1, 1)	(1, 1, 1)	(6, 7, 8)	(5, 6, 7)	(1, 2, 3)	(1, 1, 1)
T5	(1, 1, 1)	(3, 4, 5)	(4, 5, 6)	(0.13, 0.14, 0.17)	(1, 1, 1)	(2, 3, 4)	(1, 2, 3)	(1, 1, 1)
T6	(1, 1, 1)	(1, 1, 1)	(1, 1, 1)	(0.14, 0.17, 0.2)	(0.25, 0.33, 0.5)	(1, 1, 1)	(0.25, 0.33, 0.5)	(0.17, 0.2, 0.25)
T7	(2, 3, 4)	(1, 2, 3)	(0.2, 0.25, 0.33)	(0.33, 0.5, 1)	(0.33, 0.5, 1)	(2, 3, 4)	(1, 1, 1)	(1, 2, 3)
T8	(7, 8, 9)	(6, 7, 8)	(5, 6, 7)	(1, 1, 1)	(1, 1, 1)	(4, 5, 6)	(0.33, 0.5, 1)	(1, 1, 1)

Table 5 Fuzzy pairwise comparison matrix for sub-barriers of MB

	M1	M2	M3	M4	M5	M6
M1	(1, 1, 1)	(3, 4, 5)	(1, 2, 3)	(3, 4, 5)	(2, 3, 4)	(7, 8, 9)
M2	(0.2, 0.25, 0.33)	(1, 1, 1)	(0.25, 0.33, 0.5)	(0.33, 0.5, 1)	(0.17, 0.2, 0.25)	(2, 3, 4)
M3	(0.33, 0.5, 1)	(2, 3, 4)	(1, 1, 1)	(2, 3, 4)	(3, 4, 5)	(1, 2, 3)
M4	(0.2, 0.25, 0.33)	(1, 2, 3)	(0.25, 0.33, 0.5)	(1, 1, 1)	(2, 3, 4)	(1, 2, 3)
M5	(0.25, 0.33, 0.5)	(4, 5, 6)	(0.2, 0.25, 0.33)	(0.25, 0.33, 0.5)	(1, 1, 1)	(6, 7, 8)
M6	(0.11, 0.13, 0.14)	(0.25, 0.33, 0.5)	(0.33, 0.5, 1)	(0.33, 0.5, 1)	(0.13, 0.14, 0.17)	(1, 1, 1)

Table 8 shows the final weights and rankings of the main barriers. The weights of all sub-barriers were calculated using the same procedure, and the final weights and the

Table 6 Fuzzy pairwise comparison matrix for sub-barriers of OB

	O1	O2	O3	O4	O5	O6	O7
O1	(1, 1, 1)	(0.25, 0.33, 0.5)	(0.13, 0.14, 0.17)	(1, 2, 3)	(1, 1, 1)	(0.25, 0.33, 0.5)	(1, 1, 1)
O2	(2, 3, 4)	(1, 1, 1)	(0.2, 0.25, 0.33)	(1, 1, 1)	(1, 1, 1)	(1, 2, 3)	(3, 4, 5)
O3	(6, 7, 8)	(3, 4, 5)	(1, 1, 1)	(3, 4, 5)	(4, 5, 6)	(2, 3, 4)	(6, 7, 8)
O4	(0.33, 0.5, 1)	(1, 1, 1)	(0.2, 0.25, 0.33)	(1, 1, 1)	(2, 3, 4)	(1, 1, 1)	(2, 3, 4)
O5	(1, 1, 1)	(1, 1, 1)	(0.17, 0.2, 0.25)	(0.25, 0.33, 0.5)	(1, 1, 1)	(1, 2, 3)	(4, 5, 6)
O6	(2, 3, 4)	(0.33, 0.5, 1)	(0.25, 0.33, 0.5)	(1, 1, 1)	(0.33, 0.5, 1)	(1, 1, 1)	(1, 2, 3)
O7	(1, 1, 1)	(0.2, 0.25, 0.33)	(0.13, 0.14, 0.17)	(0.25, 0.33, 0.5)	(0.17, 0.2, 0.25)	(0.33, 0.5, 1)	(1, 1, 1)

Table 7 Fuzzy pairwise comparison matrix for sub-barriers of EB

	E1	E2	E3	E4	E5	E6	E7	E8
E1	(1, 1, 1)	(2, 3, 4)	(1, 2, 3)	(1, 1, 1)	(0.25, 0.33, 0.5)	(0.25, 0.33, 0.5)	(1, 2, 3)	(1, 1, 1)
E2	(0.25, 0.33, 0.5)	(1, 1, 1)	(0.33, 0.5, 1)	(1, 1, 1)	(0.25, 0.33, 0.5)	(0.33, 0.5, 1)	(1, 1, 1)	(1, 1, 1)
E3	(0.33, 0.5, 1)	(1, 2, 3)	(1, 1, 1)	(1, 1, 1)	(0.25, 0.33, 0.5)	(0.2, 0.25, 0.33)	(1, 1, 1)	(1, 1, 1)
E4	(1, 1, 1)	(1, 1, 1)	(1, 1, 1)	(1, 1, 1)	(1, 2, 3)	(1, 2, 3)	(1, 2, 3)	(1, 2, 3)
E5	(2, 3, 4)	(2, 3, 4)	(2, 3, 4)	(0.33, 0.5, 1)	(1, 1, 1)	(2, 3, 4)	(1, 2, 3)	(1, 2, 3)
E6	(2, 3, 4)	(1, 2, 3)	(3, 4, 5)	(0.33, 0.5, 1)	(0.25, 0.33, 0.5)	(1, 1, 1)	(1, 2, 3)	(1, 2, 3)
E7	(0.33, 0.5, 1)	(1, 1, 1)	(1, 1, 1)	(0.33, 0.5, 1)	(0.33, 0.5, 1)	(0.33, 0.5, 1)	(1, 1, 1)	(1, 1, 1)
E8	(1, 1, 1)	(1, 1, 1)	(1, 1, 1)	(0.33, 0.5, 1)	(0.33, 0.5, 1)	(0.33, 0.5, 1)	(1, 1, 1)	(1, 1, 1)

final ranking of the barriers are shown in Table 8. Finally, the weights of the main barriers were multiplied by the relative weights of the sub-barriers to calculate the global weights which were then used to establish the global ranking of the CPS adoption barriers, as shown in Table 8.

Table 8 Weights and rank of the barriers.

Criterion	Weight	Sub-criterion	Relative weight	Relative rank	Finalized weight	Global rank
Technological barriers (TB)	0.251	T1	0.0966	4	0.0242	14
		T2	0.0032	7	0.0008	28
		T3	0.0355	5	0.0089	22
		T4	0.3301	2	0.0828	5
		T5	0.1215	3	0.0305	12
		T6	0.0017	8	0.0004	29
		T7	0.0157	6	0.0039	26
		T8	0.3954	1	0.0991	2
Operational barriers (OB)	0.105	O1	0.0938	5	0.0098	21
		O2	0.0179	7	0.0019	27
		O3	0.4547	1	0.0478	8
		O4	0.1230	3	0.0129	18
		O5	0.1103	4	0.0116	19
		O6	0.1486	2	0.0156	16
		O7	0.0513	6	0.0054	25
Economic barriers (EB)	0.223	E1	0.1639	4	0.0365	10
		E2	0.0461	6	0.0103	20
		E3	0.0619	5	0.0138	17
		E4	0.1675	3	0.0373	9
		E5	0.2595	1	0.0578	6
		E6	0.2227	2	0.0496	7
		E7	0.0383	8	0.0085	24
		E8	0.0399	7	0.0089	23
Management barriers (MB)	0.421	M1	0.3931	1	0.1657	1
		M2	0.0799	4	0.0337	11
		M3	0.2180	2	0.0919	3
		M4	0.0595	5	0.0251	13
		M5	0.2036	3	0.0858	4
		M6	0.0459	6	0.0193	15

5 Discussion

The present study utilizes fuzzy AHP technique to compare and prioritize the barriers to the adoption of CPS in manufacturing organizations. The study provides a means to better understand the barriers that impede the adoption and implementation of CPS so that organizations can develop appropriate strategies to abolish these barriers. Once the barriers have been successfully eliminated, new pathways for achieving long-term competitive advantages in today's turbulent business environment become available. The findings show that management barriers are the most significant among all, followed by technological, economic, and operational barriers (see Table 3). The findings seem reasonable, given that senior management is responsible for driving the entire organization toward success. The ranking of sub-criteria of management barriers are found as M1 > M3 > M5 > M2 > M4 > M6, indicating the lack of enthusiasm of senior management, lack of knowledge regarding advanced technologies, and organizational inertia as the top three key obstacle to CPS adoption among the management barriers. The above findings reflect the implications that top management should demonstrate passion, adaptive behaviour, a thirst for knowledge, and a commitment towards the deployment of advanced technologies. Such leadership approach could inspire individuals in middle and lower management to work diligently for the improvement of organization and the achievement of the digital transformation. Technological barriers are ranked as second most critical barrier to CPS adoption. The ranking of the sub-barriers under the category of technological barriers is T8 > T4 > T5 > T1 > T3 > T7 > T2 > T6, which indicates that lack of convincing service provider is the most critical technological sub-barrier. Other important technological sub-barriers include issues related to data security and management, unavailability of standard solutions and reference architecture, complexity and heterogeneity of devices in CPS system, and issues related to system integration, interoperability, and compositionality. Recent market surveys have reported that as the technological service providers are working tirelessly towards the development of standard solutions for manufacturing organizations, the technologies are becoming more mature and the number of successful use cases are increasing day-by-day. However, ensuring security and effective management of data, integration of legacy-based systems with new technologies and interoperability among them, and complexity of CPS systems due to large number of heterogeneous devices are still major concern.

Organizations should seek out a technological service provider who can collaborate with internal departments to give the best technology solutions. Third among the main barriers to CPS adoption is economic barriers. The adoption of CPS systems requires huge capital investment. Furthermore, there are additional expenses associated with CPS systems such as maintenance costs, costs of energy usages, costs of conduction of training programme for workers, and wages of skilled professional who handle CPS systems. As a result, the majority of manufacturing organizations require financial support for the adoption and management of CPS systems; and in developing countries such as India, a proper financial support system and capital investment structure has yet to be devised. Organizations, having financial constraints, prefer to concentrate on attaining short-term goals rather than looking at the big picture of success. Thus, the establishment of easy financial support system and favourable taxation policies is one of the most feasible strategies to enhance the rate of adoption of CPS technologies. The ranking of the sub-barriers under the category of operational barriers stands as O3>O6>O4>O5>O1>O7>O2, which implies that scarcity of industrial technologists to lead the transformation initiatives is the key barrier. The other important barriers in this category include difficulties in establishing effective transactions between human and machines, poor in-house technological infrastructure, difficulties in reconfiguring the existing workflow, and limited knowledge of available technology solutions for various operational issues. These barriers call for hiring skilled professionals and planning for effective training of workers to identify and mitigate the different operational issues.

6 Conclusions

Due to the growing environmental uncertainty and pressure to become more digital, manufacturing organizations have begun to implement advanced technologies such as CPS in their operational routines. However, in developing countries like India, a number of barriers exists, which make effective implementation CPS extremely difficult. In real-world situations, managers are unable to make appropriate decisions to overcome these barriers at the same time. By utilizing an effective MCDM approach, the present study identifies and prioritize the barriers to the adoption of CPS in manufacturing organizations. The findings reflect that a lack of enthusiasm among senior management, lack of convincing technological service providers, limited knowledge and understanding of advanced technologies, organizational inertia, and data security and management issues are the most prominent barriers among others. Hopefully, the outcomes of this study will aid decision-makers and government authorities in developing a set of comprehensive and precise guidelines that will encourage manufacturing organizations to implement CPS in their business practices.

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References

1. Kumar P, Bhamu J, Sangwan KS (2021) Analysis of barriers to industry 4.0 adoption in manufacturing organizations: an ISM approach. Procedia CIRP 98: 85−90
2. SonyM (2020) Design of cyber physical system architecture for industry 4.0 through lean six sigma: conceptual foundations and research issues. Prod & Manuf Res 8(1): 158–181
3. MuellerE, Chen XL, Riedel R (2017) Challenges and requirements for the application of industry 4.0: a special insight with the usage of cyber-physical system. Chin J Mech Eng 30(5): 1050–1057
4. ReimannM, Ruckriegel C, Mortimer S, Bageritz S, Henshaw M, Siemieniuch C, Alonso J (2017) Road2CPS priorities and recommendations for research and innovation in cyber-physical systems. Loughborough University
5. Afrizal A, Mulyanti B, Widiaty I (2020) Development of cyber-physical system (CPS) implementation in industry 4.0. In: IOP Conference Series: Materials Science and Engineering, vol **830**(4). p 042090
6. Panetto H, Iung B, Ivanov D, Weichhart G, Wang X (2019) Challenges for the cyber-physical manufacturing enterprises of the future. Annu Rev Control 47:200–213
7. Wang L, Törngren M, Onori M (2015) Current status and advancement of cyber-physical systems in manufacturing. J Manuf Syst 37:517–527

8. Al-Ali AR, Gupta R, Nabulsi AA (2018) Cyber physical systems role in manufacturing technologies. AIP Conf Proc 1957(1):050007
9. Wankhede VA, Vinodh S (2021) Analysis of barriers of cyber-physical system adoption in small and medium enterprises using interpretive ranking process. Int J Qual & Reliab Manag. https://doi.org/10.1108/IJQRM-06-2021-0174
10. Yu W, Dillon T, Mostafa F, Rahayu W, Liu Y (2019) Implementation of industrial cyber physical system: challenges and solutions. In: 2019 IEEE International Conference on Industrial Cyber Physical Systems (ICPS), pp 173–178
11. Törngren M, Sellgren U (2018) Complexity challenges in development of cyber-physical systems. In: Principles of Modeling. Springer, Cham, pp 478–503
12. Ashibani Y, Mahmoud QH (2017) Cyber physical systems security: analysis, challenges and solutions. Comput Secur 68:81–97
13. Esterle L, Grosu R (2016) Cyber-physical systems: challenge of the 21st century. e & i Elektrotechnik Und InfStechnik 133(7): 299–303
14. Chen H (2017) Theoretical foundations for cyber-physical systems: a literature review. J Ind Integr Manag 2(03):1750013
15. Leitão P, Colombo AW, Karnouskos S (2016) Industrial automation based on cyber-physical systems technologies: prototype implementations and challenges. Comput Ind 81:11–25
16. Ferrer BR, Mohammed WM, Lastra JLM, Villalonga A, Beruvides G, Castaño F, Haber RE (2018) Towards the adoption of cyber-physical systems of systems paradigm in smart manufacturing environments. In: 2018 IEEE 16th International Conference on Industrial Informatics (INDIN). pp 792–799
17. Agrawal P, Narain R, Ullah I (2019) Analysis of barriers in implementation of digital transformation of supply chain using interpretive structural modelling approach. J Model Manag 15(1):297–317
18. ChoiS, Jun C, Zhao WB, Do Noh S (2015) Digital manufacturing in smart manufacturing systems: contribution, barriers, and future directions. In: IFIP International Conference on Advances in Production Management Systems. Springer, Cham, pp 21–29
19. Monostori L et al (2016) Cyber-physical systems in manufacturing. Cirp Annals 65(2): 621−641
20. Nota G, Matonti G, Bisogno M, Nastasia S (2020) The contribution of cyber-physical production systems to activity-based costing in manufacturing. An interventionist research approach. Int J Eng Bus Manag 12: 1847979020962301
21. Marwedel P, Engel M (2016) Cyber-physical systems: opportunities, challenges and (some) solutions. In: Management of Cyber Physical Objects in the Future Internet of Things. Springer, Cham, pp 1–30
22. Wiesner S, Hauge JB, Thoben KD (2015) Challenges for requirements engineering of cyber-physical systems in distributed environments. In: IFIP International Conference on Advances in Production Management Systems. Springer, Cham, pp 49–58
23. WangL, Wang G (2016) Big data in cyber-physical systems, digital manufacturing and industry 4.0. Int J Eng Manuf (IJEM) 6(4): 1–8
24. Singh PK, Sarkar P (2019) A framework based on fuzzy AHP-TOPSIS for prioritizing solutions to overcome the barriers in the implementation of ecodesign practices in SMEs. Int J Sust Dev World 26(6):506–521
25. Narayanan AE, Sridharan R, Kumar PR (2019) Analyzing the interactions among barriers of sustainable supply chain management practices. J Manuf Technol Manag 30(6):937–971
26. Ocampo LA (2019) Decision modeling for manufacturing sustainability with fuzzy analytic hierarchy process. Glob Bus Rev 20(1):25–41
27. Chang DY (1996) Applications of the extent analysis method on fuzzy AHP. Eur J Oper Res 95(3):649–655