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What hinders AI adoption in MSMEs of India? – Importance and interlinkages between the barriers

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Abstract

Purpose – This study aims to help MSMEs in understanding the barriers to adoption of AI and how they are interlinked with each other. There is a general consensus amongst researchers and corporates that artificial intelligence (AI) can help in better and faster decision-making. However, many medium, small and micro enterprises (MSMEs) have not adopted AI in the context of automation.

Design/methodology/approach – The authors have assigned weights to the barriers of AI implementation by using Best Worst Method (BWM). In this study, the authors argue that the more alternatives there are, the greater the chances of making an error in judgment. This is a drawback of the traditional comparison matrices that are used for assigning weights to attributes/alternatives/factors. Subsequently, we have computed the influence of the barriers on each other using the DEMATEL method. This helped us understand what the drivers of the bottlenecks are and the interlinkages between them.

Findings – The barriers identified are top management support, change resistance from employees, lack of knowledge about AI in automation, Lack of resources to implement the solution, uncertainty regarding the future of benefits, perception of job loss and subsequent conflicts and lack of perseverance. Price of automation, uncertainty regarding future and top management support were identified as factors that drive other bottlenecks.

Practical implications – The study has theoretical implications, as it corroborates the technology organization environment (TOE) framework in the context of AI automation in MSMEs. This is the first study of this type, to the best of the authors' knowledge, on MSMEs in India. Factors such as lack of top management support, change resistance, perseverance and price of the automation can be viewed as organizational blocks to AI implementation. Lack of knowledge about AI in automation and Lack of resources are technology-related barriers, whereas uncertainty regarding the future of technology and job loss are related to the environment. This has implications for the top management of MSMEs. The results did show that some bottlenecks act as drivers of other bottlenecks. Thus, the MSMEs, which inherently have limited resources, can prioritize their focus on the ones that have high driving power.

Originality/value – The authors have used the TOE framework to refer to the technological, organizational and environmental factors that affect the decisions to adopt a new technology. The decision of the business and

JEL classification – C18, M21, O14, O32

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government, to participate in the diffusion of AI, may be contingent upon monitoring the bottlenecks and designing mechanisms to enhance use of AI for automation by MSMEs across India. Thus, this study has wide policy implications.

Keywords AI, Automation, Barriers to adoption, BWM, DEMATEL, TOE framework

Paper type Research paper

1. Introduction

The past few decades have witnessed a significant increase in the use of artificial intelligence (AI) and automation in manufacturing, and this has led to concerns about the impact of AI on job losses. It is believed, generally, that technology might lead to job losses but scholars such as Wood *et al*. (2018) argued that this might not be always true, for instance, the rise of online labor platforms has created job markets for internet users that they would not have otherwise obtained. This has also helped organizations to access labor power remotely from anywhere in the world. Further, Frey and Osborne (2017) noted that, in a study involving 702 occupations in the USA, around 50% of human jobs are at risk because of computerization. Morikawa (2017) argued that AI and robotics may have favorable impacts on organizations but human capital would require upgradation, i.e. there may be shifts in employment. Krzywdzinski (2017) opined that implementation of new production concepts, such as Industry 4.0, might bring radical change to labor processes, but there is no consensus among the scholars regarding the nature of these changes. This could be helpful for highly industrialized nations, as they have a highly skilled workforce experienced in working with highly automated processes. According to Brynjolfsson and McAfee (2014), the regulation of new production systems will require highly skilled workers, whereas the low-skilled jobs will gradually disappear because of automation. Some authors such as Frey and Osborne (2013), Carr (2014) are skeptical about the benefits and argue that new technologies could reinforce the polarization of employment structures by eliminating low- and medium-skilled jobs. These dichotomous findings make many apprehend the benefits of automation.

In the context of small and medium enterprises (SMEs), in Italy, Da Roit and Iannuzzi (2023) noted that SMEs have limited technological investment and do not have a coordinated system of industrial relations in place. Thus, the structure of the SMEs is different from that of manufacturing firms and requires a special investigation as the intended benefits of technology might not be fully realized in this sector. Thus, in this context it is imperative to have a separate study on whether the MSMEs are abreast of the benefits of AI automation and how they adopt AI automation.

Mehta and Awasthi (2021) opined MSMEs to have played a big role in India's financial growth and development. In the context of India, the Ministry of Statistics and Programme Implementation states that the MSME contribution to the gross value added in all India gross domestic product (GDP) during the year 2019–2020, 2020–2021 and 2021–2022 was 30.5%, 27.2% and 29.2%, respectively, i.e. 29% to the GDP. According to the Directorate General of Commercial Intelligence and Statistics, the contribution of MSMEs to all India exports during the years 2020–2021, 2021–2022 and 2022–2023 was 49.4%, 45.0% and 43.6%, respectively [1]. Several scholars such as Dubey and Sahu (2022), Prasad and Prasad (2023) argued that MSMEs play an important role in GDP growth, as they help in the creation of more jobs in India and also businesses that use natural resources for their production of goods. Scholars such as Singh (2019) and Taneja (2013) noted that the Indian MSMEs have witnessed a rapid growth because of progress in food processing, pharmaceuticals, textiles

and apparel, retail, agriculture and the service sector. Besides, the Indian Government introduced the Atma Nirbhar Bharat Abhiyan to help entrepreneurs, especially pertaining to the MSMEs (Dubey and Sahu, 2022). According to Singh (2024), the MSME sector consistently contributes to high growth rates as compared with other similar sectors in India. According to Lahiri (2012), the MSME sector has tremendous innovation and flexibility to overcome recession. Srinivas (2013) concluded that MSMEs also create inclusive growth in the country.

However, the sector, both in India and abroad, faces several challenges as noted by various researchers such as Huang *et al.* (2004). Plethora of studies such as the ones conducted by scholars such as Alkali (2012), Frishammar *et al.* (2013), Kim *et al.* (2012), Milewski *et al.* (2015), Singh (2024) have noted MSMEs to have contributed to sustainable growth of various countries. Singh (2024) noted that SMEs struggle to survive and do not get the benefits of globalization. Besides, small businesses in Asia have outdated processes, low-skilled workers and less technical capabilities to compete with global players who provide cheaper imports. On the AI exposure and jobs, Ghosh *et al.* (2024) study a wide range of recent articles in multi-country contexts and conclude that:

> The literature at present, is dispersed, and is yet to build any consensus on deciphering the skill-types that possibly would see the largest impacts, the sectors that might see plethora of AI-enabled economic repercussions, whether indeed there will be an overall net- job destruction or net-job creation, and does that differ across economic regions.

In the Indian context, Jeswal (2012) and Trivedi (2013) argued that issues such as economic recession, low demand, finance and intense competition from international players pose a challenge to this sector. Ahamed and Raju (2023) argued technology adoption to be a serious challenge for MSMEs. This could be because of lack of understanding and professional assistance (Singh, 2019), lack of skilled manpower to use technology (Dangmei, 2017) or lack of access to ICT (Singh *et al.*, 2018). Other scholars such as Lohith *et al.* (2017) conceptualized how technological innovation affects the performance of MSMEs. Thus, lack of access and use of technology acts as a barrier to the performance of MSMEs.

Thus, the Indian MSME sector would make an interesting study not just because of its potential to make a substantial contribution to the GDP, creation of jobs and also adding value to other sectors but also for the various challenges, pertaining to adoption of technology, that it faces.

In a global context, several scholars such as Parente and Prescott (1994), Mokyr (1990), Rosenberg and Birdzell (1986) and Morison (1966) studied the issue of barriers to technology adoption and their relation to the development of a nation. Rosenberg and Birdzell (1986) argued that the West grew rich first, as there was less resistance to new technology adoption. Thus, when the barriers to new technology adoption can be identified and addressed amicably, there could be faster development of the nation as a whole. Braganza *et al.* (2021) noted that AI increases organizational efficiency. Murray (2015) argued that AI changes the way people work, thereby changing the way businesses are done. There are many applications and implementations of AI that are in use today, such as machine learning, chatbots and ChatGPT. As Deggans *et al.* (2019) noted that although the society and the economy adjust to moderate changes (Kliestik *et al.*, 2018), AI requires substantial regulations and thus more adjustments from people using it. Korinek and Stiglitz (2019) argued that when progress is fast, the behavior of the society toward acceptance of the same might be different. Thus, AI may face barriers in adoption across different sectors, especially the MSMEs, which are not big enough to absorb such changes.

The initiatives from the European Union to increase GDP by 2020, and since 2012, the American $2.2bn R&D investment policy for advanced manufacturing provide evidence for countries' strategic steps to foster national growth through promotion of Advanced Manufacturing Technologies (AMT) investment. The European Factories of the Future Association issued a roadmap to address efficient use of resources and reducing waste through technologies such as additive manufacturing. While these are macro-level initiatives with active state interventions, it is crucial to understand how private players, and most interestingly, the small businesses perceive AMT adoption and adapting to the AI revolution in particular. While it is understandable that public involvement and capex initiatives can catalyze AI-induced leap-frogging in productive transformation of economies and businesses, the urge must come through adaptive and innovative business models conceptualized at the very beginning. Earlier research (Boyer *et al.*, 1997) shows that additional organizational changes are required to unlock the potential of AMT to reap its benefits. Very few research have actually delved deep into identifying the true enablers and barriers of recent technology adoptions by business houses, such as AI; not to speak of the same adopted by the MSMEs. Stornelli *et al.* (2021) identify the need for a greater focus on positioning internal–external factors prior to and post-adoption. Their work extends the work of Machuca *et al.* (2004) with a stage-based analysis, uncovering multiphase and stage-specific barriers and enablers. The Economist [2] (May 8, 2023) mentions that firms adopting generative AI will have a general rise in labor productivity, uplifting global income manifold for many years. Interestingly, there is hardly any clear signal or consensus on the net-job destruction or net-job creation of this AI environment. The effects of AI on the job market are highly controversial, and therefore would depend on the perspectives. There exist two distinct ideological perspectives. As per the literature with a pessimistic outlook, the adoption of AI results in a decline in employment opportunities by substituting manual tasks. Therefore, there are mixed perceptions and validations of the AI-adoption business models and their underlying hypotheses, more so at the MSME level. In the Indian context, NASSCOM and Meta (2024) mention in their recent report based on a survey of 300 tech MSMEs from across five Indian cities that MSMEs play a critical role as the engine of the Indian economy and state "Integrating AI will help them to stay relevant and offer them a unique opportunity to unlock unprecedented growth, enhance productivity, and fuel sustainable innovation". In this report, they find in their sentiment analysis that 87% of the tech-MSMEs surveyed are confident that AI can improve overall productivity. Among the hurdles they find 65% of the tech-MSMEs surveyed think that they are unaware of the right tools and resources to leverage, 91% feel that technology is not widely accessible and affordable; and 59% think they have budget constraints.

The aforementioned discussion points out to the fact that there may be barriers to AI adoption in the MSME sector. Thus, the purpose of this study is to identify barriers and enablers to AI adoption in the context of the MSME sector. For this we referred to the technology organization environment (TOE) of Tornatzky and Fleischer (1990). According to Tornatzky and Fleischer (1990), the TOE framework throws light onto the various technological, organizational and environmental factors that influence technology adoption. This framework has been used by several scholastic studies such as Ediriweera and Wiewiora (2021), Zhu *et al.* (2006), Kuan and Chau (2001) in various contexts.

In the context of MSMEs, this framework has been used by Bagale (2014), to investigate the influence of organizational characteristics on e-commerce implementation in the Indian MSME sector. Ausat and Peirisal (2021) used the TOE model framework to identify and study the influence of e-commerce adoption on MSME's performance. All the studies

indicate an interaction of technology, organizations and individuals, to have a considerable influence on MSME performance.

However, the importance of these barriers may be different for different countries, states and industries. We also apprehend that barriers influence each other and thus, investigated the same. This brings us to the following research questions that we intend to address in this study:

RQ1. What are the factors that act as barriers to AI automation adoption in MSMEs?

RQ2. What is the relative importance of these barriers of AI automation adoption?

RQ3. Is there any linkage between the barriers?

For this, traditionally scholars use the subjectivity of experts as in the comparison matrix of AHP. However, when the number of comparisons is large, the inconsistency is high. To overcome this shortcoming, we have used the Best Worst Method (BWM) approach of Rezaei (2015). To investigate the influence of the barriers on each other, we have used the DEMATEL method.

Our paper is divided into five sections. After the introduction, we present the state of the literature in Section 2 followed by the methodology section. In Section 3, model description, data and methodology are presented. In Section 4, we present the results and findings of our study and its research and managerial implications. In Section 5, we discuss the limitations of our work and the directions for future research. Thus, in this study we focus on identification of the various barriers to automation in the context of MSMEs. We also investigate how the barriers influence each other.

2. Literature review

AI is a wide-ranging branch of computer science concerned with building smart machines capable of performing tasks that typically require human intelligence (Beal, 2023). The machines copy cognitive functions such as learning, communication and problem solving. Machine learning is an application of AI that allows machines to learn and become smarter from experience without being manually programmed (Mielke *et al.*, 2021).

As per definition (Rouse, 2023), automation is a term used when human inputs are used minimally or not used at all. Besides, our review of literature suggests various extents of automation exist.

There were attempts made by scholars such as Walch and Schmelzer (2022) to classify automation based on the extent of automation and AI use. As per this taxonomy, there are 4 levels of automation. In Level 0, automating repetitive tasks is carried out. For example, in data management, when the automation extracts data from a data source or performs repetitive tasks of downloading attachments. In Level 1, AI is integrated with automation, like incorporating natural language processing (NLP) and machine learning to help handle tasks with unstructured data. In Level 2 automation, the automation goes beyond NLP and machine learning and uses cognitive technology to spot patterns and anomalies and apply intelligence to process management. Level 3 is the highest level of automation which allows one to address the greatest challenges of unpredictability and variability through autonomous process discovery, process analytics and process optimization. When automation becomes an AI-based, closed loop model, where the structure of rules is continually being analyzed and changed and applied, it is defined as IT automation (Fung, 2014). This becomes zero touch automation in the true sense as the machines run the network.

As per, the jobs held by humans are affected by AI but the impact is not always negative. AI, just like any other technology, has possible harmful effects. Paul Virilio, the great

philosopher once noted that "technological development is tightly linked to the idea of the accident". If one invents the plane, he also invents the plane crash. Thus, as per Chatfield (2014), Lauterbach and Bonime-Blanc (2018) and Lauterbach (2019), the ethical concerns of innovation tend to focus on minimization and mitigating the adverse effects or "harms" and not in the elimination of harm completely. Thus, skeptics who are much focused on the harms of technology fail to adopt it faster and prefer to be laggards.

Braganza *et al.* (2021) observed that new technology affects work practices as new practices emerge. This leads to greater levels of insecurity and additional pressure on workers (Baruch, 2006; Greenhaus and Kossek, 2014; Sullivan and Baruch, 2009). Besides, technology gives more autonomy and responsibility to workers (Doucouliagos, 1995), job satisfaction, commitment and trust (Timming, 2012). This trend is intrinsically linked to the ability to move toward better work. However, to the best of our knowledge, no scholar has worked on the interrelationships between the various barriers of AI adoption. Besides, Upstill and Hall (2006) noted that new technology not only improves productivity but also helps in providing cleaner and environmentally friendly solutions.

2.1 Theoretical development

In the context of our study, we refer to some of the seminal works of various research scholars to comprehend the various barriers to adoption of new technology. In the literature, we reviewed several theories such as The Theory of Reasoned Action, The Theory of Planned Behavior, Technology Acceptance Model, The Diffusion of Innovation (DOI) Theory and the TOE before zeroing in on a particular framework.

According to the Theory of Reasoned Action (Davis, 1986), a person's intention to perform a certain behavior is an antecedent to the actual behavior. This intention is affected by attitude towards that behavior and the subjective norms, i.e. how others think about the behavior. Thus, when adopting a new technology, the intention to use the technology depends on the attitude of the employees towards the technology and their peers' opinions about the use of that technology. The Theory of Planned Behavior of Ajzen (1991) has one more determinant of intention to behavior, i.e. Behavioral Control. This factor refers to the perception of the person about the ease or difficulty of performing the behavior, i.e. how easy or difficult it is to adopt the new technology. The Technology Acceptance Model is based on these theories and argues that the acceptance of a new technology would depend on two broad categories of factors, i.e. ease of use and usefulness. However, these theories do not shed light on the effect of the organization or the sector in the adoption of the new technology. Rogers (1995) argued in the context of schools using new technology, there could be factors such as socio-cultural factor (Bereiter, 1994), personological factors such as gender, belief system of the teacher (Marcinkiewicz and Grabowski, 1992) of the teacher and exposure to technology within the profession (Anderson, 1993). Thus, Rogers (1995) argued that the sources and barriers of adoption of new technology could be internal or external. Moreover, out of all these frameworks, according to Ediriweera and Wiewiora (2021), the DOI and TOE shed light on adoption at the organizational and sector levels for enablers and barriers.

According to the DOI theory, there are five determinants of technology adoption. First, there are relative advantages, which speak on how much the new technology is better than the others. Second, compatibility describes the degree to which the innovation is perceived as consistent with the existing functions of the business. Third, complexity, i.e. the degree to which an innovation is perceived as difficult to implement. Fourth, observability, i.e. the degree to which the results of the adoption are visible, and trialability, i.e. the extent to which the new technology can be tested and tried. Although the DOI framework is very powerful,

scholars such as Oliveira and Martins (2011) have pointed out that the framework does not consider environmental factors.

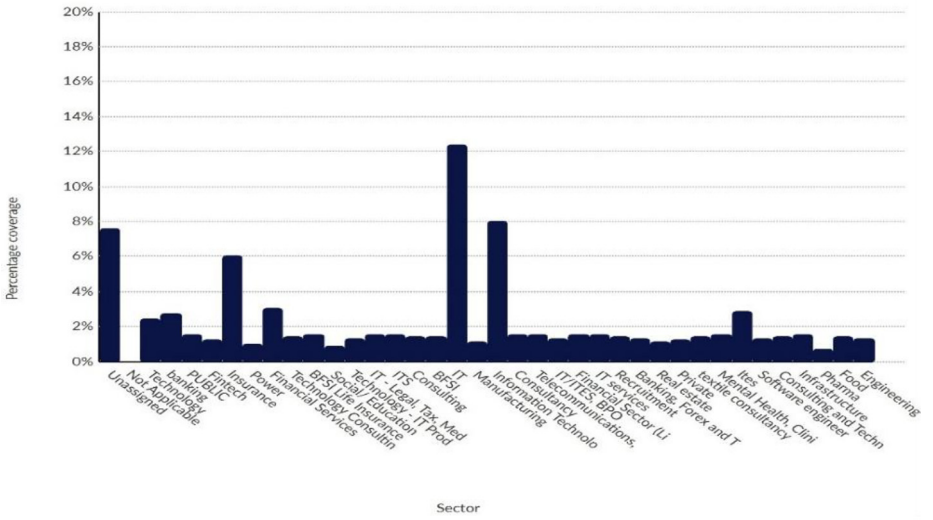
2.1.1 The technology organization environment framework. The TOE framework refers to the technological, organizational and environmental factors that affect the decisions to adopt a new technology. Technological factors that act as barriers to implementation of new technology were identified, by scholars such as Butler and Sellbom (2002), as lack of knowledge of the application of the technology, lack of access to standardized data and poor communication technology. In case of MSMEs, most of them do not have a separate IT department with tech-savvy individuals. Thus, there may be barriers stemming from the use of automation technology, lack of understanding of the benefits of automation and inability to configure automation to one's needs. Chiu *et al.* (2017) argue that the enablers of innovation at an organizational and industrial level can also be studied using this framework. Organizational factors such as cross-functional teams directly affect the adoption process of new technology. Baker (2012) noted that decentralized teams in organizations positively affect adoption. Racherla and Hu (2008) argued that the size of the firm, slack financial resources, informal structures that link the organization, etc. help in adoption. However, lack of trust, risk aversion of top management of firm, lack of knowledge among the top management, etc. act as barriers to adoption of new technology (Cabral *et al.*, 2020). This would play a role in the MSMEs as the top management is averse to risky technology, as they lack knowledge about the intended benefits of automation. The environmental factors are characteristics pertaining to the industry such as market structure, access to resources and government regulation (Ediriweera and Wiewiora, 2021). Baker (2012) observed that industries that are witnessing rapid growth are more innovative whereas the mature industries are slower to adopt new solutions. Access to resources such as skilled labor, availability of consultants and technology services suppliers have a positive impact on innovation uptake (Baker, 2012). In India, the Central Government of India has a credit linked Capital Subsidy Scheme for Technology Upgradation. Thus, the MSMEs that are more informed might have better chances to successfully implement AI automation. Therefore, the technology adoption of MSMEs is influenced by the technology, the organization and the environment. This makes the TOE framework most suitable for our study.

Thus, keeping the TOE framework in mind, we proceeded with the depth interview process.

3. Model description, data and methodology

For addressing the first research objective, in-depth interviews with owners and top management involved in 65 MSMEs were conducted to identify the barriers to adoption, and their answers were analyzed. The number of observations is adequate to perform the methodology applied here – BWM and to arrive at the conclusions drawn. The respondents were from a diverse set of sectors such as BFSI, IT, Fintech, insurance, social-education (Figure 1).

The number of employees of the firms ranged from as low as ten to a few lakhs. The opinions were both personal and official. The queries pertained to the level of automation adopted, if not adopted, the reasons for not automating were probed further, the kind of jobs, for which automation was being done, were enquired and the experience and expectations from automation were identified. Whenever the level of automation was found to be high, the respondents were asked questions on whether they had their own automation models or third-party ML models, etc. Whenever the level of automation and years of adoption were found to be higher, questions that were more specific were asked on concerns of automating



Source(s): Authors' calculation from survey data

Figure 1. Sector of employment of respondents

business processes, such as risk mitigation, unclear ROI, technology and no vendor support. The most frequently occurring terms across interviews were identified as key barriers. In the next phase, the weights of the key barriers to AI adoption were obtained by using the BWM method.

Traditionally, weights of attributes or factors are computed in MCDM either objectively or subjectively. The objectivity measures include Shannon Entropy and CRITIC. However, these methods depend on data on the attributes from all the alternatives. Thus, these methods present a limitation. The subjectivity measures such as comparison matrix used in AHP have a drawback that when the number of factors is more in number, then the chances of making judgmental errors also increase, i.e. the CR value is more than 0.1. This follows Weber–Fechner Law that states that the change of stimulus that is noticeable is a fraction of the original stimulus. Thus, it may be very difficult to distinguish between two attributes which are very close in terms of perceived importance, but it is relatively easy to compare all the attributes with the best or worst ones. In addition, if the number of attributes "*n*" is high, the number of pairwise comparisons is also quite high, i.e. ${}^{n}P_{2} - n$.

To avoid these scenarios, in this paper we used a subjectivity-based measure BWM as proposed by Rezaei (2015). In BWM, in the first step, the best and the worst attributes are identified. Subsequently, all the attributes are compared with the best and worst attributes just as in the case of comparison matrix. Thus, the total comparisons is only 2*n*-3 where, *n* is the number of attributes. In the next step, the weights of all the attributes are determined by using the results of the aforementioned comparisons. In this section, the method for obtaining the weights is briefly discussed [detailed in Appendix].

In the last phase of our analysis, we have used DEMATEL method to figure out the relationship between these factors, i.e., which factors are drivers and which are the dependents.

From the interviews, lack of top management support emerged as the most important barrier. The importance of this barrier in comparison with the rest of the barriers is given in

Table 1. For example, the lack of top management support is two times more important than the barrier "lack of resources". In a similar manner, the least significant barrier was identified as "uncertainty regarding future". The importance of all the barriers with respect to this factor is presented in Table 2. For example, the barrier "lack of resources" is six times more important than "uncertainty regarding future". After obtaining this information, the BWM method, as discussed in the aforementioned section, was applied to arrive at the weights of all the barriers. This is presented in Table 3.

For comprehending the influence of the barriers on each other, we referred to the DEMATEL method. In the first step, the respondents were asked to indicate the extent of the influence of one barrier on the other on a five-point scale where 5 denotes maximum influence and 1 denotes minimum influence. For example, in Table 4, the factor "lack of

Table 1. The preference of the most important factor/criteria compared to all other factors

The most important factor/criteria	Top management support	Lack of resources	Lack of knowledge about AI in automation	Change resistance	Uncertainty regarding future	Job loss / conflicts	Perseverance	Price
Top management support	1	2	2	3	8	3	5	2

Source(s): Authors' calculation

Table 2. The preference of all criteria over the worst criteria

The most important factor/criteria	Uncertainty regarding future
Top management support	9
Lack of resources	6
Lack of knowledge about AI in automation	5
Change resistance	3
Uncertainty regarding future	1
Job loss / conflicts	3
Perseverance	2
Price	7

Source(s): Authors' calculation

Table 3. The factors acting as barriers to AI adoption and their weights

Factor	Weight
Lack of top management support	0.232041095
Lack of resources	0.170756691
Lack of knowledge about AI in automation	0.151481534
Change resistance	0.09777516
Uncertainty regarding the future	0.026853188
Job loss/conflicts	0.09777516
Perseverance	0.052560479
Price of automation	0.170756693

Source(s): Authors' calculation

Table 4. The un-normalized data matrix depicting the influence of each factor over the others

The most important factor/criteria	Top management support	Lack of resources	Lack of knowledge about AI in automation	Change resistance	Uncertainty regarding future	Job loss / conflicts	Lack of perseverance	Price of automation
Top management support	0	5	2	2	4	4	4	1
Lack of resources	3	0	2	1	1	1	3	2
Lack of knowledge about AI in automation	4	3	0	3	3	3	2	2
Change resistance	2	1	1	0	3	4	2	1
Uncertainty regarding future	3	1	3	3	0	3	4	1
Job loss/conflicts	3	1	1	3	3	0	1	1
Lack of perseverance	2	1	1	1	1	1	0	1
Price of automation	4	2	3	1	1	1	4	0

Source(s): Authors' calculation

resources" influences the barrier "top management support" to some extent as the value is 3. This matrix was subsequently normalized and the result presented in Table 5, denoted by matrix Y. The normalization was done by dividing each matrix entry by $Max(RS)_i$ where RS_i denotes the row sum of the i^{th} row. Subsequently, $Y \times (I - Y)^{-1}$ was computed and the results are shown in Table 6. In Table 6, R_i denotes the sum of row entries of the i^{th} row whereas C_i denotes the column sum of the i^{th} column. The row sum denotes the influence of that factor on all the other factors whereas the column sum denotes the influence of all the other factors on that factor. Thus, the value (R + C) of any factor is the importance of that factor depicting its influence on other factors and the influence of other factors on it. When the (R − C) value for any factor is positive, it indicates that the factor has more influence on other factors than the influence of other factors on it. This is presented in Table 7. In Table 7, $(R + C)_i$ column denotes the importance of the i^{th} factor whereas $(R - C)_i$ indicates the relative driving power of the i^{th} factor. The factors that have higher values of R + C are both drivers and also depend on other factors. The factors with positive values of R − C are drivers, whereas the ones with negative values of R − C depend on others.

4. Results and findings

In our study, lack of top management support was identified as the most important attribute and uncertainty regarding the future was the least important. Thereafter, after all the attributes were compared with these two factors. These results are presented in Table 1 and Table 2. The best attribute was found to be 8 times more important than the worst. Thus, $A_{Bw} = 8$. Before applying the BWM results, the value of ξ^* was computed and was found to be 0.64. The CR was calculated as per equation (10) and was found to be 0.08 whereas the threshold was 0.453. This indicated that the method had inconsistencies within the limits.

Lack of top management support, change resistance, lack of knowledge about AI in automation, lack of resources, uncertainty regarding the future, job loss/conflicts and perseverance were identified as the main barriers to AI automation. Our results show that lack of top management support is the most important barrier, while uncertainty regarding the future of the implementation is the least important. The weights of the factors as computed by BWM are given in Table 3.

Our analysis with DEMATEL shown in table shows the various drivers and the dependent factors. As per DEMATEL in the first step, the extent by which a factor influences another was captured in a matrix shown in Table 4. Thereafter, this matrix data was subsequently normalized and has been displayed in Table 5 (matrix Y). The normalization was done by dividing each matrix entry by $Max(RS)_i$ where RS_i denotes the row sum of the i^{th} row. Subsequently, $Y \times (I - Y)^{-1}$ was computed and the results are shown in Table 6. In Table 6, Ri denotes the sum of row entries of each row whereas C_i denotes the column sum. In Table 7, $(R + C)_i$ column denotes the importance of the i^{th} factor whereas $(R - C)_i$ indicates the relative driving power of the i^{th} factor. The factors that have higher values of R + C are both drivers and also depend on other factors and were identified as top management support, uncertainty regarding the future, lack of knowledge about AI. (Lack of) Top management support influences the other barriers of automation most significantly. Although the factor uncertainty regarding the future was found to be least important in the BWM, but experts opined that it has the potential to influence other barriers. Lack of knowledge about AI does influence many other barriers but was moderate in its importance as per BWM. The factors with positive values of R − C are drivers, whereas the ones with negative values of R − C depend on others. From the results, the most positive value is for the factor "Lack of Knowledge about AI in automation" followed by "price of automation". The factors with most negative values of (R − C) were lack of resources and perseverance.

Table 5. The normalized data matrix (Y)

The most important factor/ criteria	Top management support	Lack of resources	Lack of knowledge about AI in automation	Change resistance	Uncertainty regarding future	Job loss / conflicts	Perseverance	Price
Top management support	0	0.227272727	0.090909	0.090909	0.181818	0.181818	0.181818	0.045455
Lack of resources	0.136363636	0	0.090909	0.045455	0.045455	0.045455	0.136364	0.090909
Lack of knowledge about AI in automation	0.181818182	0.136363636	0	0.136364	0.136364	0.136364	0.090909	0.090909
Change resistance	0.090909091	0.045454545	0.045455	0	0.136364	0.181818	0.090909	0.045455
Uncertainty regarding future	0.136363636	0.045454545	0.136364	0.136364	0	0.136364	0.181818	0.045455
Job loss / conflicts	0.136363636	0.045454545	0.045455	0.136364	0.136364	0	0.045455	0.045455
Perseverance	0.090909091	0.045454545	0.045455	0.045455	0.045455	0.045455	0	0.045455
Price of automation	0.181818182	0.090909091	0.136364	0.045455	0.045455	0.045455	0.181818	0

Source(s): Authors' calculation

Table 6. The driving power and the importance of the factors acting as barriers to AI implementation

The most important factor/ criteria	Top management support	Lack of resources	Lack of knowledge about AI in automation	Change resistance	Uncertainty regarding future	Job loss / conflicts	Perseverance	Price of automation	R	C
Top management support	0.362557	0.453397	0.31675	0.346901	0.455905	0.469781	0.512888	0.213106	3.131285	3.018858
Lack of resources	0.354972	0.177582	0.234497	0.208302	0.2367	0.245032	0.354454	0.191983	2.003523	2.178385
Lack of knowledge about AI in automation	0.509697	0.381135	0.228043	0.378177	0.418953	0.43408	0.431118	0.245017	3.02622	1.943618
Change resistance	0.328168	0.216871	0.201529	0.18577	0.332024	0.379454	0.320934	0.15378	2.11853	2.168414
Uncertainty regarding future	0.427806	0.269334	0.315763	0.350069	0.264293	0.398296	0.45663	0.184877	2.667067	2.489923
Job loss/conflicts	0.358953	0.219895	0.200509	0.301474	0.33019	0.222249	0.284061	0.151715	2.069045	2.616659
Perseverance	0.233975	0.157904	0.141755	0.15284	0.171558	0.177671	0.150668	0.113001	1.299372	2.952486
Price of automation	0.442731	0.302267	0.30477	0.244882	0.280301	0.290096	0.441732	0.132446	2.439226	1.385925

Source(s): Authors' calculation

Table 7. The importance of the factors and their driving power

Factors	R + C	R − C
Top management support	6.150143197	0.112427429
Lack of resources	4.18190821	−0.174862236
Lack of knowledge about AI in automation	4.969837381	1.082602009
Change resistance	4.286944379	−0.049883968
Uncertainty regarding future	5.156989952	0.177144344
Job loss/conflicts	4.685704315	−0.547614427
Perseverance	4.251858303	−1.653114503
Price of automation	3.82515103	1.053301352

Source(s): Authors' calculation

4.1 Managerial and theoretical implications

Our results show that if the top management is supportive of the AI implementation, then probably most of the roadblocks would be cleared. Thus, the owners and the top management need to be supportive of the implementation of AI. Our results also show that the uncertain future has the least weight. This indicates that most of the owners are not apprehensive regarding the future of AI. However, they have reasonable concerns regarding the lack of knowledge about AI, and this makes the implementation a little uncertain, as they may face loss of productivity from the employees and the lack of knowledge about AI. Incidentally, change resistance was not considered as important, and this was not as per expectation. This could be because of the fact that we had looked at MSMEs where the trade unions may not be as strong and the decisions of the top management are binding upon all the employees.

The results further show lack of resources to be the second most serious barrier to implementation of automation. This fine-tunes and confirms the findings of earlier scholars such as Verma and Nema (2019), Singh *et al.* (2018), Singh (2019) who opined poor infrastructure, in general, and lack of access to ICT, in particular, to be a hurdle to MSMEs performance.

Our results from DEMATEL method show the relative importance of the bottlenecks, their interdependencies and driving powers. This has implications for the top management of MSMEs. The results did show that there are some bottlenecks that acted as drivers of other bottlenecks. Thus, the MSMEs, which inherently have limited resources, can prioritize the ones which have high driving power given by the factor R − C. These bottlenecks once removed will automatically make other bottlenecks easier to remove. Besides, by inspecting the factors that have high R + C values one can determine which barriers have high driving power as well as high dependence on others. Thus, it serves as a parameter for determining the importance of the barriers.

The study has theoretical implications as it corroborates the TOE framework in the context of AI automation in MSMEs. This is the first study of this type, as per our knowledge, on MSMEs in India. The bottlenecks identified in our paper have given support to the TOE framework. Factors such as Lack of Top Management Support, Change resistance, perseverance and the price of the automation can be viewed as organizational blocks to AI implementation. Lack of knowledge about AI in automation and Lack of resources are technology-related barriers, whereas uncertainty regarding the future of the technology and job loss are related to the environment. Using the DEMATEL method, we got insights into the driving power of some of the barriers, i.e. how they influence other

barriers. Lack of knowledge about automation, price and lack of top management support were found to be influencing other barriers. Thus, our study also suggests that in the TOE framework some of the factors in one category might influence the ones in another category. Future studies can take cue from our work and study the effect of some of the categories in TOE on others across organizations and industries.

Besides, the government can play a role in the removal of the bottlenecks for AI implementation. The decision of the government, to participate in the diffusion of AI, may be contingent upon monitoring the bottlenecks and designing mechanisms to enhance the use of AI for automation by MSMEs across India. For example, the price of automation was a factor that affected other bottlenecks. The government may subsidize certain parts and components that may reduce the cost of automation. Top management support was another factor that influenced other bottlenecks. An implication of this is that the government can conduct training and awareness programs that would highlight the benefits of automation. Thus, this study has wide policy implications.

5. Limitations and direction for future work

Although our study was carried out rigorously for identifying the barriers of automation, it is not without limitations. In this section we present the limitations of our study along with directions for future extensions of this work. First, our study focused only on MSMEs. The work can be extended to other types of organizations and the results can be cross-validated in future studies. Further, the size of the firms can be used as a moderator variable and its effects on these barriers can be examined. Third, the study was based on the expert opinions of the owners of the MSMEs. Since this study focused only on MSMEs where the decision of the owners matters the most in implementation of AI in automation, the other stakeholders were not interrogated for their insights. It will be interesting to see whether the results would vary if the opinions of other stakeholders were also considered. For example, the concerns regarding the bottlenecks for technical workers might be quite different from those of the owners. Further, the study can be extended longitudinally and going forward, it can be checked whether the perceived bottlenecks remain the same. Finally, but not the least, future studies can consider organization culture and its influence on AI adoption in automation.

Notes

1. https://pib.gov.in/PressReleaseIframePage.aspx?PRID=1946375#:~:text=As%20per%20the%20latest%20information,27.2%25%20and%2029.2%25%20respectively. Retrieved on 23/10/2024
2. Your job is (probably) safe from artificial intelligence (economist.com).

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Appendix

The best of most important attribute is compared with all the attributes and the results are stored as:

$$A_B = \{A_{B1}, A_{B2}, \ldots A_{Bn}\}$$

where, A_{Bj} refers to the preference of the best criteria over the j^{th} criteria. This follows Saaty's (2008) scale of 1–9. We have captured this in Table 1. Similarly, the preference of all the criteria over the worst criteria is given by:

$$A_w = \{A_{1w}, A_{2w}, \ldots A_{nw}\}^T$$

where, A_{jw} refers to the preference of the j^{th} criteria over the worst criteria. This is captured in Table 2.

It is obvious that $A_{BB} = 1$ and $A_{ww} = 1$. The purpose of BWM is to assign weights for the worst attribute W_W, the best attribute W_B and all other attributes, which are neither the best nor worst, W_j, in such a manner that the maximum absolute differences are minimized for all j, i.e.:

$$\min \max_j \left\{ \left| \frac{W_B}{W_j} - A_{Bj} \right|, \left| \frac{W_j}{W_w} - A_{jw} \right| \right\}$$

$$\sum_j W_j = 1 \forall \mathrm{j} \text{ and } W_j \geq 0$$

This is equivalent to solving the following:

Min ξ

s.t.

$$\left| \frac{W_B}{W_j} - A_{Bj} \right| \leq \xi \forall \mathrm{j} \quad (1)$$

and:

$$\left| \frac{W_j}{W_w} - A_{jw} \right| \leq \xi \forall \mathrm{j} \quad (2)$$

$$\sum_j W_j = 1 \forall \mathrm{j} \quad (3)$$

and:

$$W_j \geq 0 \quad (4)$$

Solving the aforementioned linear problem yields the optimal value of ξ i.e. ξ^*

For consistency check, one must have:

$$A_{Bj} \times A_{jw} = A_{Bw} \forall \mathrm{j} \quad (5)$$

However, if there is inconsistency then.

$A_{Bj} \times A_{jw} \neq A_{Bw}$. This inequality is highest when A_{Bj} and A_{jw} are equal to $A_{Bw.}$ and this would result in a value of ξ. The equation:

$$\left(W_B/W_j\right) \times \left(W_j/W_w\right) = W_B/W_w \tag{6}$$

should always hold. Ideally, with full consistency one must have:

$$A_{Bj} = \frac{W_B}{W_j} \forall j$$

and:

$$A_{jw} = \frac{W_j}{W_w} \forall j.$$

However, from equations (1) and (2), one could see that because of inconsistency there is ξ:

$$= > A_{Bj} - \xi = \frac{W_B}{W_j} \tag{7}$$

and:

$$A_{jw} - \xi = \frac{W_j}{W_w} \tag{8}$$

For maximum inconsistency $A_{Bj} = A_{Bw} = A_{jw}$. Therefore, equation (6) can be written as:

$$\left(A_{Bw} - \xi\right) \times \left(A_{Bw} - \xi\right) = \left(A_{Bw} + \xi\right) \tag{9}$$

Equation (9) is solved for maximum possible values of ξ for various values of A_{Bw} which vary from 1 to 9 (as per Saaty's scale) and a consistency index is developed. Thereafter, consistency ratio is computed as follows:

$$\text{Consistency ratio} = \xi^* / \text{consistency index} \tag{10}$$

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