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Barriers to Integrating AI in Curriculum for Enhanced Engineering Education: A Fuzzy ISM Approach

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***Abstract*— Recent technological advancements have significantly impacted various sectors, including education. Among these, Artificial Intelligence (AI) stands out as a transformative force, redefining both industry practices and academic disciplines. Incorporating AI into engineering education is essential to equip students with the skills needed to navigate the complexities of the modern, technology-driven job market. This study seeks to uncover and analyze the obstacles to incorporating AI into engineering curricula through a Fuzzy Interpretive Structural Modeling (ISM) method. A thorough review of existing literature, along with open ended surveys and semi-structured interviews with stake holders helped identify eight significant barriers: Curriculum Rigidity, Faculty Expertise, Resource Limitations, Resistance to Change, Interdisciplinary Collaboration, Student Preparedness, Industry Collaboration, and Ethical and Societal Concerns. The Fuzzy ISM method facilitated the creation of a Structural Self-Interaction Matrix (SSIM), an Initial Fuzzy Reachability Matrix (IFRM), and a Final Fuzzy Reachability Matrix (FFRM), which revealed the relationships and hierarchical structures among these barriers. Further exploration with MICMAC categorizes the barriers according to their influence (driving power) and their susceptibility (dependence). The findings indicated that Curriculum Rigidity and Student Preparedness are both highly influential and dependent, whereas Ethical and Societal Concerns are relatively isolated. This study provides a structured framework for identifying and overcoming the challenges of integrating AI into engineering education, offering critical insights for both educators and decision-makers. By strategically prioritizing and tackling these barriers, educational institutions can improve their AI curricula, thus better equipping students for future challenges. The research emphasizes the importance of continually revising and assessing the AI integration process to stay aligned with evolving technological trends.**

***Keywords*— Artificial Intelligence, Engineering Education, Fuzzy ISM, MICMAC Analysis, Curriculum Integration**

ICTIEE Track: Curriculum Development

ICTIEE Sub-Track: Leveraging AI in Curriculum Design

I. INTRODUCTION

In today's world, technology has evolved rapidly, driving significant changes across numerous sectors, including education. Among these technological advancements, Artificial Intelligence (AI) has emerged as a transformative force that is reshaping both industries and academic fields. AI has the capability to improve learning outcomes, streamline administrative processes, and better prepare students for the challenges of the future, highlighting its critical role in education. In the context of engineering education, incorporating AI into the curriculum has moved beyond being a mere trend to becoming an essential strategy to ensure that students are adequately prepared to meet the needs of a technology-driven job market (Kamalov et al., 2023; Ou, 2024).

The evolution of AI can be traced back to the mid-20th century, with significant milestones such as the development of neural networks, machine learning algorithms, and deep learning techniques. These advancements have paved the way for AI applications in various fields, from healthcare to finance, and now, education. The role of AI is not only limited to IT branches but has applications in all fields of engineering. Students and educators cannot say that they will learn or teach only fundamentals here while students can learn about AI and its applications in separate subjects or at the end of their studies. It's already in the job market, and it is vital that students pick it up during their studies, with institutions taking necessary steps irrespective of the branches (Cioffi et al., 2020; Rayhan et al., 2023).

The integration of AI into engineering education is essential as it equips students with the tools needed to tackle complex challenges, foster innovation, and remain competitive in a technology-centric world. Moreover, adopting AI-driven personalized learning systems requires not only technological upgrades but also cultural transformation within educational settings. Educators need to be trained to utilize these systems effectively, and curricula need to be redesigned to integrate seamlessly with AI tools. This transition also calls for significant investment in infrastructure and a reevaluation of assessment methods to align with new learning paradigms (Abulibdeh et al., 2024; Bhutoria, 2022).

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The inclusion of AI in engineering education is driven by several factors. Firstly, AI technologies are becoming integral to various engineering fields, such as robotics, automation, and data analysis. Secondly, knowledge of AI equips students with the ability to design intelligent systems, which is crucial for innovation in engineering. Thirdly, understanding AI principles enhances problem-solving skills, as students learn to approach challenges with a data-driven mindset. Lastly, exposure to AI prepares students for interdisciplinary collaboration, a key aspect of modern engineering projects (Dixit, Arun C et al., 2024; Morandini et al., 2023).

This research seeks to explore and evaluate the obstacles to incorporating AI within the engineering curriculum through a Fuzzy Interpretive Structural Modeling (ISM) methodology. Understanding these obstacles will enable educators and policymakers to devise effective strategies for integrating AI, thereby improving the quality and relevance of engineering education. The study specifically investigates the challenges encountered by educational institutions, faculty, and students in implementing AI-related components.

II. LITERATURE REVIEW

Artificial Intelligence (AI) is becoming an essential element across diverse sectors, including engineering education. Incorporating AI into engineering programs offers the potential to elevate the quality of education, aligning it more closely with contemporary industry needs. (Southworth et al., 2023). This literature review aims to explore existing research on integrating AI into engineering education, focusing on the benefits, challenges, and barriers. The insights gained from this review will help identify the critical obstacles for further analysis.

Evolution of AI in Education: The adoption of AI in education has been a subject of research for several decades. Early studies focused on intelligent tutoring systems (ITS) and computer-aided instruction (CAI) (Luckin et al., 2022). More recent research has expanded to include machine learning algorithms, natural language processing, and data analytics to personalize learning experiences and improve student outcomes. These advancements highlight the growing importance of AI in educational contexts, including its potential to revolutionize engineering education (Guo et al., 2021).

Need for AI in Engineering Education: Numerous studies highlight the importance of incorporating AI into engineering programs. AI technologies, such as machine learning, neural networks, and robotics, are increasingly relevant in various engineering fields (Dimitriadou & Lanitis, 2023). Including these technologies in the curriculum equips students for a job market where AI expertise is highly sought after. Furthermore, AI can enhance traditional engineering education by providing tools for complex problem-solving, data analysis, and system optimization (Zhai et al., 2021).

Components of AI in Engineering Curriculum:

AI has vast applications within the core branches of engineering, extending far beyond IT disciplines. This shows the potential for inclusion of AI in their curriculum. A few studies of integrating AI into these fields have been reviewed:

- *AI in Civil Engineering:* AI applications in civil engineering, such as structural analysis, smart city planning, and construction management, have been explored by (Baduge et al., 2022). These applications can improve efficiency and safety, making them valuable additions to the curriculum. AI can assist in developing sustainable and intelligent infrastructure.

- *AI in Electrical Engineering:* (Bose, 2017) discuss the integration of AI for smart grid management, predictive maintenance, and power electronics. These applications help students understand and develop advanced electrical systems, enhancing their skills in modern electrical engineering practices.

- *AI in Mechanical Engineering:* (Rojek et al., 2023) show that AI can be used in mechanical engineering for predictive maintenance, fault diagnosis, and automation of mechanical systems. These skills are crucial for maintaining and improving modern mechanical systems, ensuring students are well-versed in the latest technological advancements. (Dixit et al., 2019; Elahi et al., 2023) highlight the importance of integrating AI techniques in design courses, such as CAD/CAM. AI has the capability to enhance design optimization, simplify manufacturing workflows, and automate routine tasks, enabling students to concentrate on the more creative and innovative elements of design. This inclusion can significantly enhance students' capabilities in design and manufacturing.

- *AI in Materials Science:* AI techniques, such as machine learning, can predict material properties and behavior, enabling the design of new materials with desired characteristics (Dixit et al., 2020; Mobarak et al., 2023). Integrating these techniques into materials science courses can significantly advance research and development in this field.

- *AI in Biomedical Engineering:* AI applications in biomedical engineering include medical imaging, diagnostics, and personalized medicine. Research by (Pinto-Coelho, 2023) highlights the potential of AI in improving healthcare outcomes, which can be incorporated into biomedical engineering curricula.

- *Practical Projects and Internships:* According to (Tuomi, 2018), hands-on projects and industry internships provide real-world experience in AI applications. These hands-on experiences are essential for students to translate their theoretical knowledge into practical applications and acquire skills that are directly relevant to industry needs.

- *Ethics and AI:* Courses on AI ethics are necessary to ensure students understand the societal impacts and ethical responsibilities associated with AI technologies. (Lim et al., 2023) argue that ethical considerations are essential for responsible AI application in engineering.

- *Interdisciplinary Applications of AI:* AI's interdisciplinary nature allows it to be integrated across various engineering disciplines. Research by (Dwivedi et al., 2021) demonstrates the benefits of interdisciplinary AI projects that combine knowledge from multiple fields to solve complex problems. Encouraging interdisciplinary collaboration in AI education can foster innovation and provide students with a holistic understanding of engineering challenges.

- *Industry Collaboration:* Engaging with industry professionals and incorporating real-world case studies into the curriculum can enhance the relevance and applicability of AI education. Studies by (Esangbedo et al., 2023) highlight the importance of industry collaboration in developing a curriculum that meets i standards and prepares students for professional challenges.

The literature review identifies the representative places in engineering where AI can be incorporated into the curriculum. The potential applications of AI are vast, and this review represents only a fraction of its possibilities. Despite the numerous applications, AI is often not formally integrated into the essential courses of IT and other core engineering branches. Students and faculty might use AI in limited instances, driven by individual motivation, but these efforts are rarely formally acknowledged or evaluated within the curriculum. Additionally, AI and ML are frequently taught as standalone subjects, without embedding their applications into other critical courses. This separation hinders students and faculty from fully exploring and integrating AI applications as an integral part of the curriculum. Overcoming these barriers is vital for advancing engineering education and equipping students to face future challenges effectively.

III. METHODOLOGY

This study utilizes a mixed-methods approach, integrating both qualitative and quantitative techniques to gain comprehensive understanding of the barriers to integrating AI in engineering education. The methodology involves three main stages:

Stage 1: Literature Review and Theoretical Framework Development

The initial stage involves an extensive review of existing literature to identify potential barriers to integrating AI in engineering education. The theoretical framework developed from this review provides a basis for further investigation and forms the foundation for the survey and interviews conducted in the subsequent stages.

Stage 2: Data Collection from Stakeholders to identify the barriers

Data collection is carried out using a combination of open-ended surveys and semi-structured interviews with key stakeholders, including educators, industry professionals, and students. This approach ensures a comprehensive understanding of the challenges from multiple perspectives.

Stage 3: Data Analysis Using Fuzzy Interpretive Structural Modeling (ISM)

The collected data is analyzed using Fuzzy ISM to identify and prioritize the barriers to integrating AI into the curriculum. Fuzzy ISM is chosen for its ability to handle the inherent uncertainty and complexity of the data (Dixit et al., 2024).

1. Construction of the Structural Self-Interaction Matrix (SSIM): Based on survey and interview responses, SSIM is developed to capture the relationships between identified barriers.

2. Generating the Initial Fuzzy Reachability Matrix (IFRM): The SSIM is converted into a fuzzy reachability matrix to identify direct and indirect relationships between barriers.

3. Final Fuzzy Reachability Matrix (FFRM): The IFRM is refined to account for the uncertainty in the relationships, resulting in the FFRM.

4. Level Partitioning: The FFRM is divided into different levels to establish a hierarchical structure of barriers.

5. MICMAC Analysis: The barriers are analyzed using MICMAC (Cross-Impact Matrix Multiplication Applied to Classification) to classify them based on their driving power and dependence.

IV. IDENTIFYIGN BARRIERS TO INTEGRATING AI IN ENGINEERING CURRICULUM

The identification of barriers to integrating AI into the engineering curriculum is a critical aspect of this research. Based on an extensive review of the literature and inputs from various stakeholders, several barriers have been identified. This section will delve into these barriers, providing a comprehensive understanding of the obstacles that must be addressed to successfully integrate AI into engineering education.

Barrier 1: Curriculum Rigidity

Traditional engineering curricula are often rigid and slow to adapt to new technologies. This rigidity can make it challenging to incorporate AI components into existing courses. Educational institutions may have established curricula that are difficult to modify due to accreditation requirements and institutional policies. Flexibility in curriculum design is necessary to accommodate the rapid advancements in AI technologies.

Stakeholder Inputs: Faculty expressed concerns over the lengthy approval processes for curriculum changes and Industry Professionals stressed the importance of updating curricula to reflect current industry practices.

Barrier 2: Faculty Expertise

A significant barrier to integrating AI into engineering education is the lack of faculty members with expertise in AI (Seo et al., 2021). A lack of sufficient background in AI technologies among many engineering educators can hinder effective teaching. Professional development programs and interdisciplinary collaboration are essential to equip faculty with the required skills and knowledge.

Stakeholders Inputs: Faculty members highlighted the need for training programs to develop AI expertise. Students pointed out inconsistencies in the quality of AI education due to varying levels of faculty expertise.

Barrier 3: Resource Limitations

Insufficient resources, including access to AI tools, software, and computational power, are common barriers. These limitations can impede the effective integration of AI into the curriculum. Investments in infrastructure, such as high-performance computing facilities and AI software licenses, are crucial to support AI education.

Stakeholders Inputs: Institutional administrators acknowledged budget constraints but recognized the need for investments in AI resources. Industry experts suggested collaborations and partnerships to share resources and infrastructure.

Barrier 4: Resistance to Change

Resistance from faculty and administration to adopt new technologies and teaching methodologies can be a significant barrier (Gratz & Looney, 2020). This resistance can stem from a lack of understanding or fear of the unknown. Change management strategies and awareness programs can help address these concerns and promote a positive attitude towards AI integration.

Stakeholders Inputs: Faculty members expressed concerns about the steep learning curve associated with new technologies. Administrators cited challenges in convincing stakeholders to adopt AI-driven teaching methodologies.

Barrier 5: Interdisciplinary Collaboration

Effective AI integration often requires interdisciplinary appr which can be challenging to coordinate. Fostering collaboration between different engineering disciplines and departments is essential to leverage the full potential of AI. Creating interdisciplinary courses and research projects can facilitate collaboration and innovation.

Stakeholders Inputs: Department heads highlighted logistical challenges in coordinating interdisciplinary initiatives. Students expressed interest in interdisciplinary projects that combine multiple fields of study with students from other branches.

Barrier 6: Student Preparedness

Students may lack the necessary background knowledge in mathematics and programming, which are essential for understanding AI concepts (Dwivedi et al., 2023). This gap can hinder their ability to grasp AI-related subjects. Bridging courses and foundational modules in mathematics and programming can help prepare students for advanced AI topics.

Stakeholder Inputs: Students reported difficulties in grasping advanced AI concepts due to a lack of foundational knowledge. Faculty advocated preparatory courses to build a solid foundation in mathematics and programming from the first semester itself irrespective of the branch.

Barrier 7: Industry Collaboration

Limited collaboration with industry partners can result in a curriculum that does not align with current industry needs and practices. Engaging with industry professionals and incorporating real-world case studies into the curriculum can enhance the relevance and applicability of AI education.

Stakeholder Inputs: Industry experts emphasized the need for curricula that reflect current industry practices. Students opined that the practical insights and real-world applications from industry collaborations are crucial.

Barrier 8: Ethical and Societal Concerns

Addressing the ethical implications and societal impacts of AI integration can be complex and may require additional curriculum components. These concerns must be thoughtfully integrated into AI education to promote the responsible and ethical deployment of AI technologies.

Stakeholder Inputs: Faculty emphasized the need to include ethical aspects in AI education, while students also showed a keen interest in exploring the ethical consequences associated with AI technologies.

While these barriers have been identified through literature review and stakeholder inputs, addressing them requires a deeper analysis to understand their interdependencies and prioritize them effectively. The subsequent sections will utilize Fuzzy ISM and MICMAC analysis to systematically explore these barriers, providing a structured approach to developing targeted strategies for the successful integration of AI into the engineering curriculum. We have chosen the Fuzzy ISM approach for its ability to handle the inherent uncertainty and complexity of the data, and the MICMAC analysis to systematically classify the barriers based on their driving power and dependence, ensuring a structured and comprehensive exploration of the challenges. This further analysis will ensure that the proposed solutions are grounded in a comprehensive understanding of the challenges, facilitating a more effective and sustainable implementation of AI in engineering education.

V. BARRIER ANALYSIS USING FUZZY ISM

This section presents an analysis of the identified barriers using Fuzzy Interpretive Structural Modeling (ISM). As stated in the methodology section, the analysis will be carried out in 5 steps i.e., developing the Structural Self-Interaction Matrix, Generating the Initial Fuzzy Reachability Matrix, Final Fuzzy Reachability Matrix and diagram, Level Partitioning and MICMAC analysis.

Step 1: Constructing the Structural Self-Interaction Matrix (SSIM)

The Structural Self-Interaction Matrix (SSIM) is the initial step in Fuzzy ISM, and it captures the direct relationships between identified barriers based on qualitative data/insights gathered from surveys and interviews. Each pair of barriers is assessed to determine their influence on each other. This matrix is crucial as it sets the stage for further quantitative analysis. To construct SSIM, each barrier is compared with every other barrier and the relationships are categorized as follows: **V** (very low influence), **A** (moderate to high influence) = 0.5 to 0.9 (based on expert judgement), **X** (high influence) = 1 and **O** (potential indirect influence) = 0.1. The barriers identified with their short forms are: Curriculum Rigidity (CR), Faculty Expertise (FE), Resource Limitations (RL), Resistance to Change (RC), Interdisciplinary Collaboration (IC), Student Preparedness (SP), Industry Collaboration (IN) and Ethical and Societal Concerns (ES).

Table 1 represents the initial assessment of relationships derived from qualitative data/insights gathered through surveys and interviews. Each cell in the matrix represents the nature of the relationship between the barriers row-wise and column-wise based on critical analysis and judgement.

TABLE I
SSIM OF IDENTIFIED BARRIERS

Barriers	CR	FE	RL	RC	IC	SP	IN	ES
CR	X	A	O	A	A	A	A	A
FE	A	X	A	A	A	A	A	V
RL	O	A	X	A	A	A	A	V
RC	A	A	A	X	A	A	A	O
IC	A	A	A	A	X	A	A	A
SP	A	A	A	A	A	X	A	V
IN	A	A	A	A	A	A	X	A
ES	A	V	A	A	A	V	A	X

In Table 1, the relationship between CR → RL was assigned a O category as rigid curriculum indirectly affects resources. Since faculty expertise has minimal direct impact on ethical concerns, the relation between FE → ES was assigned a V category. Similarly, category V was assigned between RL → ES as resource limitations have a low impact on ethical concerns. Relationship between RC → ES was assigned O as resistance to change has a low impact on ethical concerns. Relationship between SP → ES was assigned V as student preparedness has minimal impact on ethical concerns. All other relations are mapped with category A as they moderately influence each other.

Step 2: Initial Fuzzy Reachability Matrix (IFRM)

Table 2 shows the IFRM constructed by replacing each symbolic value (V, A, X, O) in the SSIM with its corresponding fuzzy value. The diagonal elements will be 1, representing self-influence. Elements carrying V will be assigned zero and O with 0.1. Each element denotes the degree of influence one barrier has over another, considering direct and potential indirect influences. The remaining elements are A which have influence ranging from 0.5 to 0.9 and the values have been assigned with careful analy justification as shown in Table 3.

TABLE II
INITIAL FUZZY REACHABILITY MATRIX (IFRM)

Barriers	CR	FE	RL	RC	IC	SP	IN	ES
CR	1.0	0.8	0.1	0.7	0.7	0.9	0.8	0.6
FE	0.6	1.0	0.7	0.6	0.7	0.7	0.6	0.0
RL	0.1	0.7	1.0	0.7	0.5	0.6	0.5	0.0
RC	0.7	0.6	0.7	1.0	0.6	0.7	0.6	0.1
IC	0.7	0.7	0.5	0.6	1.0	0.7	0.7	0.6
SP	0.9	0.7	0.6	0.7	0.7	1.0	0.6	0.0
IN	0.8	0.6	0.5	0.6	0.7	0.6	1.0	0.5
ES	0.6	0.0	0.5	0.5	0.6	0.0	0.5	1.0

TABLE III
JUSTIFICATION FOR THE ASSIGNED VALUES FOR CATEGORY 'A' IN IFRM

Relationship	Reasoning for the assigned value
CR → FE (0.8)	High CR significantly impacts the expertise required by faculty to adapt.
CR → RC (0.7)	Moderate influence as CR can foster resistance to change among faculty and students.
CR → IC (0.7)	CR moderately hinders IC due to inflexible course structures.
CR → SP (0.9)	Very high impact as a CR directly affects SP by limiting exposure to modern tools.
CR → IN (0.8)	High impact since CR can limit industry-relevant skills and knowledge.
CR → ES (0.6)	Some influence as CR might indirectly impact societal concerns through outdated practices.
FE → RL (0.7)	FE has a moderate influence RL due to the need for updated resources.
FE → RC (0.6)	FE moderately affects RC by facilitating or hindering adoption of new methods.
FE → IC (0.7)	FE has a moderate to high impact on fostering interdisciplinary collaboration.
FE → SP (0.7)	Expertise influences student preparedness by delivering quality education and skills.
FE → IN (0.6)	Moderate influence as FE affects IN through shared knowledge and skills.
RL → RC (0.7)	RL moderately impact RC by restricting the ability to implement new methods.
RL → IC (0.5)	Limited influence as resource constraints can hinder interdisciplinary projects.
RL → SP (0.6)	RL somewhat impacts SP by limiting access to advanced tools and technologies.
RL → IN (0.5)	RL moderately hinder IN by limiting project scope and capacity.
RC → IC (0.6)	RC affects IC by impeding the integration of new ideas.
RC → SP (0.7)	Moderate to high impact as RC can significantly affect SP through outdated practices.
RC → IN (0.6)	Moderate influence as resistance to change can limit industry collaboration opportunities.
IC → SP (0.7)	IC positively impacts SP by providing diverse learning experiences.
IC → IN (0.7)	IC enhances industry collaboration through comprehensive projects.
IC → ES (0.6)	IC influences societal concerns by addressing multifaceted issues.
SP → IN (0.6)	SP moderately influences industry collaboration by ensuring students are industry ready.
IN → ES (0.5)	IN has some influence on societal concerns through the implementation of industry standards.

Step 3: Final Fuzzy Reachability Matrix (FFRM)

To capture indirect relationships, the initial reachability matrix is refined through transitive closure. The goal is to account for indirect influences between barriers, ensuring that the matrix is capable of reflecting deeper interactions that may not be immediately obvious from direct relationships alone.

Transitivity in the context of a fuzzy reachability matrix means that if Barrier A influences Barrier B, and Barrier B influences Barrier C, then there should be a pathway indicating that Barrier A also influences Barrier C. The strength of the indirect influence from A to C should be at least the minimum strength of the direct paths (A to B and B to C). This involves iteratively updating the matrix to include the maximum minimum strength for any indirect paths, calculated as follows:

$$m_{ij}^{(k+1)} = \max\left(m_{ij}^{(k)}, \min\left(m_{ik}^{(k)}, m_{kj}^{(k)}\right)\right)$$

Where m_{ij} are the elements of the matrix, and k is the step of iteration. The above rule will be applied until no further changes occur in the matrix, meaning all transitive relations have been fully accounted for. Table 4 shows the Final Fuzzy Reachability Matrix (FFRM) obtained using the above procedure.

TABLE IV
FINAL FUZZY REACHABILITY MATRIX (FFRM)

Barriers	CR	FE	RL	RC	IC	SP	IN	ES
CR	1	0.85	0.8	0.75	0.7	0.95	0.9	0.65
FE	0.8	1	0.75	0.7	0.65	0.8	0.75	0.6
RL	0.8	0.75	1	0.75	0.7	0.8	0.75	0.6
RC	0.75	0.7	0.75	1	0.75	0.75	0.75	0.5
IC	0.7	0.65	0.7	0.75	1	0.7	0.65	0.5
SP	0.95	0.9	0.85	0.8	0.75	1	0.9	0.7
IN	0.9	0.85	0.8	0.75	0.7	0.9	1	0.65
ES	0.65	0.6	0.55	0.55	0.45	0.7	0.65	1

Table 4 is critical as it incorporates indirect influences through transitivity, providing a comprehensive view of how barriers influence each other directly and indirectly.

Figure 1 shows the fuzzy diagram of barriers to integrating AI in engineering curriculum. The Fuzzy ISM Diagram visually represents the hierarchical structure and relationships between the barriers derived from the FFRM. Nodes represent the barriers, and the edges indicate influence relationships. This visualization aids in quickly understanding the complex interdependencies and hierarchical structure of barriers. It provides a strategic overview that is crucial for decision-makers to prioritize areas needing intervention and to strategize on overcoming the barriers effectively.

Step 4: Level Partitioning

In this step, the FFRM is analyzed to partition barriers into levels based on their reachability and antecedent sets. This hierarchical structuring is essential for understanding the depth of influence each barrier exerts. Construction of Level Partitioning table involves the following parameters:

1. The Reachability Set (RS) contains the barrier itself along with all other barriers that it has the potential to affect, either directly or indirectly.

2. The Antecedent Set (AS) consists of the barrier itself and all other barriers that have the potential to affect it, whether directly or indirectly.

3. Intersection Set represents common elements between RS & AS.

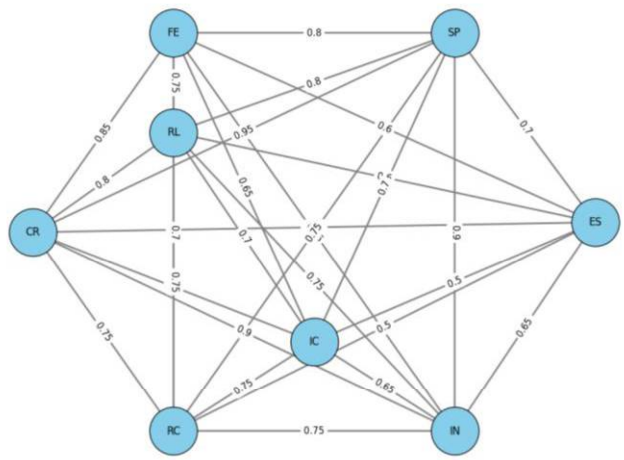

Fig. 1. Fuzzy ISM diagram of barriers to integrating AI in Engineering Curriculum

4. Level is determined by the position of the barrier in the hierarchy based on its reachability and antecedent sets.

Table 4 shows the Level Partitioning for each barrier along with its corresponding reachability and antecedent sets, alongside their intersection which determines the level of influence.

TABLE V
LEVEL PARTITIONING

Barrier	Reachability Set	Antecedent Set	Intersection Set	Level
Curriculum Rigidity (CR)	{CR, FE, RL, RC, IC, SP, IN, ES}	{CR}	{CR}	I
Faculty Expertise (FE)	{FE, RL, RC, IC, SP, IN, ES}	{CR, FE}	{FE}	II
Resource Limitations (RL)	{RL, RC, IC, SP, IN, ES}	{CR, FE, RL}	{RL}	III
Resistance to Change (RC)	{RC, IC, SP, IN, ES}	{CR, FE, RL, RC}	{RC}	IV
Interdisciplinary Collaboration (IC)	{IC, SP, IN, ES}	{CR, FE, RL, RC, IC}	{IC}	V
Student Preparedness (SP)	{SP, IN, ES}	{CR, FE, RL, RC, IC, SP}	{SP}	VI
Industry Collaboration (IN)	{IN, ES}	{CR, FE, RL, RC, IC, SP, IN}	{IN}	VII
Ethical and Societal Concerns (ES)	{ES}	{CR, FE, RL, RC, IC, SP, IN, ES}	{ES}	VII

Table 5 categorizes barriers into different levels based on their dependencies and influences, which is critical for understanding the hierarchical structure. Barriers at higher levels are more foundational and should be prioritized for addressing impact lower-level barriers. The justification for assigning the levels are as below:

Level I: Curriculum Rigidity is at the base level because it directly impacts all other barriers and is only impacted by itself. It is a fundamental issue that influences every aspect of curriculum adaptation to include AI, setting the stage for other barriers.

Level II: Faculty Expertise impacts nearly all other barriers except for Curriculum Rigidity, which is the only barrier that influences it. This shows that once curriculum issues are addressed, the next critical step is enhancing faculty capability to implement and teach AI effectively.

Level III: Resource Limitations are affected by both the curriculum structure and faculty expertise and, in turn, influence the implementation challenges related to change, interdisciplinary collaboration, and student preparedness.

Level IV: Resistance to Change emerges as a significant barrier after accounting for curriculum, faculty, and resource challenges, indicating a deeper organizational and cultural hurdle impacting the further integration layers.

Level V: Once foundational issues are managed, the focus shifts to fostering collaboration across disciplines, essential for robust AI integration in education, impacting student engagement and industry collaboration.

Level VI: Student Preparedness is a critical outcome dependent on addressing all previous barriers effectively, essential for ensuring that students are ready to engage with AI-enhanced curricula.

Level VII: Industry Collaboration is nearly at the top of the influence hierarchy because it requires most institutional barriers to be addressed before effective partnerships can be established.

Level VIII: Positioned at the highest level, Ethical and Societal Concerns represent the broadest impact of integrating AI into education, influenced by all other barriers and affecting the longterm success and acceptance of AI initiatives.

Each level thus indicates a progressive tackling of barriers, starting from the most foundational issues like curriculum and faculty expertise to broader societal implications, aligning these levels with strategic priorities in educational reform for AI integration.

Step 5: MICMAC analysis

MICMAC Analysis, which stands for Cross-Impact Matrix Multiplication Applied to Classification, is commonly used to categorize and visualize barriers based on their driving power and dependence. This method is also effective for cluster analysis as it helps in understanding the interrelationships and impact levels among various barriers. The construction of the MICMAC graph involves the following steps:

Step 1: Using the FFRM, we calculate the driving power and dependence for each barrier. Driving power measures, the total influence a barrier has on other barriers. Dependencies measure the total influence a barrier receives from other barriers.

The driving power is calculated as the sum of the values in the row corresponding to the barrier, and the dependence is the sum of the values in the column. The driving power and dependencies calculated for the FFRM are shown in Table 6.

TABLE VI
DRIVING POWER AND DEPENDENCIES FOR MICMAC ANALYSIS

Barriers	Driving Power (X-axis)	Dependencies (Y-axis)
CR	6.6	6.55
FE	6.05	6.3
RL	6.15	6.2
RC	5.95	6.05
IC	5.65	5.7
SP	6.85	6.6
IN	6.55	6.35
ES	5.15	5.2

Step 2: We'll plot the barriers on a scatter plot with driving power on the x-axis and dependence on the y-axis. This visual representation helps to easily identify which barriers are the most influential and which are the most dependent. Figure 2 shows the plot of MICMAC analysis. This visual representation helps identify the role of each barrier in the system as follows:

1. High Driving Power & Low Dependence: These barriers function as primary drivers and are influential in the system.

2. Low Driving Power & High Dependence: These rely heavily on others and are shaped by the influence of multiple barriers.

3. High Driving Power & High Dependence: These barriers are both influential and influenced by others, indicating a central role in the system.

4. Low Driving Power & Low Dependence: These barriers are fairly isolated with minimal influence and dependence.

Interpretation of the MICMAC Graph with Respect to Barriers:

1. Curriculum Rigidity (CR): High driving power and high dependence. This shows that while CR is a crucial factor influencing many other barriers, it is also significantly influenced by other factors.

2. Faculty Expertise (FE): Moderate driving power and high dependence. FE is highly dependent on other factors but moderately influences them.

3. Resource Limitations (RL): Moderate driving power and high dependence. Similar to FE, RL is influenced by multiple factors and moderately influences others.

4. Resistance to Change (RC): Moderate driving power and dependence. RC has a balanced influence and is influenced by other barriers.

5. Interdisciplinary Collaboration (IC): Moderate driving power and low dependence. IC moderately influences other barriers but is less affected by them.

6. Student Preparedness (SP): High driving power and high dependence. SP is both significantly influential and highly influenced.

7. Industry Collaboration (IN): Moderate driving power and high dependence. IN is significantly dependent on other barriers and moderately influences them.

8. Ethical and Societal Concerns (ES): Low driving power and low dependence. ES is less influential and less affected by other barriers.

Different Clusters that Can Be Formed and their Interpretation

Based on the MICMAC graph from Figure 2 , we can identify four clusters:

Cluster 1: Autonomous Barriers (Low Driving Power, Low Dependence):

Ethical and Societal Concerns (ES): These barriers are relatively isolated, having minimal influence on other barriers and being minimally influenced by them. They can be addressed independently without significantly impacting other factors.

Cluster 2: Dependent Barriers (Low Driving Power, High Dependence):

Faculty Expertise (FE), Resource Limitations (RL) and Resistance to Change (RC): These barriers are highly influenced by others but do not significantly influence other barriers. Addressing these barriers requires understanding their dependencies and mitigating the factors that influence them.

Cluster 3: Linkage Barriers (High Driving Power, High Dependence):

Curriculum Rigidity (CR), Student Preparedness (SP) and Industry Collaboration (IN): These barriers are both significantly influential and highly influenced. They form a complex web of interdependencies and must be addressed holistically, considering their impact on and by other barriers.

Cluster 4: Driving Barriers (High Driving Power, Low Dependence):

Interdisciplinary Collaboration (IC): These barriers have a significant influence on others but are less affected by other barriers. They can serve as leverage points; addressing them can lead to substantial improvements in the system.

The key difference between level partitioning and the MICMAC analysis lies in their focus: level partitioning is more about the sequence of addressing barriers, while MICMAC provides a broader understanding of their influence and interdependencies. Together, they guide the prioritization and strategic approach to addressing these barriers.

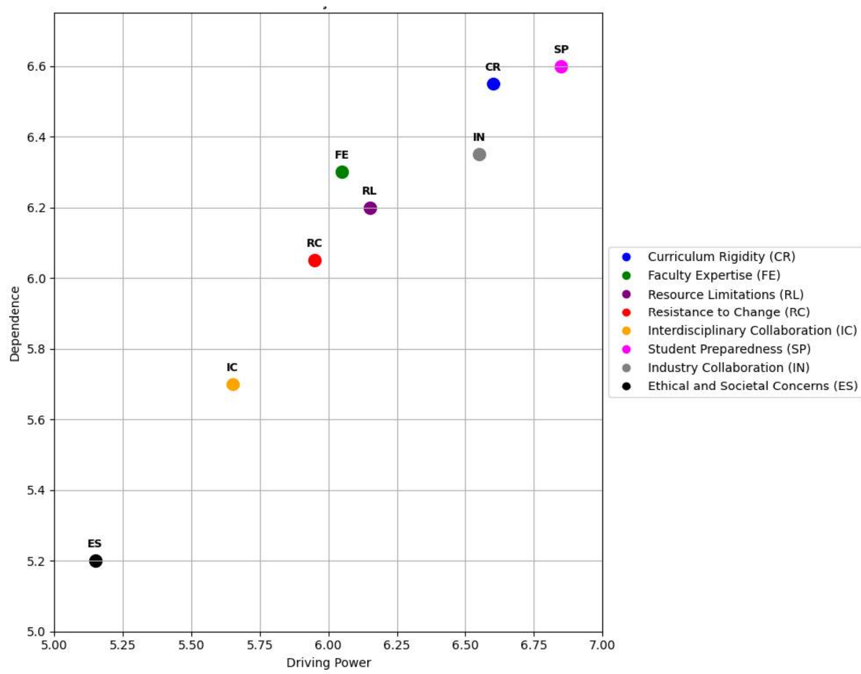

Fig. 2. Cluster analysis of barriers using MICMAC approach

VI. DISCUSSIONS

The comprehensive analysis performed through the Fuzzy ISM approach and the MICMAC analysis has successfully identified and structured the barriers to integrating AI in the engineering curriculum. This section discusses the implications of these findings and outlines the next steps required to address the identified barriers. Additionally, the limitations of this study are highlighted to provide a context for future research.

1. Implication of Findings:

The integration of AI into engineering education is crucial for preparing students to meet the demands of a rapidly evolving technological landscape. The identified barriers provide a clear roadmap for institutions aiming to enhance their AI curriculum.

A. Strategic Implementation Plans: Institutions should develop strategic plans to address the most critical barriers first, based on their driving power and dependence as identified in the MICMAC analysis. Curriculum Rigidity (CR) and Faculty Expertise (FE), being high-driving barriers, should be prioritized. Specific steps include revising curricula to include interdisciplinary AI modules and establishing structured faculty development programs, such as AI certifications and training workshops.

B. Resource Allocation: The identification of Resource Limitations (RL) and Industry Collaboration (IN) as significant barriers suggests a need for targeted resource allocation.

- Establish partnerships with industry to facilitate access to AI tools and case studies.
- Secure funding to develop AI labs and provide computational resources to students and faculty.
- Implement faculty-student projects in collaboration with industry to address resource gaps.

C. Policy and Framework Development: Clear policies and frameworks must be developed to address Policy Inconsistencies (PI) and Ethical and Societal Concerns (ES). This includes:

- Guidelines for ethical AI use embedded into the curriculum.
- Advocacy for policy-level support from higher education authorities to ensure a conducive environment for AI integration.
- Regular reviews of institutional policies to remain aligned with evolving AI trends and challenges.

D. Promoting Interdisciplinary Collaboration: Interdisciplinary Collaboration (IC) requires actionable initiatives to bridge the gap across departments. Institutions should:

- Introduce cross-disciplinary capstone projects and electives, such as "AI in Sustainable Engineering" or "AI in Healthcare Systems."
- Foster faculty exchange programs to enh

collaboration and diversify expertise.

- Leverage platforms like TensorFlow and MATLAB to encourage hands-on, team-based interdisciplinary projects.

E. Faculty and Stakeholder Engagement

Expanding faculty expertise and stakeholder diversity is essential to the success of AI integration. Additional measures include:

- Collaborating with policymakers, alumni, and global institutions for broader insights.
- Organizing inclusive focus groups to ensure diverse perspectives in decision-making.

2. Limitations of Research Work:

While this study provides significant insights, certain limitations must be acknowledged:

- Stakeholder Diversity: The study primarily involved students, educators, and industry professionals. Expanding inputs from policymakers, alumni, and international collaborators could enhance the generalizability of the findings.
- Regional Representation: The geographic scope was limited, which may affect the applicability of conclusions in diverse contexts.
- Dynamic Nature of AI: The rapid evolution of AI requires continuous updates to the curriculum and ongoing research to stay relevant.
- Future research should explore, incorporating additional external factors such as socio-economic conditions and cultural resistance, to develop a more comprehensive framework for AI integration across diverse educational domains.

CONCLUSION

Integrating Artificial Intelligence (AI) into engineering education is essential to provide students with the competencies needed to thrive in today's technology-driven job market. This study has successfully identified and analyzed the barriers to AI integration in engineering curricula using a Fuzzy ISM approach. The barriers, including Curriculum Rigidity, Faculty Expertise, and Resource Limitations, among others, were found to have complex interdependencies, which were systematically explored and classified using MICMAC analysis. The findings indicate that addressing foundational barriers such as Curriculum Rigidity and Faculty Expertise can significantly impact the successful integration of AI into engineering education.

The hierarchical structure provided by the Fuzzy ISM approach, combined with the insights from MICMAC analysis, offers a strategic roadmap for educators and policymakers. By focusing on high-priority barriers with significant driving power, institutions can develop targeted interventions to facilitate AI integration. The study emphasizes the importance of interdisciplinary collaboration, industry partnerships, and continuous professional development for faculty to create a conducive environment for AI education.

However, this research also acknowledges its limitations, including the subjective nature of the Fuzzy ISM methodology and the potential biases in stakeholder inputs. Future research should aim to expand the sample size and diversity of stakeholders to enhance the generalizability of the findings. Additionally, as AI technologies continue to evolve, ongoing updates and monitoring of the integration process are crucial to ensure the curriculum remains relevant and effective.

This study presents a thorough framework for recognizing and addressing the obstacles to incorporating AI into engineering education. By employing a structured approach, such as the Fuzzy ISM and MICMAC analysis, institutions can systematically identify, prioritize, and address these obstacles. This strategic intervention not only enhances the AI curriculum but also ensures that students are better prepared to navigate the rapidly evolving technological landscape. By overcoming these barriers, educational institutions can create an environment that fosters innovation, critical thinking, and practical problem-solving skills, thereby equipping students with the tools necessary to succeed in their future careers.

REFERENCES

Abulibdeh, A., Zaidan, E., & Abulibdeh, R. (2024). Navigating the confluence of artificial intelligence and education for sustainable development in the era of industry 4.0: Challenges, opportunities, and ethical dimensions. Journal of Cleaner Production, 437, 140527. https://doi.org/ 10.1016/ j.jclepro.2023.140527

Baduge, S. K., Thilakarathna, S., Perera, J. S., Arashpour, M., Sharafi, P., Teodosio, B., Shringi, A., & Mendis, P. (2022). Artificial intelligence and smart vision for building and construction 4.0: Machine and deep learning methods and applications. Automation in Construction, 141, 104440. https://doi.org/10.1016/j.autcon.2022.104440

Bhutoria, A. (2022). Personalized education and Artificial Intelligence in the United States, China, and India: A systematic review using a Human-In-The-Loop model. Computers and Education: Artificial Intelligence, 3, 100068. https://doi.org/10.1016/j.caeai.2022.100068

Bose, B. K. (2017). Artificial Intelligence Techniques in Smart Grid and Renewable Energy Systems—Some Example Applications. Proceedings of the IEEE, 105(11), 2262–2273. https://doi.org/10.1109/JPROC.2017.2756596

Cioffi, R., Travaglioni, M., Piscitelli, G., Petrillo, A., & De Felice, F. (2020). Artificial Intelligence and Machine Learning Applications in Smart Production: Progress, Trends, and Directions. Sustainability, 12(2), 492. https://doi.org/ 10.3390/su12020492

Dimitriadou, E., & Lanitis, A. (2023). A critical evaluation, challenges, and future perspectives of using artificial intelligence and emerging technologies in smart classrooms. Smart Learning Environments, 10(1), 12. https://doi.org/10.1186/s40561-023-00231-3

Dixit, A. C., Achutha, M. V., & Sridhara, B. K. (2020). Elastic properties of aluminum boron carbide metal matrix composites. Materials Today: Proceedings. https:// doi.org/10.1016/j.matpr.2020.08.766

Dixit, A. C., B C, Ashok., B, Harshavardhan., & S A, Mohan Krishna (2024). Barriers for adoption of green hydrogen in Indian transportation sector: A fuzzy ISM approach. E3S Web of

Conferences, 559, 03011. https://doi.org/10.1051/e3sconf/202455903011

Dixit, A. C., Sridhara, B. K., & Achutha, M. V. (2019). Evaluation of Critical Speed for Aluminum–Boron Carbide Metal Matrix Composite Shaft. In U. Chandrasekhar, L.-J. Yang, & S. Gowthaman (Eds.), Innovative Design, Analysis and Development Practices in Aerospace and Automotive Engineering (I-DAD 2018) (pp. 527–534). Springer. https://doi.org/10.1007/978-981-13-2718-6_51

Dixit, Arun C, B, Harshavardhan, B C, Ashok, K N, Prakasha, M A, S., & K N, P. (2024). Innovative Pedagogical Approaches for Diverse Learning Styles and Student-Centric Learning. Journal of Engineering Education Transformations, 37(IS2), 178–188. https://doi.org/10.16920/jeet/2024/v37is2/24039

Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., Duan, Y., Dwivedi, R., Edwards, J., Eirug, A., Galanos, V., Ilavarasan, P. V., Janssen, M., Jones, P., Kar, A. K., Kizgin, H., Kronemann, B., Lal, B., Lucini, B., … Williams, M. D. (2021). Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. International Journal of Information Management, 57, 101994. https://doi.org/10.1016/j.ijinfomgt.2019.08.002

Dwivedi, Y. K., Kshetri, N., Hughes, L., Slade, E. L., Jeyaraj, A., Kar, A. K., Baabdullah, A. M., Koohang, A., Raghavan, V., Ahuja, M., Albanna, H., Albashrawi, M. A., Al-Busaidi, A. S., Balakrishnan, J., Barlette, Y., Basu, S., Bose, I., Brooks, L., Buhalis, D., … Wright, R. (2023). Opinion Paper: "So what if ChatGPT wrote it?" Multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI for research, practice and policy. International Journal of Information Management, 71, 102642. https://doi.org/10.1016/j.ijinfomgt.2023.102642

Elahi, M., Afolaranmi, S. O., Martinez Lastra, J. L., & Perez Garcia, J. A. (2023). A comprehensive literature review of the applications of AI techniques through the lifecycle of industrial equipment. Discover Artificial Intelligence, 3(1), 43. https://doi.org/10.1007/s44163-023-00089-x

Esangbedo, C. O., Zhang, J., Esangbedo, M. O., Kone, S. D., & Xu, L. (2023). The role of industry-academia collaboration in enhancing educational opportunities and outcomes under the digital driven Industry 4.0. Journal of Infrastructure, Policy and Development, 8(1). https://doi.org/10.24294/jipd.v8i1.2569

Gratz, E., & Looney, L. (2020). Faculty Resistance to Change: An Examination of Motivators and Barriers to Teaching Online in Higher Education. International Journal of Online Pedagogy and Course Design, 10(1), 1–14. https://doi.org/10.4018/IJOPCD.2020010101

Guo, L., Wang, D., Gu, F., Li, Y., Wang, Y., & Zhou, R. (2021). Evolution and trends in intelligent tutoring systems research: A multidisciplinary and scientometric view. Asia Pacific Education Review, 22(3), 441–461. https://doi.org/10.1007/s12564-021-09697-7

Kamalov, F., Santandreu Calonge, D., & Gurrib, I. (2023). New Era of Artificial Intelligence in Education: Towards a Sustainable Multifaceted Revolution. Sustainability, 15(16), 12451. https://doi.org/10.3390/su151612451

Lim, T., Gottipati, S., & Cheong, M. L. F. (2023). Ethical Considerations for Artificial Intelligence in Educational Assessments: In J. Keengwe (Ed.), Advances in Educational Technologies and Instructional Design (pp. 32–79). IGI Global. https://doi.org/10.4018/979-8-3693-0205-7.ch003

Luckin, R., Cukurova, M., Kent, C., & Du Boulay, B. (2022). Empowering educators to be AI-ready. Computers and Education: Artificial Intelligence, 3, 100076. https://doi.org/10.1016/j.caeai.2022.100076

Mobarak, M. H., Mimona, M. A., Islam, Md. A., Hossain, N., Zohura, F. T., Imtiaz, I., & Rimon, M. I. H. (2023). Scope of machine learning in materials research—A review. Applied Surface Science Advances, 18, 100523. https://doi.org/10.1016/j.apsadv.2023.100523

Morandini, S., Fraboni, F., De Angelis, M., Puzzo, G., Giusino, D., & Pietrantoni, L. (2023). The Impact of Artificial Intelligence on Workers' Skills: Upskilling and Reskilling in Organisations. Informing Science: The International Journal of an Emerging Transdiscipline, 26, 039–068. https://doi.org/ 10.28945/5078\

Ou, S. (2024). Transforming Education: The Evolving Role of Artificial Intelligence in The Students Academic Performance. International Journal of Education and Humanities, 13(2), 163–173. https://doi.org/10.54097/cc1x7r95

Pinto-Coelho, L. (2023). How Artificial Intelligence Is Shaping Medical Imaging Technology: A Survey of Innovations and Applications. Bioengineering, 10(12), 1435. https://doi.org/10.3390/bioengineering10121435

Rayhan, A., Gross, D., & Swajan Rayhan. (2023). Exploring advancements in ai algorithms, deep learning, neural networks, and their applications in various fields. https://doi.org/10.13140/RG.2.2.18923.31522

Rojek, I., Jasiulewicz-Kaczmarek, M., Piechowski, M., & Mikołajewski, D. (2023). An Artificial Intelligence Approach for Improving Maintenance to Supervise Machine Failures and Support Their Repair. Applied Sciences, 13(8), 4971. https://doi.org/10.3390/app13084971

Seo, K., Tang, J., Roll, I., Fels, S., & Yoon, D. (2021). The impact of artificial intelligence on learner–instructor interaction in online learning. International Journal of Educational Technology in Higher Education, 18(1), 54. https://doi.org/10.1186/s41239-021-00292-9

Southworth, J., Migliaccio, K., Glover, J., Glover, J., Reed, D., McCarty, C., Brendemuhl, J., & Thomas, A. (2023). Developing a model for AI Across the curriculum: Transforming the higher education landscape via innovation in AI literacy. Computers and Education: Artificial Intelligence, 4, 100127. https://doi.org/10.1016/j.caeai.2023. 100127

Tuomi, I. (2018). The impact of artificial intelligence on learning, teaching, and education: Policies for the future (M. Cabrera, R. Vuorikari, & Y. Punie, Eds.). Publications Office of the European Union.

Zhai, X., Chu, X., Chai, C. S., Jong, M. S. Y., Istenic, A., Spector, M., Liu, J.-B., Yuan, J., & Li, Y. (2021). A Review of Artificial Intelligence (AI) in Education from 2010 to 2020. Complexity, 2021, 1–18. https://doi.org/ 10.1155/ 2021/ 8812542