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PAPER

Impact of Mobile Learning on Self-Regulated Learning Abilities of Higher Education Students

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ABSTRACT

This study examines the influence of mobile learning (m-learning) on the self-regulated learning skills of college students using the Z-number AROMAN decision-making approach. The rapid integration of mobile technologies into educational practices has transformed traditional learning environments, offering unprecedented opportunities to enhance student autonomy and engagement. This study introduces a novel method for evaluating complex and uncertain educational scenarios through the Z-number AROMAN decision-making process. This approach provides a robust framework for assessing various intricate aspects of self-regulated learning, including goal setting (GS), self-monitoring, and reflective practices. The study underscores the transformative potential of m-learning in education, underscoring the importance of leveraging such technology to foster student-centered learning environments. This study contributes to the body of literature on educational technology, offering valuable insights for educators, policymakers, and scholars seeking to effectively implement m-learning strategies to enhance student learning outcomes.

KEYWORDS

decision-making, Z-numbers, mobile learning (m-learning), the AROMAN method

1 INTRODUCTION

The implementation of mobile learning, also known as m-learning, in higher education has brought about significant changes in the way students interact with course materials and improve their learning abilities. The widespread use of mobile devices, such as smartphones and tablets, has made it easier for students to access a wide range of educational resources and tools. This empowers individuals to take control of their educational journey in a way that was previously impossible. As a result of this shift in perspective, there has been a growing interest in understanding the impact of m-learning on higher education students' ability to engage in self-regulated learning. Self-regulated learning involves various cognitive, metacognitive, and motivational strategies that help individuals set goals, monitor their

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progress, and adjust their learning strategies accordingly. Self-regulated learning is essential for academic success. Mobile technologies allow students to personalize their learning experiences based on their specific needs and interests. This promotes students' independence and responsibility in their educational pursuits. Research indicates that m-learning environments support the development and improvement of self-regulated learning skills among higher education students. Interactive mobile applications enable students to engage in learning activities at their own pace, receive immediate feedback, and monitor their progress over time. Mobile devices offer students the flexibility and accessibility to seamlessly integrate learning into their daily lives. This facilitates continuous knowledge acquisition and skill development beyond the limitations of traditional educational settings, providing a significant advantage. M-learning promotes collaborative learning by enabling students to participate in interactive experiences, interact with peers, share resources, and engage in discussions, regardless of geographical barriers. The social aspect of m-learning not only fosters a sense of community but also encourages students to actively seek assistance and support from their peers. As a result, students can enhance their ability to engage in self-regulated learning by engaging in collaborative problem-solving and sharing knowledge.

When deciding whether to incorporate m-learning into higher education courses, it is important to carefully analyze many aspects. These considerations include the effectiveness of various m-learning strategies and how well they align with students' learning needs and preferences. Evaluating different approaches to m-learning, such as interactive mobile applications, video-based instruction, and game-based learning (GBL), is a crucial part of the decision-making process. The assessment of these methods is based on factors related to self-regulated learning skills, such as goal setting (GS), time management, self-monitoring, seeking help, self-assessment, and motivation. Educational institutions can determine the most effective m-learning options for enhancing students' self-regulated learning abilities through analysis and decision-making processes. Efficient resources and strategic implementation of m-learning initiatives are vital for maximizing their impact on student learning outcomes. This approach also ensures that resources are used effectively. M-learning has the potential to significantly change traditional learning models, empowering students to become proactive, engaged, and self-directed learners in the digital era. The ultimate goal of integrating m-learning into higher education is seamless integration.

1.1 Motivation and contribution

The rapid integration of mobile technologies into educational frameworks, which has fundamentally altered traditional learning environments, is the driving force behind this study. The technological advancements offer researchers unparalleled potential to enhance student autonomy and involvement, which are essential components of effective learning. The objective of this study is to investigate the impact of m-learning on improving self-regulated learning abilities. The goal is to fill a significant gap in the current understanding of how technology can promote self-directed learning among college students.

This study makes a significant contribution by applying the Z-number AROMAN decision-making approach to assess the complex and uncertain nature of educational outcomes. Researchers often utilize the Z-number technique as a reliable framework to explore different aspects of self-regulated learning, such as GS, self-monitoring, and self-reflection. This method is particularly well-suited for addressing the ambiguity and variability that are common in educational settings. It provides a thorough evaluation of the effectiveness of mobile learning.

This study highlights the capacity of m-learning to transform traditional learning environments into student-centered ones. It emphasizes the importance of mobile technology in promoting self-regulation and underscores the need for educators to incorporate these tools into their instructional approaches to enhance personalized and autonomous learning experiences. The insights derived from this research are extremely valuable for researchers, educators, policymakers, and academics, as they provide practical guidance and evidence-based strategies for implementing m-learning programs.

1.2 Structure of the paper

The paper is organized as follows: In Section 2, the literature on multi-criteria decision-making procedures is examined. Section 3 provides basic terminology related to Z-numbers. Section 4 focuses on the suggested Z-number AROMAN method. Section 5 offers an overview of the case study application, presents the results, discusses the theoretical limits, explores the managerial implications, and includes a comparison analysis. Section 6 reviews the findings and outlines future study directions, ultimately concluding the report.

2 LITERATURE REVIEW

Studies have demonstrated that making decisions in complex systems often requires individuals to navigate through uncertainties, ambiguities, and subjective judgments. Researchers have found that conventional decision-making models often struggle to adequately address these challenges. Z-number theory provides a comprehensive framework for capturing and managing uncertainty by representing ambiguous and imprecise information [1]. Researchers can utilize Z-number logic to represent the inherent uncertainty in decision criteria and preferences, facilitating more flexible and comprehensive decision-making processes [2, 3].

The AROMAN approach has gained significant recognition and is extensively used in several sectors due to its exceptional performance and wide range of applications. The methodology proposed by Bošković et al. [4] offers a distinctive strategy for addressing decision-making issues, as exemplified in their analysis of electric car choices. Building upon this initial foundation, later studies have further refined and applied the AROMAN approach in many settings. The MEREC-AROMAN approach, created by Kara et al. [5], is used to assess the levels of sustainable competitiveness in Turkey. In addition, Bošković et al. [6] put forward an enhanced AROMAN methodology for selecting cargo bike delivery solutions. As a researcher, I have investigated the incorporation of fuzzy logic into the AROMAN framework to improve decision-making processes. Nikolić et al. [7] employed an interval type-2 fuzzy AROMAN technique to improve the sustainability of postal networks in rural areas. Likewise, our research team, Čubranić-Dobrodolac et al. [8], suggested a combined fuzzy-AROMAN-Fuller method to choose professional drivers. The AROMAN approach is highly versatile and applicable in various fields, including environmental engineering and sports event management. Alrasheedi et al. [9] proposed an interval-valued intuitionistic fuzzy AROMAN technique for selecting sustainable wastewater treatment technologies, emphasizing its suitability for making important environmental decisions.

In another study, Hu et al. [10] introduced an intuitionistic fuzzy SWARA-AROMAN framework with the aim of improving sports event management.

The AROMAN approach is essential for evaluating the performance of complex systems and assisting in decision-making in dynamic contexts. The model presented by Yalçın et al. [11] utilizes intuitionistic fuzzy logic to evaluate the efficiency of EcoPorts. The study showcases the efficacy of this strategy in assessing sustainability metrics. In addition, Mishra et al. [12] introduced a new method known as the integrated picture fuzzy standard deviation and pivot pairwise assessment method. This methodology was employed to analyze the determinants that impact the process of digital transformation in higher education institutions. The study emphasized the efficacy of the AROMAN technique in strategic planning. Additional methodological progress is incorporating cutting-edge strategies to address specific decision-making obstacles. Kara et al. [13] utilized a Fermatean fuzzy-based model to select truck routing software in last-mile delivery organizations, highlighting the model's capacity to adjust to evolving technical landscapes. In addition, Xiang et al. [14] have proposed a linear programming-based fuzzy AROMAN method to evaluate the advancement of the digital economy in provincial regions. This strategy can be employed in regional development planning to augment its efficacy. The AROMAN approach is widely acknowledged as a versatile and strong decision-making tool in many sectors because of its flexibility, effectiveness, and capacity to adjust to intricate choice contexts. The method undergoes continuous improvement and integration with new methodologies to ensure its evolution, providing significant insights and help for researchers dealing with complex difficulties.

To develop a thorough understanding of decision-making processes across various domains, we will analyze recent research contributions. Moghrani et al. [15] introduced a hybrid RPI-MCDM approach to assess the risks in a belt conveyor system located in Bir El Ater Mine, Algeria. Kumar et al. [16] analyzed the sustainability disclosures of Indian corporations in their study. They utilized the GRI-G4 framework and applied MCDM approaches to evaluate and prioritize these companies based on their sustainability performances. Ramana et al. [17] discussed the prioritization of sites for solar power plants in an uncertain environment. Their study emphasized the complex nature of decision-making in the development of renewable energy infrastructure and the significance of considering uncertainty in the site selection process. Berbiche et al. [18] conducted a study on enhancing the resilience and efficiency of supply chains by implementing decision-making automation using fuzzy logic, as outlined in their research. Khotimah et al. [19] introduced a combined clustering and AHP-TOPSIS decision support architecture. Zhang [20] presented a hybrid methodology in the field of engineering and technology that integrates rough set theory and deep learning to improve the prediction accuracy of thermodynamic parameters. This approach shows promise for enhancing precision and reliability in this field. Altork and Alamayreh [21] carried out a study to optimize hybrid heating systems for residential buildings in Jordan. Their study focused on identifying the most suitable stations and conducting economic evaluations to determine the most effective heating systems for residential structures. Nanduri et al. [22] proposed a revised fuzzy method to automatically categorize cyber hate speech on online social networks in their research. The fuzzy rule-based algorithm for accurately forecasting cardiac disease in data lakes was developed by Mani and Munusamy [23]. Singh et al. [24] conducted a study to explore various parametric evaluation methodologies to improve the reliability of Internet of Things (IoT) systems. Vasudevan et al. [25] have made significant advancements in the study of computational fluid dynamics modeling techniques, particularly in relation to isolated and urban street canyon configurations. The method developed by Yaakob and Gegov [26] utilizes TOPSIS and Z-numbers to effectively manage subjective assessments in collective decision-making. Tüysüz and Kahraman [27] introduced the CODAS technique as a solution to the issue of ambiguity in decision criteria. The CODAS technique incorporates Z-fuzzy numbers, as detailed in the reference. Peng et al. [28] used Z-numbers to enhance the process of multicriteria decision-making. By employing Z-numbers, the researchers successfully captured the hierarchical relationships of dominance and support among the various criteria under evaluation. Azman et al. [29] proposed combining Fuzzy VIKOR with Z-numbers as a decision-making tool for complex problems. The research presented here illustrates the versatility of Z-numbers in improving decision-making processes across multiple fields.

3 PRELIMINARIES

This portion of the study explores some essential IFS notions applicable to the universal set X.

Definition 3.1. A Z-number is a mathematical construct introduced by Zadeh [1]. It consists of a pair of fuzzy numbers (A, B), where:

- A represents a restriction on the values that a variable can take.
- B represents the reliability or certainty of the restriction A.

Mathematically, a Z-number is expressed as: $Z = (A, B)$, where A is a fuzzy subset [30] of a universal set X (the domain of discourse), and B is a fuzzy subset of the interval $[0, 1]$, representing the probability or confidence level associated with A.

Here we used the golden rule representative value method for the ranking of Z-numbers given by Cheng et al. [31].

Example 3.1. Consider a scenario where we need to estimate the delivery time for a package.

Fuzzy constraint (A): Delivery time

The delivery time is uncertain but can be described using a fuzzy number. Let's say the delivery time is roughly 5 to 7 days. We represent this as a fuzzy number A with values in the set {5, 6, 7}. The membership values for these days might be:

$$A = \{(5, 0.6), (6, 1.0), (7, 0.8)\}$$

This indicates that day 5 has a membership value of 0.6 (moderate possibility), day 6 has a membership value of 1.0 (high possibility), and day 7 has a membership value of 0.8 (fairly high possibility).

Fuzzy reliability (B): Confidence in delivery time

The confidence in this estimate can also be represented as a fuzzy number. Suppose we are "fairly certain" about the delivery time being between 5 and 7 days. We describe this confidence using a fuzzy term B with values in the set {0.6, 0.8, 1.0}. The membership values might be:

$$B = \{(0.6, 0.5), (0.8, 0.7), (1.0, 1.0)\}$$

This indicates that a confidence level of 0.6 has a membership value of 0.5 (somewhat likely), 0.8 has a membership value of 0.7 (quite likely), and 1.0 has a membership value of 1.0 (very likely).

Together, the Z-number Z is represented as $Z = (A, B)$, where A captures the fuzzy constraint on the delivery time and B captures the fuzzy reliability of this constraint.

To utilize this Z-number in decision-making or further analysis, it often needs to be converted into a more manageable form.

4 DECISION-MAKING ALGORITHM

In this exploration of an MCDM conundrum, each of the n viable solutions will be evaluated based on m different qualities and ranked appropriately. It is of the utmost significance to assemble a team of p highly competent professionals, each of whose ratings must be more than zero but whose sum must equal one. In this algorithm, the alternative $Q_j(i = 1, 2, \ldots, r)$ was picked by the professionals, and the criteria $C_i(i = 1, 2, \ldots, s)$ were also chosen; hence, the evaluation result is presented in terms of Z-numbers. Moreover, $\mathfrak{W}_t$ is the WV for the decision variable C_i satisfying the conditions, $\mathfrak{W}_t \geq 0$ and $\sum_{t=1}^{s} \mathfrak{W}_t = 1$.

Algorithm

Step 1: Obtain the decision matrix ε^g using the Z-numbers from the DMs.

Step 2: Compose the score matrix by using the SF of the Z-numbers.

Step 3: Standardize the input data in the decision-making matrix through normalization. After creating the matrix with input data, the subsequent step entails organizing the data into intervals spanning from 0 to 1. Two distinct methods are employed for normalizing the data through standardization.

Normalization 1 (Linear):

$$\beth_{ij} = \frac{\xi_{ij}^{\gamma} - \xi_{ij}^{\gamma}}{\xi_{ij}^{\gamma} - \xi_{ij}^{\gamma}}, i = 1,2,\ldots,r; j = 1,2,\ldots,s \tag{1}$$

Normalization 2 (Vector):

$$\Xi_{ij}^{*} = \frac{\xi_{ij}^{\gamma\wedge}}{\sqrt{\sum_{i=1}^{m} \xi_{ij}^{\gamma_{ij}^{\wedge}}}}, \ i = 1,2,\ldots,r; j = 1,2,\ldots,s \tag{2}$$

Step 4: Utilize averaged aggregation normalization to standardize the input data. This systematic method ensures consistent and meaningful comparisons across various criteria during the data normalization process. The process of aggregated average normalization involves the application of Equation (3).

$$\beth_{ij}^{\text{norm}} = \frac{\chi \beth_{ij} + (1-\chi)\beth_{ij}^{*}}{2}, i = 1,2,\ldots,r; j = 1,2,\ldots,s \tag{3}$$

where $\beth_{ij}^{\text{norm}}$ denotes the result of aggregated average normalization, and where X functions as a weighting factor within the range of 0 to 1. In our specific context, we assign the value of X as 0.5.

Step 5: Perform the multiplication of the aggregated averaged normalized-making matrix by the criteria weights to yield a weighted decision-making matrix, in accordance with Equation (4).

$$\hat{\beth}_{ij} = W_{ij} \cdot \beth_{ij}^{\text{norm}}, i = 1,2,\ldots,r; j = 1,2,\ldots,s \tag{4}$$

Step 6: Articulate the normalized weighted values distinctly for the criteria type min(ω_i) and the max type (Ω_i) utilizing Equation (5). This equation presents a clear framework for computing the normalized weighted values, ensuring a comprehensive representation of the criteria under both minimization and maximization considerations.

$$\omega_{\beth(i)} = \sum_{j=1}^{n} \hat{\beth}_{ij}^{(\min)}, \; i = 1,2,\ldots,r \,;\, j = 1,2,\ldots,s \tag{5}$$

Step 7: Determine the conclusive ranking of alternatives by considering all relevant factors and evaluations. This final ranking encapsulates the comprehensive assessment of the alternatives based on the applied methodologies and criteria, providing a clear order that reflects their overall performance and suitability in the decision-making context:

$$R_i = \omega^{\xi^{\gamma\wedge}} + \Omega_i^{(1-\xi^{\gamma\wedge})}, \; i = 1,2,\ldots,r \tag{6}$$

In this context, (R_i) serves as the label for the ranked alternatives, while $\xi^{\gamma\wedge}$ represents the coefficient degree associated with the criterion type. Given the consideration of both criterion types, a value of 0.5 is assigned to $\xi^{\gamma\wedge}$.

A pictorial view of the proposed algorithm can be seen in Figure 1.

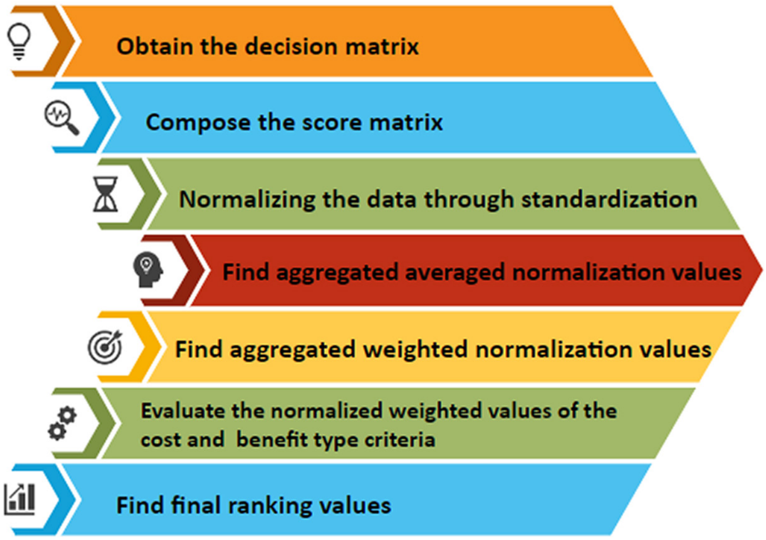

Fig. 1. Pictorial view of the proposed algorithm

5 CASE STUDY

The integration of mobile devices into educational settings has significantly expanded the scope of m-learning. An increasing body of study is focusing on the ramifications of m-learning for self-regulated learning (SRL). SRL is a comprehensive concept that encompasses a range of abilities, empowering students to efficiently manage and guide their own learning activities. The abilities encompassed in this context of SRL include GS, self-monitoring, and self-reflection. Higher education institutions are actively seeking m-learning solutions that can effectively enhance students' SRL skills. These institutions are actively pursuing these tactics. The Z-number decision-making process serves as a robust framework to evaluate and compare the effectiveness of different m-learning systems, considering the inherent complexities and differences in educational outcomes. The objective of this method is to provide a comprehensive approach to assessing the influence of various m-learning tools and strategies on students' ability to independently regulate their learning. This approach considers both the reliability of the information and the underlying ambiguity surrounding it. By employing this approach, educational researchers and policymakers can gain a profound understanding of which m-learning strategies are most favorable for fostering SRL. This knowledge will then inform the creation and adoption of more efficient educational technologies and practices.

5.1 Definition of alternatives

Interactive mobile apps (IMA): IMA provides a dynamic learning strategy that promotes active participation and interactivity through various features such as quizzes, flashcards, interactive exercises, and gamified aspects. Prominent examples of these applications include Duolingo, renowned for its language acquisition capabilities; Khan Academy, which provides a diverse array of disciplines, and Quizlet, a helpful tool for studying. These platforms are widely acclaimed for their engaging quality, offering customized learning routes, immediate feedback systems, and unparalleled accessibility, enabling students to pursue education at their convenience and from any place. However, developing high-quality interactive mobile applications necessitates a substantial commitment of both time and resources. To achieve a seamless integration of interactive components and uphold educational authenticity, meticulous attention to detail and robust development procedures are essential. Additionally, the wide range of applications available may make it easier for students to become distracted by non-educational content, which will affect their overall learning experience. Thus, it is imperative for educators and developers to concentrate on creating applications that are abundant in content and prioritize instructional significance while reducing the attractiveness of irrelevant applications. Educational apps vary significantly in terms of their quality and efficacy. While several applications offer comprehensive and meticulously curated educational resources, others may not adhere to academic benchmarks, leading to disparities in learning achievements. Therefore, it is imperative for students and instructors to meticulously select programs that align with their educational objectives and provide significant learning prospects. Despite the inherent challenges, interactive mobile applications remain an essential component of contemporary education, offering unparalleled chances for involvement and enriching the learning process.

Mobile learning management systems (MLMS): MLMSs are of paramount importance in modern education as they enable the smooth dissemination and management of educational resources through the utilization of mobile devices. Prominent instances such as Moodle Mobile, Blackboard Mobile Learn, and Canvas Student have garnered widespread recognition for their ability to enhance the scholastic experience. These systems provide instructors and students with a streamlined platform to access course materials, submit assignments, participate in discussion forums, and remain current in real-time. Although MLMS provides a multitude of advantages, it also presents distinct challenges. One significant concern pertains to their reliance on a dependable Internet connection, which may present obstacles in areas with limited connectivity or in the event of network outages. Moreover, as users acclimatize to the features and interface of these platforms, they may experience a phase of adaptation that influences their overall user experience. In addition, sporadic technological malfunctions and system failures could potentially transpire, impeding the educational process and causing user dissatisfaction. MLMS has exhibited considerable benefits, significantly augmenting the effectiveness and efficiency of instructional delivery. MLMS systems offer instructors and students a practical and user-friendly means to participate in educational activities remotely, from any location, and at their own convenience. Ensuring that all individuals have equitable and consistent access to high-quality education is of the utmost importance, particularly in light of the continuous progress in technology. This entails addressing the limitations of MLMS, including challenges related to internet connectivity and complexities within the user interface.

Video-based learning (VBL): VBL is an educational method that primarily utilizes video content to deliver academic information. This method is specifically designed to accommodate various learning styles, allowing individuals to pause, rewind, and replay content as necessary. This feature improves comprehension and aids in retaining information. The widespread adoption of VBL has significantly increased the accessibility of educational resources, enabling learners to easily access a wide range of specialized information from any location with an internet connection. However, it is important to acknowledge that relying solely on video content can lead to passive absorption of information, especially if it lacks interactive elements or opportunities for active engagement. Additionally, a significant challenge of VBL is the need for a considerable amount of bandwidth, which may pose difficulties for students with limited internet connectivity or data access. The importance of considering inclusivity and accessibility of educational materials becomes evident when implementing video-based teaching methods, highlighting the disparities in access to digital resources. To address the risk of passive learning and tackle accessibility issues, educators and instructional designers are advised to integrate interactive elements, such as quizzes, debates, and hands-on activities, into video-based lessons. By promoting active participation and fostering learner engagement with the material, VBL can be a powerful tool for facilitating deep understanding and creating meaningful learning experiences.

Game-based learning: GBL revolutionizes conventional teaching approaches by integrating dynamic game design ideas, thereby enhancing engagement, motivation, and knowledge retention. GBL's captivating and interactive methodology stimulates learners, fostering the development of critical thinking and problem-solving skills. While GBL offers numerous benefits, it also presents intricate challenges. Successfully blending educational content with engaging game features requires adept skills and intentional design choices. Moreover, the significance of deliberate execution and moderation is underscored due to concerns about excessive screen time. Additionally, the effective implementation of GBL relies on robust technological infrastructure, ensuring seamless accessibility and smooth functionality in various educational settings. GBL stands at the forefront of educational innovation, providing an interactive platform for learners to develop essential skills and spark their enthusiasm for discovery and learning. Its ability to surpass traditional teaching constraints highlights its importance in shaping the future of education, equipping learners with the tools needed to excel in a constantly evolving knowledge landscape.

Social media integration (SMI): By utilizing SMI, educational institutions can harness platforms such as Facebook, Twitter, and LinkedIn to promote seamless communication, collaboration, and the dissemination of instructional content. This method encourages collaboration among peers, facilitates immediate conversation, and offers access to a broad array of varied information and viewpoints.

The presence of non-educational content, which has the potential to divert students, reduces the integration's effectiveness. Furthermore, it is crucial to tackle privacy concerns and the possible hazards of cyberbullying by introducing proactive ways to mitigate them. Developing efficient integration tactics entails cultivating secure and nurturing online learning environments where instructional material takes precedence over superfluous diversions. This encompasses the execution of robust privacy settings, strict enforcement of community norms, and the availability of resources to rapidly tackle cases of cyberbullying. Furthermore, it is imperative for instructors to actively engage in discussions, oversee content, and foster constructive interactions with students on these platforms. To completely maximize the benefits of social contact and collaborative learning, it is essential to meticulously strategize and facilitate the process. Teachers possess the capacity to meticulously choose and arrange valuable information, foster reflective discussions, and facilitate the sharing of knowledge among pupils. Through the use of tools such as groups, chats, and forums, learners are afforded the option to collaborate on projects, share ideas, and offer mutual assistance to one another along their learning journey.

Podcast learning (PL): PL has gained significant popularity as an efficient method of delivering instructional knowledge through audio recordings. It provides a variety of formats, such as lectures, interviews, and narratives, making it a versatile approach to learning. Prominent instances such as TED Talks Education, The EdSurge Podcast, and Harvard Business Review IdeaCast have showcased the efficacy of knowledge dissemination. Podcasts provide a distinct benefit in terms of versatility, allowing individuals to acquire knowledge while in motion or engage in multiple tasks simultaneously. Furthermore, podcasts offer a medium for a diverse array of viewpoints and useful knowledge, enriching the educational experience. Acquiring knowledge via podcasts might present significant difficulties. Some individuals may encounter difficulties comprehending the content in the absence of visual aids. Remaining attentive during audio-based learning sessions can be particularly difficult, particularly in the presence of environmental distractions. Furthermore, the production of top-notch audio content necessitates a significant level of commitment, exertion, and assets. It requires proficiency in audio engineering and the generation of content. Despite the challenges, PL is a vital instrument in the educational field, offering accessible and captivating opportunities for obtaining knowledge and enrichment.

5.2 Definition of criteria

Goal setting (C1): GS is crucial for achieving academic achievement in the realm of education. It demonstrates pupils' capacity to establish attainable learning goals and strategize the required actions to achieve them. This crucial talent not only directs learning endeavors but also sustains motivation and facilitates the ongoing evaluation of progress. MLMS, or multi-level marketing systems, are valuable assets in this pursuit, providing students with robust resources to articulate and monitor their objectives with efficiency. Structured game levels and embedded learning objectives are essential in promoting a culture of intentional GS among learners in the dynamic environments of GBL and visual-based learning.

Time management (C2): Effective time management is essential for students to efficiently juggle their academic obligations with other commitments and fulfill deadlines. Learning management systems (LMS) offer a variety of beneficial functionalities, such as calendars, reminders, and time tracking tools, that aid students in maintaining organization and effectively managing their schedules. IMA improves the learning experience by incorporating timers and progress monitors, enabling students to efficiently manage their time while studying. The PL platform is renowned for its remarkable adaptability, enabling students to acquire knowledge while engaging in many tasks, thereby enhancing productivity and optimizing learning potential.

Self-monitoring (C3): Self-monitoring is an essential ability in education that enables learners to reflect on their learning strategies and make the requisite modifications for improved outcomes. This approach is essential for the identification and resolution of deficiencies while also fostering a culture of ongoing enhancement. IMA are highly proficient in this domain, as they possess the capability to offer prompt feedback and comprehensive progress monitoring capabilities, allowing students to closely monitor their learning advancement. Similarly, MLMS are essential in empowering students to independently assess their academic advancement through the provision of comprehensive analytics and tracking capabilities. This enables students to contemplate their academic progress over extended periods of time. Furthermore, GBL improves self-monitoring endeavors by integrating feedback mechanisms into gaming interfaces. Learners can evaluate their success using real-time analytics and in-game quizzes.

Help-seeking (C4): In the domain of self-regulated learning, the capacity to actively seek help when necessary is a vital skill that fosters collaboration and facilitates a more profound understanding of the topic. Through the incorporation of social media, students can readily get peer support and engage in collaborative problem-solving activities. This integration offers a broad scope and facilitates real-time interaction. Conversely, MLMS provides regulated settings that promote behaviors involving requesting help. These settings consist of features such as discussion boards and direct messaging with instructors. Learners are empowered to actively seek help and engage in peer-driven learning initiatives by utilizing interactive mobile applications. These apps serve as a complement to existing platforms and incorporate community-oriented features and additional resources. By incorporating diverse technological tools and platforms, educational institutions can create an environment where students actively seek help as a crucial aspect of their self-regulated learning process, ultimately enhancing academic performance and personal growth.

Self-evaluation (C5): Self-evaluation is a vital competency in the field of educational pedagogy, representing the essence of ongoing progress and the cultivation of a growth mindset. It functions as an essential instrument for students, enabling them to evaluate their progress and educational achievements in connection with predetermined goals and standard benchmarks. VBL is an efficacious instrument that facilitates comprehensive review and introspection among students regarding their comprehension of video material. Furthermore, MLMS equips students with an assortment of sophisticated tools capable of monitoring and evaluating their development throughout the course of time. Furthermore, IMA provides an extensive selection of quizzes and assessments, enabling students to monitor their educational progress and evaluate their comprehension on an engaging platform. Learning is enabled to reflect, readjust, and embark on a journey of continuous development through the utilization of these varied approaches.

Motivation (C6): Motivation has a vital role in influencing students' learning experiences, affecting their level of involvement and perseverance in academic pursuits. GBL is a potent tool for stimulating learners through the use of captivating gameplay mechanics and gratifying experiences. IMA offers personalized learning paths, engaging learners with interactive content and immediate feedback, hence promoting intrinsic motivation. Incorporating social media into the educational setting cultivates a robust sense of camaraderie and promotes cooperation among classmates, thereby enhancing motivation through mutual assistance. Furthermore, VBL offers a plethora of inspiration, allowing students to delve into other viewpoints and acquire useful insights from professionals, potentially sparking their excitement for learning. Through the strategic use of various instructional methods, instructors can motivate students to approach difficulties with resolve and eagerness, ultimately resulting in their achievement in self-directed learning.

5.3 Experimental results

There are six alternatives given as above, Q_1 = IMA, Q_2 = MLMS, Q_3 = VBL, Q_4 = GBL, Q_5 = SMI and Q_6 = PL. All criteria have equal in this case.

Step 1: Obtain the decision matrix $\mathcal{E}^{g}_{(p)} = \left(\mathfrak{Y}^{(p)}_{ji}\right)_{n\times m}$ using the Z-numbers from the DM, given in Table 1.

Table 1. Normalized decision matrix

	C_1	C_2	C_3	C_4	C_5	C_6
Q_1	(0.529, 0.842)	(0.276, 0.139)	(0.194, 0.758)	(0.663, 0.245)	(0.721, 0.538)	(0.193, 0.682)
Q_2	(0.345, 0.763)	(0.567, 0.896)	(0.485, 0.213)	(0.874, 0.398)	(0.092, 0.658)	(0.543, 0.237)
Q_3	(0.217, 0.639)	(0.781, 0.347)	(0.629, 0.518)	(0.176, 0.425)	(0.825, 0.742)	(0.281, 0.196)
Q_4	(0.385, 0.297)	(0.413, 0.612)	(0.347, 0.235)	(0.762, 0.187)	(0.194, 0.521)	(0.718, 0.813)
Q_5	(0.291, 0.582)	(0.219, 0.375)	(0.493, 0.684)	(0.492, 0.719)	(0.154, 0.284)	(0.375, 0.539)
Q_6	(0.536, 0.462)	(0.851, 0.467)	(0.362, 0.152)	(0.652, 0.385)	(0.526, 0.252)	(0.217, 0.623)

Step 2: Construct the score matrix, by utilizing the SF, given in Table 2.

Table 2. Score matrix

Q_1	0.7834	0.3127	0.8972	0.1013	0.5729	0.3652
Q_2	0.4835	0.6093	0.1467	0.7481	0.4234	0.9832
Q_3	0.6821	0.5712	0.7904	0.3651	0.2357	0.4238
Q_4	0.1209	0.3948	0.2764	0.5468	0.1845	0.6534
Q_5	0.9283	0.2671	0.5786	0.8345	0.6392	0.4928
Q_6	0.5426	0.3325	0.3452	0.1345	0.6537	0.3245

Step 3: Normalize the fuzzy decision matrix, linear and vector normalization given in Tables 3 and 4, respectively.

Table 3. Linear normalization of fuzzy decision matrix

0.8205	0.1333	1.0000	0.0000	0.8278	0.0618
0.4491	1.0000	0.0000	0.8822	0.5092	1.0000
0.6951	0.8887	0.8577	0.3598	0.1091	0.1508
0.0000	0.3732	0.1728	0.6076	0.0000	0.4993
1.0000	0.0000	0.5755	1.0000	0.9691	0.2555
0.5223	0.1911	0.2645	0.0453	1.0000	0.0000

Table 4. Vector normalization of fuzzy decision matrix

0.4971	0.2938	0.6374	0.0773	0.4786	0.2548
0.3068	0.5724	0.1042	0.5710	0.3537	0.6859
0.4328	0.5366	0.5615	0.2787	0.1969	0.2957
0.0767	0.3709	0.1964	0.4173	0.1541	0.4558
0.5891	0.2509	0.4110	0.6369	0.5340	0.3438
0.3443	0.3124	0.2452	0.1027	0.5461	0.2264

Step 4: Find aggregated averaged normalization values, by taking the value of ξ is 0.50, given in Table 5.

Table 5. Aggregated averaged normalization values

0.3294	0.1068	0.4093	0.0193	0.3266	0.0791
0.1890	0.3931	0.0261	0.3633	0.2157	0.4215
0.2820	0.3563	0.3548	0.1596	0.0765	0.1116
0.0192	0.1860	0.0923	0.2562	0.0385	0.2388
0.3973	0.0627	0.2466	0.4092	0.3758	0.1498
0.2167	0.1259	0.1274	0.0370	0.3865	0.0566

Step 5: Compute the weighted decision matrix, given in Table 6.

Table 6. Aggregated weighted normalization values

0.0550	0.0178	0.0684	0.0032	0.0545	0.0132
0.0316	0.0656	0.0044	0.0607	0.0360	0.0704
0.0471	0.0595	0.0593	0.0267	0.0128	0.0186
0.0032	0.0311	0.0154	0.0428	0.0064	0.0399
0.0663	0.0105	0.0412	0.0683	0.0628	0.0250
0.0362	0.0210	0.0213	0.0062	0.0645	0.0095

Steps 6 and 7: Evaluate the normalized weighted values of the cost type criteria and the benefit type criteria, and final ranking values y_i, given in Table 7.

Table 7. Final ranking values

y_1	0.512939
y_2	0.664497
y_3	0.641665
y_4	0.485613
y_5	0.529855
y_6	0.481178

As per these values ranking will be, $Q_2 > Q_3 > Q_5 > Q_1 > Q_4 > Q_6$.

5.4 Comparative analysis

In our thorough comparative research, we extensively evaluated the feasibility and effectiveness of various decision-making methods within the proposed framework. By conducting detailed investigations and integrating major validation and robustness checks at each stage, we ensured the reliability and consistency of our results. These efforts highlight the overall importance of our research, establishing a solid basis for our conclusions. Table 8 provides a succinct summary of the key findings from our study. Each examined factor contributes significantly to revealing nuanced insights, thus offering a comprehensive understanding of the advantages and disadvantages of different decision-making techniques.

Table 8. T-Comparison results

Reference	Methodologies	Rankings
[26]	TOPSIS	$Q_2 > Q_5 > Q_3 > Q_6 > Q_4 > Q_1$
[27]	CODAS	$Q_2 > Q_6 > Q_5 > Q_4 > Q_1 > Q_3$
[28]	ELECTRE-III	$Q_2 > Q_3 > Q_5 > Q_4 > Q_1 > Q_6$
[29]	VIKOR	$Q_2 > Q_1 > Q_3 > Q_5 > Q_4 > Q_6$
Proposed		$Q_2 > Q_3 > Q_5 > Q_1 > Q_4 > Q_6$

5.5 Theoretical limitations

The theoretical framework employed in this investigation, while proficient in addressing the intricacy and unpredictability of educational settings, does possess specific constraints. The Z-number AROMAN decision-making approach, despite its superior capabilities in integrating information reliability and managing ambiguity, may encounter challenges in practical application. The primary reason for this is the demanding computational needs and the requirement for precise input data. Furthermore, it is crucial to acknowledge that subjective evaluations in educational environments may vary in their interpretation and dependability as a result of the varied viewpoints and experiences of the individuals involved. The Z-number methodology provides a thorough framework for evaluating many facets of self-regulated learning, such as goal establishment, self-monitoring, and reflection. Nevertheless, it may not comprehensively consider the fluid and progressive characteristics of these abilities as they mature throughout time. The assessment's fixed character may not accurately capture the dynamic changes and adjustments in student learning habits over time. Furthermore, the utilization of technological platforms for the gathering and examination of data may result in biases related to the accessibility of technology and the competency of users, thereby impacting the precision of the outcomes. These limitations highlight the significance of interpreting the data carefully and underscore the importance of doing qualitative research to improve our comprehension of the influence of m-learning on self-regulated learning.

5.6 Managerial implications

The findings of this study have substantial significance for educational management and policymakers that aim to enhance student learning outcomes through the use of technology. Integrating m-learning technologies can significantly improve students' capacity to self-regulate their own learning, a crucial factor in attaining academic achievement and cultivating a lifetime passion for learning. It is imperative for educational managers to prioritize the investment in interactive mobile applications, MLMS, and other m-learning platforms that enable GS, self-monitoring, and self-reflection. The use of the Z-number AROMAN decision-making methodology in assessing m-learning efforts highlights the importance of utilizing dependable, data-driven methods to evaluate educational technologies. Managers can make educated decisions by thoroughly evaluating m-learning alternatives using this approach. This guarantees that the chosen tactics are appropriate for improving self-regulated learning. Policymakers should consider the potential of m-learning to democratize education by offering high-quality materials to a broader student population. Investments in infrastructure, such as robust internet connectivity and adequate technical assistance, are essential for optimizing the benefits of m-learning technology.

6 CONCLUSIONS

Ultimately, this study highlights the significant influence of m-learning on the self-regulated learning capabilities of college students, utilizing the Z-number AROMAN decision-making approach. The rapid integration of mobile technologies into educational paradigms has brought about a new era of learning, providing unique opportunities to empower students and increase their involvement. This research introduces a new framework, the Z-number AROMAN decision-making process, which aims to navigate complex and uncertain educational landscapes. It effectively assesses important aspects of self-regulated learning, including GS, self-monitoring, and reflective practices. The findings highlight the significant impact of m-learning in transforming educational practices, emphasizing the need to utilize this technology to foster student-centered learning environments. This study provides valuable insights for educators, policymakers, and scholars interested in implementing m-learning strategies to enhance student learning outcomes. By contributing to the existing body of literature on educational technology, it offers actionable information that can be put into practice. As educational institutions increasingly adopt digital innovation, the results of this research provide a valuable and timely resource for driving meaningful progress in the fields of m-learning and student-centered education.

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