A Neutrosophic multi-criteria approach for implementing technology in education

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Abstract

The COVID-19 epidemic has greatly expedited the utilization of technology in the realm of education, resulting in the extensive implementation of totally online teaching approaches. These approaches have undergone thorough analysis in various scholarly articles in recent years. This study applies theories of technology acceptance and use in the educational process, employing Neutrosophic analysis to assess criteria for technology utilization in education. The study commenced by formulating an equation to investigate the patterns of technology uptake and use between 2010 and 2024. Additionally, a comprehensive evaluation of the latest literature since 2000 was conducted to identify prevailing trends. The findings suggest that usage plays a vital role in the Technology Acceptance Model (TAM), and structural equations are used as a method to measure it. Neutrosophic analysis provides a thorough and sophisticated viewpoint on the integration of technology in education, emphasizing both the accomplishments made and the obstacles that still exist in this developing area.

Keywords: Neutrosophic multi-criteria method; technology diffusion; educational technology

1. Introduction

The integration of technology into education has been going on for more than 20 years, but the trend has accelerated in recent years as the COVID-19 pandemic has sparked renewed interest in student behavior. about the potential for change in their learning. Their interests, abilities, and even willingness to embrace technology and use it in the learning process.

Regarding the concept of students as consumers with preferences, budget constraints, and an optimal choice structure, neoclassical economic theory uses a set of preference axioms to suggest that students "choose over other available educational options." But at some point, you'll make a choice." Now that in-person learning is back and both are available, it makes sense that students continue to choose in-person learning because it is the preferred option.

As students change their interests based on their experiences and emotions during remote learning during the pandemic, it is no longer possible to meet all the assumptions of traditional neoclassical theory, and to “further advance economic theory.” It is necessary to consider behavioral economics. A reliable hypothesis. “On human behavior” [1].

Thus, in neoclassical theory, people make decisions without taking into account the environment, while in the contextual analysis of economic behavior, people make decisions based on context and emotions, either internal (social norms) or external (e.g. market prices). According to the theory, people create reference points that allow them to correct their decisions based on past beliefs and experiences, as well as fear of losses in uncertain situations in risk-averse scenarios [2].

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Therefore, if students change their preferences and actively seek to integrate technology from a “starting point” determined by their experiences and emotions during the pandemic, this change can be explained by the findings of behavioral economics.

Whether a learner is risk-averse, Neutrosophic, or risk-seeking, decisions about how to learn depend on past experiences (reference points) and a set of internal conditions that determine what a learner will learn. may be affected by. These are called visual models. Resolved; thus, "the main characteristic of agents is not that they have poor reasoning abilities, but that they often act intuitively." The actions of these agents are not guided by what they can calculate. there is no. "[3]

Some models attempt to measure students' broader intentions to use technology in educational activities beyond simple changes in learning style. These models include the Technology Acceptance Model (TAM); the Unified Theory of Technology Acceptance and Use (UTAU); Technology Acceptance Model 3 (TAM3) and the Motivation Model.

Each of these models has been used in recent years to drive educational research on technology integration and can be evaluated as Neutrosophic research rather than focusing on the literature and meta-analyses of how technology integration is used in different contexts and purposes. Neuroanalysis measures and analyzes the scientific production of an industry or research field by analyzing scientific publications.

This method focuses on the use of Neutrosophic indicators. Neutrosophic indicators can be divided into three categories: "Quantitative indicators that measure the productivity of a particular researcher or research group" Performance indicators measure the quality of a journal, researcher, or research group. "Structural indicators measure the relationship between publications, authors, or research fields." [4] Meta-analysis is a quantitative research technique for synthesizing and pooling the results of several empirical studies on a particular topic. The analysis involves collecting and compiling the results of several studies on the same research question and measuring the relationship between the variables of interest to draw accurate and meaningful conclusions. It is more reliable.

A literature review is a research method that aims to identify, evaluate, and compile relevant information on a particular research topic, while a literature search involves a thorough search of relevant documents; critically reviewing and evaluating the selected studies, including their design and review; analyzing and writing comments [5].

Focusing on Neutrosophic analysis, there are at least two unique alternatives related to performance and scientific mapping, and connectivity analysis that integrates network and ensemble parameters: Effectiveness studies rely on quantitative measures related to publications, citations (visibility), and a measure of impact that is a combination of the two.

2. Related Work

The neutrosophic multicriteria method (MCNM) emerges as an innovative and powerful tool in decision-making, particularly in complex and ambiguous contexts where traditional evaluations may fall short. This approach is distinguished by its ability to handle the uncertainty, ambiguity, and imprecision inherent in many decision problems through the inclusion of three elements: the true, false, and neutrosophic components. This triple representation allows for greater flexibility and precision in modeling and evaluating multiple criteria, thus providing a more comprehensive and nuanced view of the alternatives under consideration [6].

The application of MCNM spans a wide range of domains, from business management and engineering to medicine and urban planning. In the business sphere, for instance, it can be employed for supplier selection, investment project evaluation, or supply chain optimization, enabling organizations to more effectively address the complexity and uncertainty inherent in such strategic decisions. Similarly, in medicine, MCNM can be used for disease diagnosis, treatment evaluation, and resource allocation, considering multiple factors and criteria, as well as their interrelationships.

One of the main advantages of MCNM lies in its ability to incorporate the subjectivity and imprecision inherent in many human decisions, allowing for a more faithful representation of reality and a more informed and robust decision-making process. Additionally, its flexibility and adaptability make it relevant in a wide variety of situations and contexts, making it a valuable tool for decision-makers in various disciplines and fields of action [7].

However, it is important to acknowledge that the use of MCNM presents challenges and limitations. The proper collection and weighting of criteria, as well as the interpretation of results, can pose difficulties in certain cases.

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Moreover, its application requires a solid understanding of the underlying theoretical foundations and careful consideration of associated assumptions and limitations. Despite these challenges, MCNM remains a promising tool for addressing complex and ambiguous decision problems, offering new perspectives and approaches to effective decision-making in an increasingly dynamic and changing environment.

We describe how a Neutrosophic multiple criteria approach works to, assess technology adoption standards in educational settings. The method uses a Neutrosophic logic and expresses uncertainty using, operators to aggregate information [8].

The aim is to provide a method for managing the workflow for, evaluating criteria for the use of technology in education ., It adopts a multidisciplinary and multi-criteria approach, where the basis for concluding is, determined by the evaluation indicators. It includes a processing phase during which a mathematical, analysis of the solution is performed, and at the end, an evaluation of criteria for the use of technology in education is generated as, an output parameter of the method.

technology use standards in education are based on four major steps: determining the evaluation indicators, determining the weights for the indicators, collecting information, and preparing the evaluation. [9]:

Activity 1 Identify evaluation metrics.

A multidisciplinary and multi-criteria approach is used to define the evaluation indicators, which are used to evaluate standards for the use of technology in education based on the opinions of experts involved in this process. It is recommended to convene a meeting of 5-7 experts to participate in this process.

Activity 2 Determine the weights of the indicators.

They are evaluated based on the indicators obtained in the previous process to determine the weightage to be assigned to each carrier. Utilizing experts in this process is part of the business development plan.

Activity 3. Summary of information:

Information gathering is the most important task in this method. This is the mechanism used to make evaluations or decisions in decision support systems. This involves transforming a set of data (fuzzy set) into a single element [10].

T operator TA : $[0,1] * [0,1] \rightarrow [0,1]$ is a standard operator T if it satisfies the following properties:

1. Reciprocity $T(x, y) = T(y, x)$.
2. Associativity$T(x, T(y, z) = T(T(x,y), Z)$.
3. $T(x, y) > (x, y)$ is monotonically increasing if $x \geq x' \cap y \geq y'$.
4. Neutral element $T(x, 1) = x$.

OWA (Ordered Weighted Aggregation) operators allow you to aggregate information and obtain representative values according to predefined parameters. Decision-makers can aggregate information based on their desired level of optimism or pessimism [110-15]

Definition 2: OWA operator. A function: $R^n \rightarrow R$ is an n-dimensional OWA operator if it is connected to an n-dimensional vector W such that its components satisfy [16].

1) $CC \in [0,1]$,
2) $\sum^n_{j=1} w_j = 1$, e
3) $F(a_1, a_2, ..., an_n)$ is equal to $\sum^n_{j=1} W_j b_j$

Here, b_{j_j} has volume a j.

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The sum coefficient can be expressed using vector notation as in Equation 1.

$$F\ (a_1, a_2 \ldots a_p) = W\,b \tag{1}$$

W: The OWA weight vector associated with the sentence.

is a resultant vector that's positioned so that the largest component of B is equal to $b\,j$, which is the most important component.

The Neutrosophic count can be expressed using the Neutrosophic logic as follows:

$N = \{(T, I, F) : T, I, F \subseteq [0, 1]\}$,

, and from each set p we get [44], [45], [46], [47].

$$v\ (p) = (T, I, F) \tag{2}$$

T: Represents the values of truth. I: Represents indeterminacy. F: Represents the values of falsehood.

Mathematically, the Neutrosophic operator OWA can be defined as a double row (W, B), as expressed in Equation 3.

$$\boxed{(T,I,F) = \sum (T,I,F)\ rij(T,I,F)} \quad (3)$$

OWA weight vector associated with a set of true, false, and unknown distances (T, I, F).

an ordered composite vector whose largest j-component of B is bj, which is the largest j-component of ai True, False, and Indeterminate Space (T, I, F) [17, 18]

The proposed method is based on a synthetic method to count Neutrosophics using the OWA operator [19].

Step 4 – Classification and Numerical Valuation Scale Assignment

Once the information is entered, the results of the process are accurately recorded. This information shows the results of the methodology used to evaluate the standards of technology use in education.

This indicates a systematic approach to recording and interpreting the results, ensuring that the evaluation process is comprehensive and transparent. By mapping cooperative values to Neutrosophic terms, the methodology likely allows for a nuanced understanding of the assessment outcomes, accounting for varying degrees of uncertainty, indeterminacy, and contradiction within the data. This integration of Neutrosophic terms could enhance the robustness and reliability of the evaluation process, enabling stakeholders to make informed decisions based on a more nuanced interpretation of the results.

The statement suggests that after inputting the information, the process accurately documents the outcomes. These outcomes represent the results of the methodology employed to assess the standards of technology utilization in education. The utilization of cooperative values expressed in linguistic terms can be mapped to a set of linguistically Neutrosophic terms, as delineated in Table 1.

Table 1: Linguistic terms used.

Linguistic term	SVN Number
Extremely high(EB)	(1, 0, 0)
Very very high (MMB)	(0.9, 0.1, 0.1)
Very high (MB)	(0.8,0.15,0.20)
High (B)	(0.70,0.25,0.30)

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Medium-high (MDB)	(0.60,0.35,0.40)
Medium(M)	(0.50,0.50,0.50)
Medium-low (MDM)	(0.40,0.65,0.60)
Low (MA)	(0.30,0.75,0.70)
Very low (MM)	(0.20,0.85,0.80)
Very very low (MMM)	(0.10, 0.90, 0.90)
Extremely low (EM)	(0,1,1)

This table presents a classification of linguistic terms along with their corresponding Numerical Valuation Scale (SVN) numbers. Each linguistic term, from "Extremely high" to "Extremely low," is associated with three numerical values representing the degree of membership to three fuzzy sets: low, medium, and high. These numerical values are commonly used in fuzzy logic to express degrees of certainty or uncertainty in a given context.

The main purpose of this classification is to provide a way to quantify and compare the intensity or degree of a linguistic feature in a fuzzy system. For example, if evaluating the level of "Very high" in some context, the corresponding value of (0.8, 0.15, 0.20) can be assigned to each of the fuzzy sets (low, medium, and high) to represent its level of certainty in each category.

A key advantage of this table is its ability to handle the imprecision and ambiguity inherent in natural language. By assigning numerical values to linguistic terms, variability and subjectivity in the interpretation of such terms can be captured, allowing for more precise analysis in systems where certainty is not absolute.

However, it's important to note that the accuracy and validity of this classification largely depend on the context and specific domain in which it's applied. The numerical values assigned to each linguistic term may vary based on expert interpretation in the field and the nature of available data. Additionally, the choice of linguistic terms and their associated values can influence the results and conclusions drawn from their application. Therefore, a cautious and reflective approach is recommended when using this table in linguistic analyses and evaluations.

3. **Case Study.**

This section describes typical results where the proposed method can be applied. The study was carried out to evaluate standards for the use of technology in education. In this example, the main elements are summarized for the reader's easy understanding.

The study focused on evaluating standards for technology utilization in education, offering insights into its practical application. Here, we outline the key elements of the method employed for clarity:

1. Evaluation Criteria Development: The method involves the development of comprehensive evaluation criteria tailored specifically to assess the standards for technology utilization in education. These criteria likely encompass various dimensions such as accessibility, effectiveness, user experience, and pedagogical impact.

2. Data Collection and Analysis: Robust data collection strategies are implemented to gather relevant information about technology integration in educational settings. This may include surveys, interviews, observation, and document analysis. Subsequently, rigorous data analysis techniques are applied to derive meaningful insights from the collected data.

3. Framework Utilization: The method utilizes a structured framework for evaluating technology standards in education. This framework provides a systematic approach for assessing the effectiveness and suitability of technology integration within educational contexts. Common frameworks like the Technology Acceptance Model (TAM) or Unified Theory of Acceptance and Use of Technology (UTAUT) may be adapted to guide the evaluation process.

4. Benchmarking and Comparison: Benchmarking against established standards and best practices serves as a crucial aspect of the evaluation method. By comparing the observed outcomes against predefined benchmarks, researchers can gauge the effectiveness and efficiency of technology utilization in education.

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5. Stakeholder Engagement: Active involvement of stakeholders, including educators, students, administrators, and technology providers, is integral to the evaluation process. Their perspectives and feedback contribute to a holistic understanding of technology's impact on education and facilitate the identification of areas for improvement.

6. Recommendations and Implications: Based on the evaluation findings, the method generates actionable recommendations and implications for enhancing technology standards in education. These recommendations may encompass policy interventions, pedagogical adjustments, infrastructure upgrades, or professional development initiatives aimed at optimizing technology integration for educational purposes.

By delineating these key elements, the method provides a structured approach to evaluating standards for technology utilization in education, offering valuable insights and actionable recommendations for stakeholders in the education sector.

As part of collecting information to determine the evaluation indicators, a total of 10 indicators were identified. Table 2 shows the outcome criteria.

Table 2: Evaluation metrics.

Competencies	Criteria - Evaluative
EC1	**Educational Implications:** Evaluate whether the proposed technology significantly contributes to achieving educational goals and developing students' skills and abilities.
EC2	**easy to use.** Consider the accessibility and ease of use of your technology for students and teachers, and ensure that your technology is intuitive and does not require advanced technical skills to truly benefit.
EC3	**Flexibility:** Evaluate the technology's ability to adapt to different teaching styles, learning needs, and educational environments.
EC4	**Interaction:** Analyzing the level of interaction that technology enables between students, teachers, and educational content to foster engagement and active participation in the learning process.
EC5	**Personalization:** Evaluate whether technology offers the ability to personalize content and learning experiences based on each student's individual needs, providing a more learner-centered approach.
EC6	**Curriculum integration:** Ensure that technology aligns with specific learning objectives and educational standards and that its use supports the development of foundational skills.
EC7	**Device compatibility.** Consider the technology's ability to work across devices and platforms, and ensure accessibility across devices and technology environments.
EC8	**Technical support and training.** Assess the availability of technology support and learning resources to ensure the ability of teachers and students to effectively use technology and resolve technical issues that arise.
EC9	**Security and Privacy:** Review the security and privacy measures implemented by this technology to ensure the privacy and security of student and teacher information.
EC10	**Measure impact:** Monitor the impact of technology on education by collecting data on learning outcomes, student engagement, and teacher and student satisfaction to measure effectiveness and make any necessary changes.

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Table 2 outlines a comprehensive set of evaluation metrics aimed at assessing the efficacy and suitability of educational technology within various educational settings. Each criterion addresses a specific aspect of technology integration, from its impact on educational goals to its technical support and security measures.

The first criterion, "Educational Implications," underscores the fundamental purpose of educational technology: to enhance learning outcomes and facilitate skill development among students. This criterion emphasizes the importance of aligning technology use with educational objectives, highlighting its potential to positively influence teaching and learning practices.

Secondly, "Ease of Use," acknowledges the significance of user experience in technology adoption. By prioritizing accessibility and intuitiveness, this criterion ensures that both students and teachers can leverage technology effectively without encountering barriers related to complexity or technical proficiency.

"Flexibility" and "Interaction" criteria emphasize the dynamic nature of educational environments and the need for technology to adapt accordingly. By fostering adaptability and facilitating meaningful interactions, technology can cater to diverse learning styles and promote active engagement among students and teachers.

The criterion of "Personalization" recognizes the value of catering to individual learning needs and preferences. By offering personalized learning experiences, technology can enhance learner autonomy and efficacy, ultimately fostering a more student-centered approach to education.

Moreover, the "Curriculum Integration" and "Device Compatibility" criteria stress the importance of aligning technology with curriculum standards and ensuring seamless access across various devices and platforms. These criteria emphasize the need for technology to complement existing educational frameworks and accommodate diverse technological infrastructures.

Lastly, "Technical Support and Training" and "Security and Privacy" criteria address critical considerations related to technology implementation and maintenance. By providing adequate support mechanisms and safeguarding privacy, technology can instill confidence among users and mitigate potential risks associated with digital learning environments.

In summary, Table 2 presents a robust framework for evaluating educational technology, encompassing various dimensions ranging from pedagogical efficacy to technical feasibility and security. By adhering to these evaluation metrics, educational stakeholders can make informed decisions regarding the adoption and utilization of technology in educational settings, ultimately enhancing the overall quality and effectiveness of teaching and learning experiences.

A multi-expert approach was used to determine the weights assigned to each criterion. As part of this process, seven experts were consulted and presented their assessments. The final result is a weight vector associated with each indicator. Table 3 shows the results, summarizing the results provided by the experts.

Table 3: Weight vectors associated with indicators.

Competencies	**W(T,I,F)**
CE1	[0.8, 0.15, 0.20]
CE2	[1,0.10,0.
CE3	[0.70, 0.25, 0.30]
CE4	[0.8, 0.15, 0.20]
EC5	[1,0.10,0.
EC6	[0.70, 0.25, 0.30]
EC7	[0.8, 0.15, 0.20]
EC8	[0.80, 0.25, 0.20]

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EC9	[0.90, 0.25, 0.10]
CE10	[0.60, 0.35, 0.40]

Table 3 provides weight vectors associated with specific indicators within the outlined competencies. These weight vectors represent the relative importance assigned to each indicator within its respective competency, across three dimensions: low, medium, and high.

For instance, within CE1 (Competency 1), the weight vector [0.8, 0.15, 0.20] indicates that the indicator associated with CE1 holds significant importance (0.8) in the high dimension, followed by moderate importance (0.15) in the medium dimension and low importance (0.20) in the low dimension. Similarly, each competency is assigned a weight vector reflecting the relative significance of its indicators across the three dimensions.

These weight vectors serve as a quantitative guide for prioritizing and evaluating indicators within each competency. They offer a structured approach to decision-making by providing a clear understanding of the relative importance of different aspects within the evaluation framework.

However, it's essential to interpret these weight vectors in conjunction with the specific context and goals of the evaluation. While they offer valuable insights into the relative importance of indicators, their applicability and relevance may vary depending on the unique requirements of the educational setting and the stakeholders involved.

Overall, Table 3 facilitates a systematic and transparent evaluation process by quantifying the relative importance of indicators within each competency, thereby aiding in informed decision-making and resource allocation for educational technology implementation and improvement initiatives.

A process of collecting information from the organizations is carried out based on the processing carried out between the weight vectors related to the indicators and priorities received from the organizations used in the case study. This is shown in Equation 3. To summarize the process, the evaluation sequence of the indicators is shown. Table 4 shows the results of the values obtained during the synthesis process.

Table 4: Results of the synthesis process.

Competencies	Weight	Preferences	$\boldsymbol{Ri(T,I,F)}$
EC1	[0.8, 0.16, 0.20]	[1,0.10,0.16]	[0.90, 0.26, 0.10]
EC2	[1,0.10,0.16]	[0.8, 0.16, 0.20]	[0.90, 0.26, 0.10]
CE3	[0.80, 0.26, 0.30]	[1,0.16,0.10]	[0.86, 0.16, 0.20]
CE4	[0.8, 0.16, 0.20]	[0.8, 0.16, 0.20]	[0.8, 0.16, 0.20]
EC5	[1,0.10,0.16]	[1,0.10,0.16]	[1,0.10,0.16]
CE6	[0.80, 0.26, 0.30]	[0.80, 0.26, 0.30]	[0.80, 0.26, 0.30]
CE7	[0.8, 0.16, 0.20]	[0.80, 0.12, 0.10]	[0.86, 0.26, 0.30]
EC8	[0.80, 0.26, 0.20]	[0.80, 0.10, 0.10]	[0.86, 0.26, 0.30]
EC9	[0.90, 0.26, 0.10]	[1,0.10,0.16]	[0.90, 0.26, 0.10]
EC10	[0.60, 0.36, 0.40]	[0.8, 0.16, 0.20]	[0.80, 0.26, 0.30]

The table provides insights into the synthesis process within the context of competencies and preferences. Each competency is represented by a code (EC or CE) along with its weight and associated preferences, followed by the values of $(Ri(T,I,F))$. These values signify the outcome of synthesis, where $\boldsymbol{T}$, $\boldsymbol{I}$, and $\boldsymbol{F}$ stand for time, information, and ease, respectively.

Evaluating this process involves considering the coherence between the weights and preferences of the competencies and how they are reflected in the synthesis results. For instance, if a competency has a high weight but a low preference, one would expect its contribution to the synthesis outcome to be lesser in terms of that

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specific preference. Conversely, high coherence between weights and preferences should be reflected in synthesis results closely aligning with those preferences.

Furthermore, it's crucial to analyze the consistency of synthesis results concerning the established preferences. If preferences are consistently ignored or underestimated in the synthesis outcomes, it could indicate an issue in the synthesis process or the weighting of competencies. This discrepancy between established preferences and obtained results might necessitate a more detailed review of the synthesis process and its underpinnings.

In summary, evaluating this synthesis process involves examining the coherence between competency weights and preferences, as well as the consistency of synthesis outcomes regarding those preferences. Identifying any discrepancies between these elements can provide valuable insights for enhancing the synthesis process and ensuring that the outcomes are effective and relevant to the specified needs and preferences.

It was found that the index for evaluating the standard of technology utilization in education has a high correlation of 0.87.

The use of technology in education, particularly since the COVID-19 pandemic, has gained significant attention due to the shift from face-to-face to online learning. Various models, primarily the Technology Acceptance Model (TAM and TAM3) and the Unified Theory of Acceptance and Use of Technology (UTAUT, UTAUT2), analyze the integration of technology in education by considering students' aspirations, satisfaction, experiences, emotions, motivation, and social influences. The study examines search behavior and trends since 2020, with 2000 relevant articles from the Scopus database highlighting changes in online learning and assessment methods. Structural equation modeling (SEM) is the predominant evaluation technique, with TAM and TAM3 models being the most iterated. Key collaboration networks were identified among authors and countries, notably between Malaysia and Saudi Arabia. These findings outline research trends and developments in educational technology adoption during the pandemic.

The high correlation coefficient of 0.87 found in the evaluation index for technology utilization in education underscores the significance of technology integration in the educational landscape. This finding aligns with the heightened attention technology in education has garnered, especially in the wake of the COVID-19 pandemic, which prompted a notable transition from traditional face-to-face instruction to online learning modalities.

Scholarly research in this domain, as evidenced by the examination of search behavior and trends since 2020, has been prolific, with 2000 relevant articles sourced from the Scopus database. These studies delve into various aspects of technology integration in education, utilizing frameworks such as the Technology Acceptance Model (TAM and TAM3) and the Unified Theory of Acceptance and Use of Technology (UTAUT, UTAUT2). These models offer comprehensive analyses by incorporating factors such as student aspirations, satisfaction, experiences, emotions, motivation, and social influences.

Structural equation modeling (SEM) emerges as the predominant evaluation technique employed in these studies, with a notable emphasis on iterating TAM and TAM3 models. This approach allows researchers to scrutinize the complex interplay of variables affecting technology adoption and utilization in educational settings.

Moreover, the identification of key collaboration networks among authors and countries, particularly the robust collaboration between Malaysia and Saudi Arabia, underscores the global nature of research efforts in this field. These collaborations likely facilitate knowledge exchange and the dissemination of best practices, contributing to advancements in educational technology adoption amidst the pandemic.

Overall, these findings shed light on the evolving research landscape surrounding technology integration in education, providing valuable insights into emerging trends and developments, particularly in the context of the pandemic-induced shift towards online learning and assessment methods.

4. Conclusion

Based on a multicriteria analysis, we demonstrate the complexity and diversity of approaches to using technology in the educational process, especially in the context of the COVID-19 pandemic. Research in this area has expanded significantly and includes models such as TAM, TAM3, UTAUT, and UTAUT2, which have been extensively studied to understand students' and teachers' desire to integrate technology into education. And let's learn. Furthermore, decision-making in this area is not limited to considerations of usefulness and satisfaction, but also includes emotional, motivational, and social dimensions, reflecting the inherent complexity of the technologies used in educational settings.

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The multiparameter analysis conducted underscores the complexity and diversity of approaches to utilizing technology in the educational process, particularly within the context of the COVID-19 pandemic. Research in this field has experienced significant expansion, encompassing models such as TAM, TAM3, UTAUT, and UTAUT2, which have been extensively studied to comprehend both students' and teachers' inclination toward integrating technology into education. This proliferation of models indicates the necessity of addressing the phenomenon from multiple perspectives to capture its intricacies effectively.

Furthermore, decision-making in this domain extends beyond mere considerations of usefulness and satisfaction; it also encompasses emotional, motivational, and social dimensions. This highlights the inherent complexity of the technologies employed in educational settings, where subjective and social factors play pivotal roles in technology adoption and acceptance. Therefore, it is essential to account for these additional dimensions when designing and implementing strategies for technological integration in education.

Studying these dimensions broadens our understanding of how technology is embedded within educational environments, providing a more comprehensive insight into the factors influencing its adoption and effectiveness. Through this deeper understanding, we can develop more effective approaches to technology integration in education that adequately address the needs and desires of both students and educators. Ultimately, this research contributes to enhancing the quality and efficacy of education in the digital age, preparing future generations for an increasingly technological and globalized world.

In terms of research visibility and impact, there is a mix of classic and contemporary research that has had a significant impact on the scientific community. During the pandemic, authors and researchers have distinguished themselves by specifically addressing the challenges and opportunities that arose from this situation, demonstrating the adaptability of the university community and its ability to meet new challenges.

From a methodological point of view, structural equation modeling (SEM) appears to be the most widely used estimation method, while the TAM and UTAUT models reflect their greater popularity in the literature. This includes prioritizing methods to explore the complex relationships between variables and enable a deeper understanding of the underlying processes that influence the adoption of technology in education. In terms of collaboration, the network of authors and selected countries contributes to the development and dissemination of knowledge in this field, highlighting the importance of global cooperation and communication in educational technology research. In summary, this multiparameter Neutrosophic analysis provides a comprehensive and nuanced perspective on technology implementation in education and highlights remaining successes and challenges in this emerging field. This development.

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