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PAPER

A Framework Model for Exploring Factors for Measuring E-Learning Systems and Its Relevant Outcomes via AHP

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ABSTRACT

Universities have focused on learning outcomes as a metric for evaluating the quality assurance of educational systems. However, due to the absence of a clear guide on measuring outcomes and analysing them accordingly to improve the educational cycle, educators struggled to efficiently and effectively address shortcomings. By proposing a new framework, this study fills this gap and provides a guided approach to measuring learning outcomes in the context of university e-learning systems. Facilitated by a comprehensive research literature review of 102 articles, filtered from 271 articles using the PRISMA method, the opinions of five experts regarding e-learning systems and their outcomes were analysed using the analytical hierarchy process (AHP) to provide priority rankings. Teaching methods, teaching quality, learning environment, and students emerged as the main factors, along with their sub-factors. Moreover, our experts from diverse educational and geographical backgrounds provide added value, enabling the framework to be implemented across various environments and fields. Ultimately, this framework accurately measures sub-factors to identify the strengths and weaknesses of educational variables. The proposed framework is a step in the right direction, enabling the design of a suitable system that takes into account users' needs when assessing e-learning outcomes.

KEYWORDS

e-learning system, online learning, factors influencing e-learning outcomes, learning outcomes

1 INTRODUCTION

Due to the global pandemic caused by COVID-19, the demand for e-learning increased drastically as most institutes relied on online learning to deliver their course content, lectures, exams, etc. [1], [2]. This development brought great benefits, such as offering students an easier way to navigate all aspects of their education, providing them with a greater opportunity to engage in the technological aspects of teaching, and acclimating them to the online world. In some ways, the events caused

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by COVID-19 revolutionised education as a whole, and specifically online learning, as developers and designers were obliged to improve the services and facilities provided to institutions and their students.[3] Educational institutions operate online through platforms such as Blackboard, Microsoft Teams, and others to provide sufficient resources to students, enabling them to meet their educational requirements and achieve their qualifications without any complications. However, this does not mean that there are no difficulties. The lack of familiarity of some societies with the use of the Internet has created problems for educational institutions [4], [5]. These problems include the absence of specific criteria to evaluate the educational process and insufficient time for training. These problems confirm the need for a framework model that assists in evaluating e-learning outcomes.

E-learning essentially provides students with a 24-hour educational service where they can access all their course materials in one system [6]. Additionally, they can review recorded seminars and lectures to revisit key points they may have missed or to reinforce the information conveyed by the lecturer. In addition, students using these platforms can easily track their online educational progress, as well as their performance on their exams and quizzes, without needing to contact a staff member [7]. However, the process of measuring the factors that influence e-learning outcomes has not been adequately assessed. More research and advancements are necessary to ensure that online learning reaches its maximum potential. Once these factors are identified, educational institutes can adjust certain aspects of their programme to accommodate all individuals involved in the educational process and provide the best possible facilities. These gaps in research confirm the need for a framework model that assists in evaluating e-learning outcomes.

Certain questions arose during this study, prompting research to address them:

RQ1. What are the main factors that can influence the evaluation of learning outcomes when using e-learning systems?
RQ2. What are the sub-factors that can influence the evaluation of learning outcomes when using e-learning systems?
RQ3. How can we classify factors based on the priority of e-learning systems when measuring learning outcomes?
RQ4. What is the relationship between the factors that can influence the measurement of e-learning systems?

These questions serve as a guide for researchers, enabling a clear understanding of the factors that influence e-learning outcomes. This understanding is crucial for enhancing the effectiveness of educational programmes and curricula. Answering the first question allows the researcher to identify the primary factors influencing the evaluation of learning outcomes in e-learning systems. This information provides educators with the key elements that affect learning outcomes, allowing them to focus on these factors when assessing learning outcomes. The second question breaks down the variables that constitute these main factors to offer the reader a clear understanding of the factor's scope. Question three explores the classification of factors based on. By identifying these factors in order of importance, educational institutions can tailor their strategies to enhance student performance and ultimately fulfil learning outcomes. The final question explores the relationship between factors that influence the measurement of e-learning outcomes. This study contributes to a comprehensive understanding of the relationship between these factors and how they mutually influence each other. Therefore, incorporating a holistic approach to educational planning is essential to ultimately achieving e-learning outcomes.

While most other studies investigate e-learning outcomes, this study aims to explore the factors influencing those outcomes during evaluation and to create a framework model that can track the progress of each factor. Offering a theoretical model makes it easier for individuals interested in the educational process to identify the strengths and weaknesses of their systems. This enables them to address deficiencies in educational outcomes and enhance them in the future, rather than relying on general systems that do not offer insightful data on academic performance. The study addresses the research gap related to the absence of a scale that measures the significant impact of e-learning outcome factors. It utilises the analytical hierarchy process (AHP) tool, offering a systematic guide for developers and researchers to improve effectiveness and efficiency.

The remainder of this paper is organised into the following sections: a comprehensive literature review to establish a strong foundation for the results obtained by this research; a methodology breaking down the steps taken to generate the findings of this study; a results and discussion section analysing the data gathered while providing rationale and logic for the outcomes of this study and a conclusion followed by limitations and potential future areas of research.

2 LITERATURE REVIEW

2.1 Tools to measure variables effecting e-learning systems

Many software programmes and systems fail to achieve their goals because their developers neglect to consider the research findings of previous studies or prioritise the requirements of end users and their needs adequately. There are many tools available to measure various variables that may impact educational learning systems. For example, some studies used the DeLone and McLean information model [8] to measure complex dependent variables in information systems, while others utilised the transferable learning orientations (TLO) tool to assess the propensity for lifelong learning [9, 10]. Other studies have utilised the technology acceptance model (TAM) to assess user acceptance of information technology [11], including system learning tools. The expectation-confirmation model (ECM) also investigates how individuals adapt to e-learning systems and continue using them [12]. However, all these methods and models aim to measure general factors that could influence e-learning systems rather than learning outcomes. According to our knowledge, this is the first attempt to determine the main factors that influence the measurement of learning outcomes when using e-learning platforms.

2.2 Learning outcomes definition

There are many definitions of the term "learning outcomes" that can be classified based on the purpose for which it is used. According to [13], a learning outcome is a "written statement of what the successful student or learner is expected to be able to do at the end of the module, course unit, or qualification." Meanwhile, [14] defined a learning outcome as "the specification of what a student should learn as the result of a period of specified and supported study." Additionally, there are different perceptions of the term based on how learning outcomes are utilized. Learning outcomes, however, can help measure effectiveness and accountability, as well as guide curriculum planning and development; these are the key functional categories of learning outcomes. Hence, there are two ways to evaluate learning outcomes: directly and indirectly. The direct method would involve using a standardised test, while the indirect method would include analysing graduation rates, conducting surveys of alumni, and tracking the number of students who apply to postgraduate courses. Nevertheless, this is not the right way to measure students' learning and the skills they gain from their education during their studies [15].

2.3 E-learning

The definition of e-learning is still ambiguous, and there is no internationally agreed-upon definition yet. While some define e-learning as a flexible, interactive, self-paced, and elaborate pedagogical method that introduces educational approaches using a wide variety of platforms [16], others define it as "learning supported by digital electronic tools and media" [17].

The correlation between the use of e-learning systems and its consequences in relation to the influence of oversight is discussed by [18]. In this study, Islam conceptualises e-learning outcomes based on academic achievement, perceived learning assistance, and various other factors. He concluded that he did not regulate the two connections. E-learning heavily relies on two main foundations, i.e., digital technology and internet applications. These foundations utilise various tools based on the environment, Internet speed, and the quality of technology. They are used for teaching through media, virtual settings, and communication platforms. Schools and universities utilise e-learning through regular courses or semesters, allowing students to engage with the programmes offered by their institution.

[19] examined the factors influencing the implementation of e-learning elements that affect student satisfaction with the use of e-learning in Jordan through an integrated model. They concluded that five main factors affect student satisfaction, including computer self-efficacy, system quality, perceived ease of use, usefulness, and information quality. However, their study did not address how user satisfaction can be measured in terms of these five factors. This emphasises the importance of developing a model that can measure the factors influencing the outcomes of e-learning systems.

According to scanning electron microscopy (SEM) analysis, a student's approach to learning has a significant effect on their perception of it [20]. Conversely, students' attitude towards learning was not statistically significant in relation to the surface approaches ($p > .05$). Results show that high levels of academic performance are not necessarily related to educational levels of motivation and perception; however, autonomous learners had better perceived learning outcomes. These outcomes provide a solid foundation, proving that students' educational motivation and perception are independent of their performance in an online learning environment. A certain perspective on this scenario suggests that this phenomenon can be explained by variations in perception and execution of learning. The former is norm-referenced, while the latter is criteria-referenced.

[21] presents a theoretical model to assess the impact of readiness variables on the relationship between e-learning factors and outcomes. According to the data, the most significant factor influencing e-learning outcomes is organisational readiness, and the most essential aspect is the motivation and training of instructors. These findings have the potential to assist all parties involved in the educational aspect of e-learning systems.

[22] investigated the factors that could hinder or support university students' utilisation of e-learning technologies. According to the findings, performance

expectations, social influence, habits, and other factors all had a significant impact on behavioural intention (BI). The elements are recognised as essential in understanding the adoption of technology.

The purpose of the study conducted by [23] was to explore different forms of training or teaching activities that enhance learning satisfaction and to determine how employee satisfaction can be improved through the use of e-learning systems. The findings revealed that the four factors (technology, educational content, motivation, and attitude) all had a significant impact on employees' satisfaction with learning. This study, despite its importance, did not provide a clear framework or methodology for effectively measuring these four factors.

[24] applied structural equation modelling to analyse intrinsic and extrinsic motivation, as well as self-regulated learning strategies, in relation to student satisfaction and perceived educational learning outcomes. Intrinsic factors had a greater influence on e-learning outcomes than extrinsic factors. However, this study did not address specific methodologies for measuring the effects of these factors in evaluating learning outcomes through e-learning systems.

In their study, [25] investigated the variables that influence the integration of e-learning systems (ELS) in all settings by employing an augmented technology acceptance model (TAM). Results confirm the significance of subjective norms on perceived usefulness, as observed in the original TAM findings. These findings indicate an expanded TAM for ELS. This study enhances the theory and lays the groundwork for understanding students' e-learning system adoption behaviours, which are effective. However, this double-edged sword means that it focuses on patterns rather than identifying key factors influencing learning outcome measurements.

[26] investigated factors influencing the adoption of e-learning courses in elementary and secondary schools in the Czech Republic. The teachers' voluntary engagement and positive expectations significantly influenced the acceptance of e-learning courses. Emphasising psychological elements is crucial, as opposed to characteristics such as teachers' age, teachers' gender, school type, and so on, which had no significant impact. This study focused solely on the role of the teacher without considering other factors.

[27] empirically examined seven key factors: culture, expertise, support, ease of use, computer self-efficacy, content, and reliability. Regression analysis revealed that support, ease of use, reliability, computer self-efficacy, and culture have a significant impact on e-learning outcomes, while the other two factors showed no significant effect. Principal component analysis and the LMS method identify technical support as the most significant factor influencing web-based education. The study contributes by highlighting the complexity of measuring external factors, including technical aspects, culture, and usability issues.

[28] utilised the Biggs-Moore learning model to evaluate students' perceptions of e-learning variables. The perceived learning outcomes in e-learning consider effectiveness, quantity, and productivity. According to the results of this research, collaborative efforts combined with critical thinking help to identify that process variables are influenced by the initial perception of e-learning, which in turn directly and indirectly affects perceived e-learning outcomes.

Environment, learners, courses, instructors, design, and technology form the six dimensions of the integrated model developed by [29]. This model reveals which factors promote successful e-learning. The results revealed the critical factors influencing a learner's perceived satisfaction. These factors include diversity, perceived usefulness, ease of use, instructor attitudes toward e-learning, flexibility and quality, and learner computer anxiety. The flaws revealed in the study could serve as a foundation for institutions to improve their e-learning implementation. This research's strength lies in providing insights into the factors that influence student satisfaction. However, it did not offer a model to quantify the impact of these factors on student satisfaction.

Some studies discussed the extent of student satisfaction, the acceptance of electronic platforms, and their impact on student outcomes [30, 31, 32, 33, 34]. Nevertheless, these studies did not provide an organised framework that can be referenced when trying to determine student satisfaction or how they impacted student outcomes, which resulted in a lack of accuracy and practicality.

The TAM is a suitable theoretical framework for comprehending user acceptance of e-learning [35]. E-learning was the most important concept for explaining the model's causal process. Perceived usefulness, technical support, computer anxiety, self-efficacy, social influence, enjoyment, system interactivity, and many other factors influence behavioural intention in the use of e-learning. The results of this research revealed practical difficulties for the relevant leaders, their target audience, and developers in these projects concerning the overall success of e-learning [36].

Previous research has primarily concentrated on identifying factors influencing e-learning outcomes without proposing a methodology, even in theory, for evaluating these outcomes based on the factors. This lack of a clear evaluation method hinders the ability to measure e-learning outcomes accurately, which in turn limits opportunities for enhancing and advancing e-learning outcomes. Furthermore, there is no specific model that can be practically relied upon to measure the learning outcomes of e-learning by monitoring the influencing factors. The aforementioned gaps in research serve as the foundation for this study to achieve its goals.

3 METHODOLOGY

3.1 Overview

This study utilises two data collection methods: a literature review of previous studies and expert evaluation through AHP. These methods allowed the study to identify and evaluate the factors impacting university e-learning outcomes. Initially, a comprehensive literature review of previous studies was conducted to gather and assess the information. This review identified four main factors and a total of 19 sub-factors that influence e-learning outcomes. Afterwards, the experts evaluated the sub-factors influencing e-learning outcomes by completing the AHP questionnaire to determine the importance of each sub-factor gathered from the literature review [37, 38]. Once the rankings of these sub-factors were rearranged, the official framework model was established. The following sub-sections discuss these steps in detail.

3.2 Data from previous studies to preliminarily establish the proposed framework model

Previous studies' evidence was extrapolated to assist in assessing our data and to underscore the evaluation's strength, ensuring its reliability and effectiveness. This study involved the analysis of a total of 271 studies through various steps and criteria. The first step was to search for research articles related to our study by including keywords in the search bar, such as e-learning outcomes, learning outcomes,

outcomes, factors, learning outcome factors, e-learning interfaces, etc. This search was conducted on specific publishing sites to gather reliable and relevant data. These websites included PubMed, ACM, Google Scholar, Springer, and Elsevier. Throughout the data-gathering process, 169 research articles were dismissed because the researcher deemed them unclear, realised that they did not include factors affecting e-learning outcomes, or determined that they were not within the scope of this study. The remaining 102 articles were thoroughly examined and analysed to identify recurring factors that were continuously mentioned. The criteria for selecting these research studies include relevance to this study, the presence of specific keywords, and the accessibility of the full article to the researcher. Figure 1 illustrates the systematic review of this paper following PRISMA guidelines.

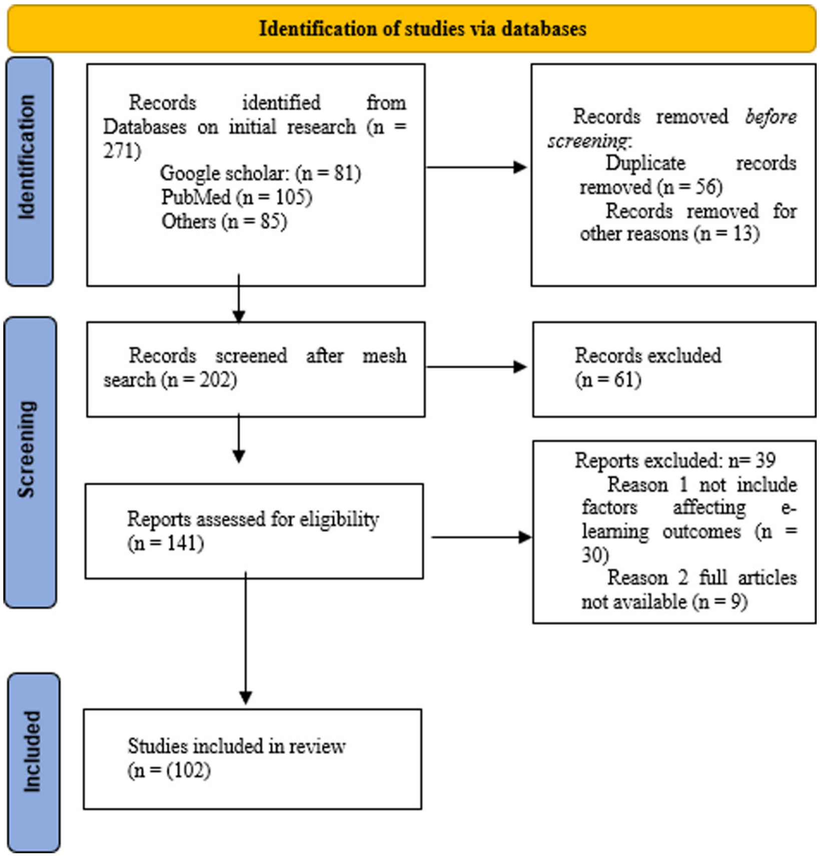

Fig. 1. PRISMA 2020 flow diagram for updated systematic reviews that included searches of databases

Through a literature review, this study identified four main factors for assessing university e-learning systems and their outcomes: teaching methods, teaching quality, learning environment, and students. However, these factors alone are generalised and might be ambiguous to educators, curriculum developers, educational administrators, and so on, due to the lack of specificity. Therefore, to further clarify the components of the main factors, sub-factors were established using the same method. This enables our proposed framework model to be utilised and applied more widely across various fields and educational domains, thereby increasing the relevance of this research. Table 1 presents the primary factors identified from the literature review, accompanied by a concise description, relevant sub-factors, and the corresponding references used to collect each factor.

Table 1. Main factors with their relevant description, sub-factors, and references for the proposed framework model

Main Factor	Description	Sub Factor	References
Teaching Methods	"Teaching methods denote various strategies that the teacher uses to deliver his/her subject matter to the students in the classroom based on the instructional objectives to bring about learning." [39]	Teaching Style	[40, 41, 42, 43, 44, 45, 46, 47, 48]
		Quizzes and Assignments	[49, 50, 51]
		Type of Exam Questions	[52, 53]
Teaching Quality	"The quality of interactions between students and teachers; while teacher quality refers to the quality of those aspects of interactions that can be attributed to the teacher." [54]	The Quality of Syllabus	[55, 56]
		Teacher Interaction	[57, 58]
		Teacher's Experience	[59, 60]
		Course Contents	[61, 62]
Learning Environment	"Learning environments are the material and social conditions that provide learners with opportunities to learn." [63]	Facilities	[64, 65, 66]
		Location	[67, 68, 69, 70]
		Level of Infrastructure Availability	[71, 72, 73, 74, 75]
Student	"Housing quality, purchasing power: transportation services and goods, number of household members." [76]	Students Economic Background	[77, 78, 79, 80, 81, 82, 83]
		Students' Performances	[84, 85, 86, 87, 88, 89]
		Attendance	[90, 91, 92, 93]
	"Learning motivation as the intention or desire of students participating and devoting to learning, which was performed on students' selection for specific learning activities and the strength to continuously devote to such activities." [94]	Leaning motivation	[95, 96, 97, 98, 99, 100]
		Friends & Families	[101,102, 103, 104, 105, 106]
	"The student concentration is the percentage of minority students in the school and the district where the teacher works, while the segregation of students measures the racial and ethnic student distribution across schools within the district." [107]	Concentration	[108, 109, 110]
		Personal Skills	[111, 112, 113]
	Cooperative learning is "the instructional use of small groups so that students Work together to maximize their own and each other's Learning." [114]	Cooperative Learning	[115, 116, 117, 118]
	"The perception of enjoyment and accomplishment in the learning environment." [119]	Satisfaction	[120, 121, 122, 123, 124]

3.3 Expert selection criteria

According to Nielsen, the optimal number of experts who should participate in a heuristic evaluation is three to five [125], as he believed that including more experts would not prove to be useful. Therefore, this research gathered five experts (refer to Table 2) through a rigorous selection criteria process. The criteria for selecting our expert recruits included experience in teaching through university e-learning systems, a diverse range of specialties (such as human-computer interaction, software engineering, and usability evaluation), and varied geographical teaching environments (including Algeria, Saudi Arabia, and the UK). This was done to gather valuable feedback by evaluating the factors that influence e-learning outcomes.

All experts in this study hold a PhD qualification in their relevant areas of expertise and have demonstrated e-learning experience by publishing at least one research study in this field.

Table 2. Expert demographics

Experts	Age	Gender	Speciality	Position	Experience	Country
1	43	Male	Software Engineering	Lecturer	15 years	Algeria
2	47	Male	Usability Evaluation	Senior Lecturer	22 years	Saudi Arabia
3	53	Male	Usability Evaluation	Vice Dean of Distance Learning	26 years	Saudi Arabia
4	39	Male	Human Computer Interaction	Lecturer	10 years	United Kingdom
5	54	Male	Human Computer Interaction	Senior Lecturer	24 years	United Kingdom

The decision to recruit experts from various fields of expertise is crucial to ensuring a comprehensive evaluation of our proposed model based on their personal experiences and domain knowledge. HCI users provide more insightful feedback on user experience, interface design, and usability, among other factors, all of which are essential in categorising the level of importance of our factors. On the other hand, software engineering experts added more relevance to the results because of their extensive knowledge of system robustness, reliability, stability, and functionality. Experts specialising in the field of usability evaluation assess effectiveness, efficiency, interface design, and user satisfaction from a user-centric perspective. Their feedback primarily focuses on the ultimate goal of the system, which is to enhance user engagement, satisfaction, and content retention, thereby improving learning outcomes. Overall, the abundance of these different perspectives during the evaluation of the proposed model of our learning outcomes enables a more holistic assessment. It acknowledges multiple fields of expertise, thereby strengthening the reliability and enhancing the value of our research while eliminating disciplinary bias.

The emphasis on gathering experts from different regions is significant for this research. Different cultures and socio-economic backgrounds shape perspectives on evaluation in the fields of usability, HCI, education, and other related areas. This approach provides a comprehensive view of the proposed learning outcome factors. The diverse behaviour patterns observed in various regions worldwide contribute to the comprehensive evaluation data provided by these experts, making the research globally relevant by eliminating geographical bias.

Last but not least, the main criteria for selecting these participants include current teaching positions at universities, along with previous and current involvement in researching and teaching through university e-learning systems, to ensure their relevance to this study. Given the dynamic nature of the e-learning field, the practical experience and ongoing engagement of our experts will offer up-to-date and directly relevant insights for our research. By collecting input from teachers who are actively implementing learning outcomes, we aim to enhance the likelihood of today's students achieving these outcomes. The results of this research will ultimately benefit educators by enabling them to break down learning outcomes into factors and their relevant sub-factors. This systematic approach will help ensure optimal results in the classroom.

3.4 Ranking the level of importance of the variables in our model via AHP analysis

This study established a preliminary conceptual framework based on a thorough literature review. The framework includes factors and sub-factors that assess e-learning systems and their corresponding outcomes. To assess the importance of these factors and further validate our framework model, we gathered five experts to evaluate this model and assist in extracting the priority rankings of this proposal. Based on their valuable experience and current outlook on university e-learning systems, the results of their evaluation are crucial for establishing an accurate framework model. This categorization based on importance would enable developers to address the issues identified in their system chronologically, prioritising variables based on their significance. This approach would enhance the effectiveness and efficiency of their problem-solving process.

Assigning rankings to the elements of our model provides it with a unique level of reliability and effectiveness. This allows learning outcome evaluators, educators, curriculum developers, and others to systematically follow the model and evaluate various aspects of their e-learning systems' learning outcomes based on the importance level of each variable. A strategic, directed, and focused approach that prioritises influential sub-factors facilitates the effective and efficient achievement of desired results. To achieve this goal, researchers use AHP, an online statistical analysis tool (https://bpmsg.com/ahp/index.php) that focuses on pairwise comparisons of subjective criteria [126], [127]. In the context of this research, the sub-factors are considered subjective criteria, while the main factors are objective criteria. In AHP terminology [128], [129], the decision hierarchy consists of level 0, representing the objective criteria, and level 1, representing the subjective criteria. Level 0 can contain only one variable, whereas level 1 can contain multiple variables prone to changes in rankings of importance [130]. Therefore, each factor and its corresponding sub-factors are individually assessed to determine their significance within their respective categories.

The AHP questionnaire presents the user with the question, "Which criterion is more important, and by how much on a scale of 1 to 9." The scale spans from one to nine, where one signifies "equal importance" and nine signifies "extreme importance." Table 3, illustrating the basic scale of pairwise comparison devised by the founder of AHP, delineates the complete scale employed in this statistical methodology. This table was presented to the experts during the evaluation to guide them in their scoring tasks. As a pairwise comparison tool, each sub-criterion is measured sequentially against another. Therefore, using the Gauss formula [131, 132, 128], which is a simple mathematical formula discovered by Gauss, helps determine the sum of a series under investigation. It is calculated using an algebraic formula where 'n' represents the number of variables that the user inputs into the AHP [126, 133]. We can determine the number of questions each expert will answer during the experiment. In this research, each expert will answer a total of 48 questions: three questions on teaching methods, six questions on teaching quality, three questions on learning environment, and 36 questions on the category of students. For each main factor project completed with AHP, the user is provided with a consistency ratio, which determines the reliability of the dataset by comparing the judgements of the experts for each section. A value of more than 10% represents unreliable data, whereas the closer the value is to zero, the more reliable the dataset becomes.

Table 3. Fundamental scales for AHP pairwise comparisons (Saaty 1987)

Intensity of Importance on an Absolute Scale	Definition	Explanation
1	Equal importance	Two activities contribute equally to the objective
3	Moderate importance of one over another	Experience and judgement strongly favour one activity over another
5	Essential or strong importance	Experience and judgement strongly favour one activity over another
7	Very strong importance	An activity is strongly favoured, and its dominance demonstrated in practice
9	Extreme importance	The evidence favouring one activity over another is of the highest possible order of affirmation
2, 4, 6, 8	Intermediate values between the two adjacent judgements	When compromise is needed
Reciprocals	If activity i has one of the above numbers assigned to it when compared with activity j, then j has the reciprocal value when compared with i	
Rationales	Ratios arising from the scale	If consistency were to be forced by obtaining n numerical values to span the matrix

4 RESULTS AND DISCUSSION

The results of this study, derived from the literature review and AHP, pinpoint the most important factors affecting e-learning outcomes. This paves the way for the final form of our proposed framework model. Furthermore, consistency ratios, which represent the reliability of the data, add value to our results. Table 4 displays the detailed AHP analytical results provided by the experts for each factor and its corresponding sub-factors. The following sections will discuss each category in detail.

Table 4. AHP results of expert evaluation

Main Factor	Sub-Factor	Priority (%)	Rank	Consistency Ratio (%)
Teaching Methods	Teaching Style	61.5%	1	0.1%
	Quizzes and Assignments	6.6%	3	
	Types of Exam Questions	31.9%	2	
Teaching Quality	Quality of Syllabus	6.2%	4	1.1%
	Teacher's Experience	25.7%	2	
	Teacher Interaction	61.4%	1	
	Course Contents	6.7%	3	

(Continued)

Table 4. AHP results of expert evaluation *(Continued)*

Main Factor	Sub-Factor	Priority (%)	Rank	Consistency Ratio (%)
Learning Environment	Facilities	32.3%	2	1%
	Location	58.8%	1	
	Level of Infrastructure Availability	8.9%	3	
Students	Students Economic Background	2.3%	7	3.9%
	Students Performances	22.0%	2	
	Attendance	31.2%	1	
	Learning Motivation	4.0%	6	
	Friends and Families	2.1%	8	
	Concentration	2.1%	8	
	Personal Skills	4.9%	5	
	Cooperative Learning	14.6%	4	
	Satisfaction	16.8%	3	

4.1 Teaching methods

The category of teaching methods encompasses the techniques and procedures that lecturers and professors use to deliver the intended curriculum content to their students [134]. However, due to the various approaches that can be undertaken, the degree of importance varies [135]. Based on a comprehensive literature review, this research identified three sub-factors (teaching style, quizzes and assignments, and types of exam questions), which were subsequently evaluated by experts using the AHP. Analytical results reveal that, according to expert evaluation, teaching style is the most important element in this category, with a priority percentage of 61.5%, followed by the types of exam questions, which received a score of 31.9%. On the other hand, according to the analytical results, quizzes and assignments are the least impactful factor in this category, attaining only 6.6% priority through AHP. The low priority percentage in this section may be related to the use of quizzes and assignments, which vary across universities depending on the course requirements. For example, in a language course, students are required to submit assignments that carry more weight, whereas in science-related courses, priority is given to practical skills and exams. Therefore, the impact of this factor on overall learning outcomes varies. Further reliability is provided to the main factor "teaching methods" by the consistency ratio, which was almost perfect (0.1). These results align with the evidence gathered from the literature review, as numerous research articles endorse the notion that teaching style and the types of exam questions are crucial [136, 137, 138, 139]. Types of exam questions that rank second in terms of priority can be explained as an influential determinant of learning outcomes. Exams display statistical figures that can be used to assess the level of understanding of the students. Therefore, providing the appropriate type of questions for the students' level is crucial for evaluating their achievement of the learning objectives.

4.2 Teaching quality

As per the comprehensive literature review, teaching quality is divided into four sub-factors: syllabus quality, teacher's experience, teacher interaction, and course content. As a continuous process across all sub-factors, experts evaluated them according to their level of importance using the AHP. The results demonstrate that teacher interaction is the most important sub-factor (61.4%), followed by the teacher's experience (25.7%), course content (6.7%), and syllabus quality (6.2%). According to previous studies [53, 54], the first three sub-factors in the rankings can be assessed through surveys, simplifying the measurement of their impact on learning outcomes in e-learning systems. On the other hand, scoring syllabus quality as the least important sub-factor supports previous studies [50, 52] and adds reliability to the findings of this research. A high level of reliability was achieved, as this section attained a consistency ratio of 1.1%. As indicated in the literature review from various sources, teacher interaction emerges as a clear priority in this section. The influence of the teacher's relationship with the student on their motivation to achieve learning objectives and the level of involvement expected from students during teaching seminars is significant. Although the teachers' experience ranked second, it still holds significance in determining the achievement of learning outcomes. Teachers can utilise their past experiences in current scenarios, thereby increasing the probability of fulfilling learning outcomes. In addition, course contents influence the level of learning objectives. Providing course materials that are too challenging for students to comprehend based on their current level of knowledge can be demoralising and further impede students' progress.

4.3 Learning environment

The learning environment is defined as a combination of social conditions and materials that provide students with the prospects and opportunities to learn effectively [66, 139]. The three elements of the learning environment derived from the literature review (facilities, location, and level of infrastructure availability) enhance students' learning opportunities, although they vary in importance. The variables in this section can be easily measured through surveys, as indicated in the literature review [67, 73, 77]. Expert evaluation of AHP results demonstrates that location is the most impactful sub-factor (58.8%) influencing e-learning outcomes. Facilities and the level of infrastructure availability were less important factors, scoring 32.3% and 8.9%, respectively. The consistency ratio in this section (1.0%) indicates a high level of reliability and consensus among the experts. Location emerged as the most important variable in measuring learning outcomes, according to the experts. Previous research indicates that location is a significant factor that includes ease of access to facilities for students and promotes a safe learning environment, keeping students away from any harmful or immoral activities. The abundance of these aspects lends significant weight to this variable in measuring learning outcomes.

4.4 Student

Students are the largest category in this framework model. It is divided into the greatest number of sub-factors (nine). This indicates that the student is the most influential factor in measuring e-learning outcomes in the context of university e-learning systems and has many underlying elements that require analysis to deduce the most important sub-factors from within this heavily loaded section.

According to the AHP results, attendance is depicted as the most crucial variable in assessing e-learning outcomes, closely followed by students' performance (31.2% and 22.0%, respectively). These two variables are easily trackable and monitored. Therefore, it is not surprising that their influence and importance in measuring e-learning outcomes are highly ranked. Furthermore, attendance promotes healthy study habits among students, aiding in the retention of information during seminars and lectures. It also enhances their engagement, laying a solid foundation for students to achieve their learning objectives. Performance is measured through the results of the students' tests and exams. Consistently performing well as a student increases the likelihood of achieving learning objectives compared to inconsistent performances overall.

Due to extensive research on satisfaction, various methods of measuring it have been established using surveys [126, 127]. The satisfaction of students is interconnected with their learning motivation, driving them to engage more and ultimately achieve their learning outcomes. Ranking third in the priority rankings of this variable, with a priority score of 16.8%, this section holds significant importance in measuring outcomes in comparison to university e-learning systems.

Although previous research data reports that personal skills are difficult to measure [115], the results of the AHP analysis based on expert evaluation show that personal skills have a medium relative importance, ranking fifth with a priority score of 4.9%.

Although previous studies have theoretically measured learning motivation using multiple methods, such as t-tests and ANOVA [97], in an attempt to grasp its importance [98, 101], suggesting it can affect e-learning outcomes, ambiguity persists regarding the objective measurement of this variable. This can be seen in the evaluators' results, which demonstrate that they believed it to be of lesser importance compared to the other subfactors. This is indicated by the AHP scores of this section, which ranked in the lower percentile in terms of priority rankings (sixth) and priority score (4.0%).

Although students' economic backgrounds are relatively measurable [87], the literature review and expert evaluation consider it an insignificant variable for measuring learning outcomes compared to other sub-factors in this section. Out of the nine sub-factors in this category, students' economic backgrounds ranked seventh, with a priority score of 2.3%.

Finally, the lowest scoring sub-factors in this section are concentration and friends and family, attaining equal priority scores of 2.1%, which positions them in joint eighth place. One of the many reasons why these sub-factors are not considered vital in measuring e-learning outcomes is their difficulty to measure [104, 105]. There is no direct method of measuring these variables that allows for an objective determination of their influence on e-learning outcomes. Unlike attendance, which is based on mathematical data, and the relationships between performance and e-learning systems, which can be established scientifically. Thus, researchers struggle to gather relevant and reliable data to support or reject their claims in these areas. Consequently, more research is required from other perspectives to delve deeper into these sub-factors that are challenging to measure but still impact e-learning outcomes.

The low consistency ratio of this main factor (3.9%) confirms the reliability of the dataset and the results collected for analysis.

In this section, measurable variables such as attendance are included, making it easy to track and address any arising challenges. However, intangible aspects such as motivation, which vary from one student to another, can make it quite challenging to address these variables adequately and in a timely manner.

4.5 Proposed framework model for measuring university e-learning systems and its relevant outcomes

Based on the expert evaluation and the sum of the averages of their scores, the revised rankings of the sub-factors reshuffled the appearance of the preliminary framework model. Figure 2 displays these changes, presenting the official proposed evaluative framework model for measuring university e-learning systems and their relevant outcomes based on priority rankings gathered via AHP analysis of the expert evaluation of each sub-factor. Based on teaching methods, teaching style remained at the top with a priority of 61.5%, while types of exam questions (31.9%) shifted to second place, followed by quizzes and assignments (6.2%). Before our experiment, the quality of the syllabus, which was ranked first, fell to last place (6.2%), while teacher interaction, previously ranked third, rose to first place (61.4%) in our priority ranking system. Based on the variables of the learning environment, location emerged as the most influential factor (58.8%), while the level of infrastructure availability remained the least influential (8.9%), mirroring the situation before the experiment. The variable of student, containing nine factors, underwent a complete shuffle, with attendance being identified as the most important factor (31.2%). Results showed that concentration and friends and family achieved the same priority ranking (2.1%); therefore, the researcher assigned concentration a higher rank in the final model based on alphabetical order.

The benefit of this model over others in its field is that it provides a clear guide for developers on which factors should be heavily emphasised when trying to achieve learning outcomes. Furthermore, it displays the importance of each factor based on various research studies as well as the experience of experts involved in this field of study. Nevertheless, the researcher acknowledges that the possible implications of this model include difficulty in assessing intangible variables such as learning motivation, as well as the challenge of evaluating variables like family, as it would necessitate delving into the family issues of the student and may be perceived as encroaching on the boundaries of a teacher. Therefore, a clear scope of assessment cannot be provided for these aspects of e-learning outcomes.

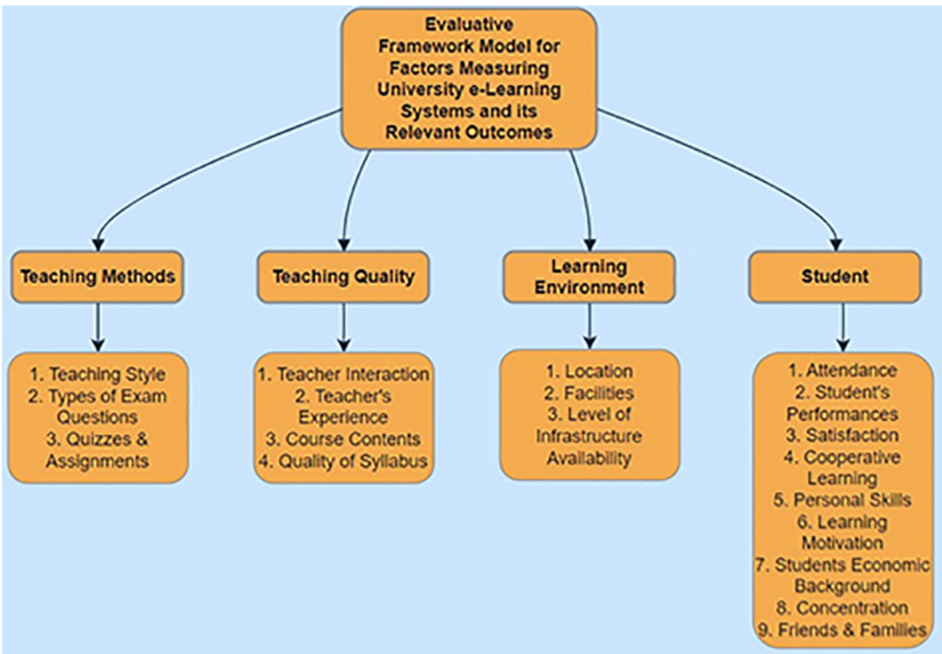

Fig. 2. Framework model for factors measuring e-learning systems and their relevant outcomes based on priority rankings

5 CONCLUSION

The aim of this study was to establish an evaluative framework for measuring university e-learning systems and their outcomes. This was achieved primarily by extrapolating factors and sub-factors from the comprehensive literature review conducted in this research, followed by the implementation of AHP analysis with the assistance of valuable expert opinions to determine priority rankings. The four main factors were teaching methods, teaching quality, learning environment, and students (RQ1), along with a total of 19 sub-factors (RQ2) across all sections. The main factor "student" had the most sub-factors, totalling nine. These sub-factors within their respective categories were adjusted based on priority according to the expert evaluation using the AHP (RQ3). For instance, the most important factor in teaching methods was teaching style, followed by types of exam questions, quizzes, and assignments. Across all main factors, this study found that sub-factors that were difficult to measure and calculate usually attained lower priority scores, whereas sub-factors with established methods of measurement and monitoring, as well as extensive research, attained higher priority scores. For example, in the "student" section, attendance can be easily measured, and research has shown direct links between attendance and learning outcomes, highlighting the significance of this category. On the other hand, friends and family are not straightforward variables to measure, nor do they have relevant and sufficient research data. As a result, the evaluators considered it to be the least important sub-factor of this category (RQ4).

This study acknowledges the importance of minimising bias and endeavours to achieve this goal by implementing comprehensive and rigorous multi-step expert selection criteria. By setting conditions for participation (current teaching activity, past and present e-learning system experience, varied specialty backgrounds, and diverse environmental backgrounds), this study eliminated disciplinary and geographical biases. This approach enhances the likelihood of obtaining valuable and broadly representative results, making the framework applicable to experts from diverse disciplines worldwide, across various environments and societies.

The theoretical contribution of this study is that, unlike many other studies, it investigates the factors influencing e-learning outcomes rather than investigating e-learning outcomes themselves. By conducting a comprehensive literature review of 102 research articles and obtaining expert evaluation of the gathered data, this study identified the most significant factors and sub-factors influencing e-learning outcomes. This study has enabled practical contributions to the research field by developing a new evaluative framework model for university e-learning systems. This model assists evaluators, educators, curriculum developers, and others in assessing the achievement of e-learning outcomes by considering the relevant influencing factors based on their respective levels of importance. The prioritisation of these sub-factors enables users in the field of university e-learning systems to adopt a systematic and targeted approach. By focusing on the most critical factors first, they can enhance the effectiveness of their interventions and achieve their learning goals more efficiently. After that, the framework could be used again to measure the impact of these factors and how changes in attendance, for example, can increase the likelihood of achieving learning outcomes. Based on the measured outcomes, adjustments and continuous refinements can be made to this framework as necessary. If not, it can remain a tool that guides educators, curriculum developers, etc. in reconsidering their strategies accordingly.

In summary, the primary advantage of this evaluative framework is that it serves as a strategic guide, providing tools to enhance learning outcomes by displaying the factors that influence these outcomes in descending order of priority within university e-learning systems. Educators can analyse the reasons hindering the achievement of their learning outcomes chronologically, prioritising them. By addressing the most impactful factors first, they can attain better results and reach desired goals in shorter time frames. This will enhance students' learning experience, improve academic outcomes, and more easily fulfil the overall achievement of learning outcomes. In addition, feedback from future implementers of this framework will benefit the development cycle and ensure that the framework continuously evolves to align with the ever-changing educational landscape. The abundance of these factors makes this evaluative framework a promising tool in the field of university e-learning systems in the present and future, while also addressing any shortcomings that may arise in future applications of this model. This may include a reshuffling of the factors assigned due to adequate and reliable practical findings. The researcher also suggests assessing the priority rankings of the four main variables as a whole in relation to each other based on the various methodologies implemented in our study, as well as considering a practical aspect of measurement.

6 FUTURE RESEARCH AND LIMITATIONS

This study can be expanded by incorporating additional undiscovered factors that may influence e-learning outcomes through further exploration of related literature, thereby enhancing the system. The role of gender as a factor affecting e-learning outcomes should also be investigated. The adaptability of this framework should be assessed by comparing its effectiveness with MOOCs and online learning platforms. The research utilised experts, excluding students, which may introduce subjective bias. The students might provide a different perspective on the factors influencing e-learning outcomes, as achieving learning outcomes involves both students and teachers.

7 REFERENCES

[1] A. M. Maatuk, E. K. Elberkawi, S. Aljawarneh, H. Rashaideh, and H. Alharbi, "The COVID-19 pandemic and e-learning: Challenges and opportunities from the perspective of students and instructors," *Journal of Computing in Higher Education*, vol. 34, no. 1, pp. 21–38, 2021. https://doi.org/10.1007/s12528-021-09274-2

[2] T. Favale, F. Soro, M. Trevisan, I. Drago, and M. Mellia, "Campus traffic and e-learning during COVID-19 pandemic," *Computer Networks*, vol. 176, p. 107290, 2020. https://doi.org/10.1016/j.comnet.2020.107290

[3] B. Kang, "How the COVID-19 pandemic is reshaping the education service," *The Future of Service Post-COVID-19 Pandemic*, vol. 1, pp. 15–36, 2021. https://doi.org/10.1007/978-981-33-4126-5_2

[4] H. Zelelew, Z. Teshome, T. Tadesse, and Y. Keleta, "Planting the seeds of innovative e-learning platform in higher education institutions in Ethiopia: The case of ET online college," *E-Learning and Digital Media*, vol. 20, no. 2, pp. 115–137, 2022. https://doi.org/10.1177/20427530221108030

[5] A. Bozkurt *et al.*, "A global outlook to the interruption of education due to COVID-19 pandemic: Navigating in a time of uncertainty and crisis," *Asian Journal of Distance Education*, vol. 15, no. 1, pp. 1–126, 2020. https://doi.org/10.5281/zenodo.3878572

[6] G. Oliveira, J. Grenha Teixeira, A. Torres, and C. Morais, "An exploratory study on the emergency remote education experience of higher education students and teachers during the COVID-19 pandemic," *British Journal of Educational Technology*, vol. 52, no. 4, pp. 1357–1376, 2021. https://doi.org/10.1111/bjet.13112

[7] S. Jacques, A. Ouahabi, and T. Lequeu, "Remote knowledge acquisition and assessment during the COVID-19 pandemic," *International Journal of Engineering Pedagogy (iJEP)*, vol. 10, no. 6, pp. 120–138, 2020. https://doi.org/10.3991/ijep.v10i6.16205

[8] W. H. DeLone and E. R. McLean, "Measuring e-commerce success: Applying the DeLone & McLean information systems success model," *International Journal of Electronic Commerce*, vol. 9, no. 1, pp. 31–47, 2004. https://doi.org/10.1080/10864415.2004.11044317

[9] N. Simper, J. Kaupp, B. Frank, and J. Scott, "Development of the transferable learning orientations tool: Providing metacognitive opportunities and meaningful feedback for students and instructors," *Assessment & Evaluation in Higher Education*, vol. 41, no. 8, pp. 1159–1175, 2015. https://doi.org/10.1080/02602938.2015.1070117

[10] B. M. Frank, N. Simper, and J. A. Kaupp, "How we know they're learning: Comparing approaches to longitudinal assessment of transferable learning outcomes," in *2016 ASEE Annual Conference & Exposition*, New Orleans, Louisiana, 2016. https://doi.org/10.18260/p.25493

[11] R. Scherer, F. Siddiq, and J. Tondeur, "The Technology Acceptance Model (TAM): A meta-analytic structural equation modeling approach to explaining teachers' adoption of digital technology in education," *Computers & Education*, vol. 128, pp. 13–35, 2019. https://doi.org/10.1016/j.compedu.2018.09.009

[12] A. Bhattacherjee, "Understanding information systems continuance: An expectation-confirmation model," *MIS Quarterly*, vol. 25, no. 3, pp. 351–370, 2001. https://doi.org/10.2307/3250921

[13] S. Adam, "Using learning outcomes: A consideration of the nature, role, application and implications for European education of employing 'learning outcomes' at the local, national and international levels," in *Bologna Seminar*, Heriot-Watt University, 2004.

[14] L. Harvey, "Analytic Quality Glossary, Quality Research International," 2004.

[15] A. R. Pesimo, "Developing the learning outcomes of the students through microscale experiments in chemistry," *Open Access Library Journal (OALib)*, vol. 1, no. e479, pp. 1–11, 2014. https://doi.org/10.4236/oalib.1100479

[16] S. Zarei and S. Mohammadi, "Challenges of higher education related to e-learning in developing countries during COVID-19 spread: A review of the perspectives of students, instructors, policymakers, and ICT experts," *Environmental Science and Pollution Research*, vol. 29, pp. 85562–85568, 2021. https://doi.org/10.1007/s11356-021-14647-2

[17] N. Sandu and E. Gide, "Analysis of the main factors affecting the adoption of cloud based interactive mobile learning in the Australian higher education sector," *International Journal of Interactive Mobile Technologies (iJIM),* vol. 12, no. 4, pp. 43–58, 2018. https://doi.org/10.3991/ijim.v12i4.9200

[18] A. K. M. N. Islam, "E-learning system use and its outcomes: Moderating role of perceived compatibility," *Telematics and Informatics*, vol. 33, no. 1, pp. 48–55, 2016. https://doi.org/10.1016/j.tele.2015.06.010

[19] Q. Hammouri and E. Abu-Shanab, "Exploring factors affecting users' satisfaction toward e-learning systems," *International Journal of Information and Communication Technology Education (IJICTE)*, vol. 14, no. 1, pp. 44–57, 2018. https://doi.org/10.4018/IJICTE.2018010104

[20] H. Yurdugül and N. M. Çetin, "Investigation of the relationship between learning process and learning outcomes in e-learning environments," *Eurasian Journal of Educational Research*, vol. 15, no. 59, pp. 57–74, 2015. https://doi.org/10.14689/ejer.2015.59.4

[21] A. Keramati, M. Afshari-Mofrad, and A. Kamrani, "The role of readiness factors in e-learning outcomes: An empirical study," *Computers & Education*, vol. 57, no. 3, pp. 1919–1929, 2011. https://doi.org/10.1016/j.compedu.2011.04.005

[22] A. Tarhini, R. Masa'deh, K. A. Al-Busaidi, A. B. Mohammed, and M. Maqableh, "Factors influencing students' adoption of e-learning: A structural equation modeling approach," *Journal of International Education in Business*, vol. 10, no. 2, pp. 164–182, 2017. https://doi.org/10.1108/JIEB-09-2016-0032

[23] N. Jafari Navimipour and B. Zareie, "A model for assessing the impact of e-learning systems on employees' satisfaction," *Computers in Human Behavior*, vol. 53, pp. 475–485, 2015. https://doi.org/10.1016/j.chb.2015.07.026

[24] S. Anon, "The effects of student motivation and self-regulated learning strategies on student's perceived e-learning outcomes and satisfaction," *Journal of Higher Education Theory and Practice*, vol. 19, no. 7, 2019. https://doi.org/10.33423/jhetp.v19i7.2529

[25] Y. Lee, "An empirical investigation into factors influencing the adoption of an e-learning system," *Online Information Review*, vol. 30, no. 5, pp. 517–541, 2006. https://doi.org/10.1108/14684520610706406

[26] N. Hrtoňová, J. Kohout, L. Rohlíková, and J. Zounek, "Factors influencing acceptance of e-learning by teachers in the Czech Republic," *Computers in Human Behavior*, vol. 51, pp. 873–879, 2015. https://doi.org/10.1016/j.chb.2014.11.018

[27] S. Ghazinoory and M. Afshari-Mofrad, "Ranking different factors which affect e-learning outcomes," *International Journal of Computer Theory and Engineering*, vol. 4, no. 2, pp. 234–237, 2012. https://doi.org/10.7763/IJCTE.2012.V4.458

[28] M. Haverila, "Factors related to perceived learning outcomes in e-learning," *International Journal of Knowledge and Learning*, vol. 6, no. 4, pp. 308–328, 2010. https://doi.org/10.1504/IJKL.2010.038652

[29] P.-C. Sun, R. J. Tsai, G. Finger, Y.-Y. Chen, and D. Yeh, "What drives a successful e-Learning? An empirical investigation of the critical factors influencing learner satisfaction," *Computers & Education*, vol. 50, no. 4, pp. 1183–1202, 2008. https://doi.org/10.1016/j.compedu.2006.11.007

[30] H. Baber, "Determinants of students' perceived learning outcome and satisfaction in online learning during the pandemic of COVID19," *Journal of Education and E-Learning Research*, vol. 7, no. 3, pp. 285–292, 2020. https://doi.org/10.20448/journal.509.2020.73.285.292

[31] Y. Daultani, M. Goswami, A. Kumar, and S. Pratap, "Perceived outcomes of e-learning: Identifying key attributes affecting user satisfaction in higher education institutes," *Measuring Business Excellence*, vol. 25, no. 2, pp. 216–229, 2021. https://doi.org/10.1108/MBE-07-2020-0110

[32] C. Darawong and A. Widayati, "Improving student satisfaction and learning outcomes with service quality of online courses: Evidence from Thai and Indonesian higher education institutions," *Journal of Applied Research in Higher Education*, vol. 14, no. 4, pp. 1245–1259, 2021. https://doi.org/10.1108/JARHE-02-2021-0074

[33] Z. Yu, M. Gao, and L. Wang, "The effect of educational games on learning outcomes, student motivation, engagement and satisfaction," *Journal of Educational Computing Research*, vol. 59, no. 3, pp. 522–546, 2020. https://doi.org/10.1177/0735633120969214

[34] Y. Georgiou and E. A. Kyza, "Relations between student motivation, immersion and learning outcomes in location-based augmented reality settings," *Computers in Human Behavior*, vol. 89, pp. 173–181, 2018. https://doi.org/10.1016/j.chb.2018.08.011

[35] S. R. Natasia, Y. T. Wiranti, and A. Parastika, "Acceptance analysis of NUADU as e-learning platform using the Technology Acceptance Model (TAM) approach," *Procedia Computer Science*, vol. 197, pp. 512–520, 2022. https://doi.org/10.1016/j.procs.2021.12.168

[36] B. Al Kurdi, M. Alshurideh, S. A. Salloum, Z. M. Obeidat, and R. M. Al-dweeri, "An empirical investigation into examination of factors influencing university students' behavior towards elearning acceptance using SEM approach," *International Journal of Interactive Mobile Technologies (iJIM)*, vol. 14, no. 2, pp. 19–41, 2020. https://doi.org/10.3991/ijim.v14i02.11115
[37] R. W. Saaty, "The analytic hierarchy process—what it is and how it is used," *Mathematical Modelling*, vol. 9, nos. 3–5, pp. 161–176, 1987. https://doi.org/10.1016/0270-0255(87)90473-8
[38] F. Li, K. K. Phoon, X. Du, and M. Zhang, "Improved AHP method and its application in risk identification," *Journal of Construction Engineering and Management*, vol. 139, no. 3, pp. 312–320, 2013. https://doi.org/10.1061/(ASCE)CO.1943-7862.0000605
[39] T. Ebiere Dorgu, "Different teaching methods: A panacea for effective curriculum implementation in the classroom," *International Journal of Secondary Education*, vol. 3, no. 6, pp. 77–87, 2015. https://doi.org/10.11648/j.ijsedu.s.2015030601.13
[40] N. J. Entwistle, *Styles of Learning and Teaching: An Integrated Outline of Educational Psychology for Students' Teachers, and Lecturers.* London: David Fulton Publishers, 2016.
[41] L. Ingvarson, M. Meiers, and A. Beavis, "Factors affecting the impact of professional development programs on teachers' knowledge, practice, student outcomes & efficacy," *Education Policy Analysis Archives*, vol. 13, no. 10, p. 10, 2005. https://doi.org/10.14507/epaa.v13n10.2005
[42] H. Noga, "Applying chosen teaching methods in technical education," *International Journal of Engineering Pedagogy (iJEP)*, vol. 4, no. 4, pp. 23–26, 2014. https://doi.org/10.3991/ijep.v4i4.3855
[43] C. Emejidio and Gepila Jr., "Students' learning styles and preferred teaching styles in Philippine classroom," *International Journal of Psychosocial Rehabilitation*, vol. 24, no. 4, pp. 2725–2734, 2020. https://doi.org/10.37200/IJPR/V24I4/PR201380
[44] S. Alnujaidi, "The difference between EFL students' preferred learning styles and EFL teachers' preferred teaching styles in Saudi Arabia," *English Language Teaching*, vol. 12, no. 1, 2019. https://doi.org/10.5539/elt.v12n1p90
[45] M. Toyama and Y. Yamazaki, "Are there effects of a match between learning style and teaching style in an EFL classroom?" *Innovation in Language Learning and Teaching*, vol. 14, no. 3, pp. 243–258, 2020. https://doi.org/10.1080/17501229.2019.1575386
[46] J. Kerby, Z. N. Shukur, and J. Shalhoub, "The relationships between learning outcomes and methods of teaching anatomy as perceived by medical students," *Clinical Anatomy*, vol. 24, no. 4, pp. 489–497, 2010. https://doi.org/10.1002/ca.21059
[47] F. Latifi and H. Kasumi, "Teachers' perspectives on innovative and interactive teaching methods: Perspective of mobile learning," *International Journal of Interactive Mobile Technologies (iJIM)*, vol. 16, no. 23, pp. 73–83, 2022. https://doi.org/10.3991/ijim.v16i23.36217
[48] T. Budiman and F. Franky, "The relationship pattern of internet usage frequency, generation Z characteristics, and teaching method in the Millennium Era," *International Journal of Interactive Mobile Technologies (iJIM)*, vol. 15, no. 18, pp. 178–185, 2021. https://doi.org/10.3991/ijim.v15i18.24555
[49] T. A. Nicholl and K. Lou, "A model for small-group problem-based learning in a large class facilitated by one instructor," *American Journal of Pharmaceutical Education*, vol. 76, no. 6, p. 117, 2012. https://doi.org/10.5688/ajpe766117
[50] C. S. Tucker, B. Pursel, and A. Divinsky, "Mining student-generated textual data in MOOCS and quantifying their effects on student performance and learning outcomes," in *2014 ASEE Annual Conference & Exposition*, 2014. https://doi.org/10.18260/1-2--22840
[51] D. R. Sadler, "Three in-course assessment reforms to improve higher education learning outcomes," *Assessment & Evaluation in Higher Education*, vol. 41, no. 7, pp. 1081–1099, 2015. https://doi.org/10.1080/02602938.2015.1064858

[52] F. Zulkifli, R. Z. Abidin, and Z. Mohamed, "Evaluating the quality of exam questions: A multidimensional item response," *International Journal of Recent Technology and Engineering*, vol. 8, no. 2S11, pp. 606–612, 2019. https://doi.org/10.35940/ijrte.B1094.0982S1119

[53] R. Machová, E. Korcsmáros, Z. Šeben, L. Fehér, and Z. Tóth, "Developing the competences of generation Z with innovative teaching methods in the context of the requirement of labour market by industry 4.0," *International Journal of Advanced Corporate Learning (iJAC)*, vol. 14, no. 2, pp. 17–26, 2021. https://doi.org/10.3991/ijac.v14i2.24993

[54] J. Joyce, D. H. Gitomer, and C. J. Iaconangelo, "Classroom assignments as measures of teaching quality," *Learning and Instruction*, vol. 54, pp. 48–61, 2018. https://doi.org/10.1016/j.learninstruc.2017.08.001

[55] J. Ulfvarson and L. Oxelmark, "Developing an assessment tool for intended learning outcomes in clinical practice for nursing students," *Nurse Education Today*, vol. 32, no. 6, pp. 703–708, 2012. https://doi.org/10.1016/j.nedt.2011.09.010

[56] Z. R. Wolf, K. E. Czekanski, and P. M. Dillon, "Course syllabi: Components and outcomes assessment," *Journal of Nursing Education and Practice*, vol. 4, no. 1, 2014. https://doi.org/10.5430/jnep.v4n1p100

[57] E. Kyndt, D. Gijbels, I. Grosemans, and V. Donche, "Teachers' everyday professional development," *Review of Educational Research*, vol. 86, no. 4, pp. 1111–1150, 2016. https://doi.org/10.3102/0034654315627864

[58] P. Fernández-Berrocal, M. J. Gutiérrez-Cobo, J. Rodriguez-Corrales, and R. Cabello, "Teachers' affective well-being and teaching experience: The protective role of perceived emotional intelligence," *Frontiers in Psychology*, vol. 8, 2017. https://doi.org/10.3389/fpsyg.2017.02227

[59] M. C. Araujo, P. Carneiro, Y. Cruz-Aguayo, and N. Schady, "Teacher quality and learning outcomes in Kindergarten," *The Quarterly Journal of Economics*, vol. 131, no. 3, pp. 1415–1453, 2016. https://doi.org/10.1093/qje/qjw016

[60] A. Panayiotou *et al.*, "Teacher behavior and student outcomes: Results of a European study," *Educational Assessment, Evaluation and Accountability*, vol. 26, pp. 73–93, 2014. https://doi.org/10.1007/s11092-013-9182-x

[61] T. Saba, "Retraction note: Implications of e-learning systems and self-efficiency on students' outcomes: A model approach," *Human-Centric Computing and Information Sciences*, vol. 3, no. 11, 2013. https://doi.org/10.1186/2192-1962-3-11

[62] S. Sarkar, S. Mohapatra, and J. Sundarakrishnan, "Assessing impact of technology based digital equalizer programme on improving student learning outcomes," *Education and Information Technologies*, vol. 22, pp. 195–213, 2015. https://doi.org/10.1007/s10639-015-9434-0

[63] K. Illeris, "A model for learning in working life," *Journal of Workplace Learning*, vol. 16, no. 8, pp. 431–441, 2004. https://doi.org/10.1108/13665620410566405

[64] E. A. Mulyani, M. Alpusari, and E. D. Putra, "The effect of learning facilities and family environment on motivation to learn of prospective elementary teacher education on online learning," *Journal of Teaching and Learning in Elementary Education (JTLEE)*, vol. 4, no. 1, p. 89, 2021. https://doi.org/10.33578/jtlee.v4i1.7866

[65] C. Jain and N. Prasad, "Teachers perspective on quality of teaching in schools," in *Quality of Secondary Education in India*, 2017, pp. 189–207. https://doi.org/10.1007/978-981-10-4929-3_12

[66] C. J. Khanlarian and R. Singh, "An exploratory study of the online learning environment," *Issues in Accounting Education*, vol. 29, no. 1, pp. 117–147, 2014. https://doi.org/10.2308/iace-50614

[67] B. Detlor, H. Julien, R. Willson, A. Serenko, and M. Lavallee, "Learning outcomes of information literacy instruction at business schools," *Journal of the American Society for Information Science and Technology*, vol. 62, no. 3, pp. 572–585, 2011. https://doi.org/10.1002/asi.21474

[68] D. S. K. Chan, "Associations between student learning outcomes from their clinical placement and their perceptions of the social climate of the clinical learning environment," *International Journal of Nursing Studies*, vol. 39, no. 5, pp. 517–524, 2002. https://doi.org/10.1016/S0020-7489(01)00057-8

[69] G.-J. Hwang, S.-C. Chang, P.-Y. Chen, and X.-Y. Chen, "Effects of integrating an active learning-promoting mechanism into location-based real-world learning environments on students' learning performances and behaviors," *Educational Technology Research and Development*, vol. 66, pp. 451–474, 2017. https://doi.org/10.1007/s11423-017-9567-5

[70] B. J. Fraser, K. G. Tobin, and C. J. Mcrobbie, *Second International Handbook of Science Education*. Dordrecht; New York: Springer, 2012. https://doi.org/10.1007/978-1-4020-9041-7

[71] J. M. Ngwaru and M. Oluga, "Educational infrastructure and resources for sustainable access to schooling and outcomes: The case of early literacy development in Southern Tanzania," *Africa Education Review*, vol. 12, no. 1, pp. 88–108, 2015. https://doi.org/10.1080/18146627.2015.1036570

[72] F. S. Nasiri, S. Ghanbari, M. R. Ardalan, and I. Karimi, "Effect of infrastructure and faculty readiness in effective implementation of e-learning based on Technology Acceptance Model (TAM)," *Education Strategies in Medical Sciences*, vol. 7, no. 5, pp. 329–338, 2014.

[73] M. Yangambi, "Impact of school infrastructures on students learning and performance: Case of three public schools in a developing country," *Creative Education*, vol. 14, no. 4, pp. 788–809, 2023. https://doi.org/10.4236/ce.2023.144052

[74] L. Refnita, "A model of integrated assessment for structure I subject at university level," in *Proceedings of ISELT FBS Universitas Negeri Padang*, 2013, pp. 155–164.

[75] J. Enrique Hinostroza, S. Isaacs, and M. Bougroum, "Information and communications technologies for improving learning opportunities and outcomes in developing countries," in *Learning and Education in Developing Countries: Research and Policy for the Post-2015 UN Development Goals*, 2014, pp. 42–57. https://doi.org/10.1057/9781137455970_3

[76] Gladys Lopez Acevedo, "Learning outcomes and school cost-effectiveness in Mexico: The PARE program," *Policy Research Working Papers*, 1999. https://doi.org/10.1596/1813-9450-2128

[77] C. Okioga, "The impact of students' socio-economic background on academic performance in Universities, a case of students in Kisii University College," *American International Journal of Social Science*, vol. 2, no. 2, pp. 38–46, 2013.

[78] F. Ogunshola, "The effects of parental socio-economic status on academic performance of students in selected schools in Edu Lga of Kwara State, Nigeria," 2012.

[79] J. Bakker, E. Denessen, and M. Brus-Laeven, "Socio-economic background, parental involvement and teacher perceptions of these in relation to pupil achievement," *Educational Studies*, vol. 33, no. 2, pp. 177–192, 2007. https://doi.org/10.1080/03055690601068345

[80] K. R. Pant, "Influences of parental socio-economic status on academic achievement: A case study of rural communities in Kailali, Nepal," *Contemporary Research: An Interdisciplinary Academic Journal*, vol. 4, no. 1, pp. 95–109, 2020. https://doi.org/10.3126/craiaj.v4i1.32753

[81] M. Javed, "Investigating factors affecting students' subject selection at secondary school level," *International Journal of Information and Education Technology*, vol. 8, no. 11, pp. 815–820, 2018. https://doi.org/10.18178/ijiet.2018.8.11.1145

[82] S. Fajar, M. Hussain, H. Sarwar, M. Afzal, and S. A. Gilani, "Factors affecting academic performance of undergraduate nursing students," *International Journal of Social Sciences and Management*, vol. 6, no. 1, pp. 7–16, 2019. https://doi.org/10.3126/ijssm.v6i1.22561

[83] C. Rolleston, Z. James, and Elisabetta Aurino, "Exploring the effect of educational opportunity and inequality on learning outcomes in Ethiopia, Peru, India, and Vietnam," 2013.

[84] M. V. López-Pérez, M. C. Pérez-López, and L. Rodríguez-Ariza, "Blended learning in higher education: Students' perceptions and their relation to outcomes," *Computers & Education*, vol. 56, no. 3, pp. 818–826, 2011. https://doi.org/10.1016/j.compedu.2010.10.023

[85] C. Jain and N. Prasad, "Understanding factors affecting student outcomes and learning behaviour," in *Quality of Secondary Education in India,* Springer, 2018, pp. 163–187. https://doi.org/10.1007/978-981-10-4929-3_11

[86] C. S. Tucker, B. Pursel, and A. Divinsky, "Mining student-generated textual data in MOOCS and quantifying their effects on student performance and learning outcomes," in *2014 ASEE Annual Conference & Exposition*, 2020. https://doi.org/10.18260/1-2--22840

[87] C.-C. Chang, K.-H. Tseng, and S.-J. Lou, "A comparative analysis of the consistency and difference among teacher-assessment, student self-assessment and peer-assessment in a web-based portfolio assessment environment for high school students," *Computers & Education*, vol. 58, no. 1, pp. 303–320, 2012. https://doi.org/10.1016/j.compedu.2011.08.005

[88] S.-C. Liew, J. Sidhu, and A. Barua, "The relationship between learning preferences (styles and approaches) and learning outcomes among pre-clinical undergraduate medical students," *BMC Medical Education*, vol. 15, 2015. https://doi.org/10.1186/s12909-015-0327-0

[89] K. Blaine Lawlor and M. J. Hornyak, "Smart goals: How the application of smart goals can contribute to achievement of student learning outcomes," *Developments in Business Simulation and Experiential Learning*, vol. 39, 2012.

[90] D. W. Kwak, C. Sherwood, and K. K. Tang, "Class attendance and learning outcome," *Empirical Economics*, vol. 57, pp. 177–203, 2018. https://doi.org/10.1007/s00181-018-1434-7

[91] G. A. Tetteh, "Effects of classroom attendance and learning strategies on the learning outcome," *Journal of International Education in Business*, vol. 11, no. 2, pp. 195–219, 2018. https://doi.org/10.1108/JIEB-01-2017-0004

[92] A.-L. Hoffmann and K. Lerche, "Class attendance and university performance," *SSRN*, cege discussion papers, no. 286, 2016. https://doi.org/10.2139/ssrn.2805378

[93] D. M. Horton, S. D. Wiederman, and D. A. Saint, "Assessment outcome is weakly correlated with lecture attendance: Influence of learning style and use of alternative materials," *Advances in Physiology Education*, vol. 36, no. 2, pp. 108–115, 2012. https://doi.org/10.1152/advan.00111.2011

[94] N. K. Şahbaz, "Evaluation of reading attitudes of 8th grade students in primary education according to various variables," *Educational Research and Reviews,* vol. 7, no. 26, pp. 571–576, 2012. https://doi.org/10.5897/err12.101

[95] P. R. Pintrich, "A motivational science perspective on the role of student motivation in learning and teaching contexts," *Journal of Educational Psychology*, vol. 95, no. 4, pp. 667–686, 2003. https://doi.org/10.1037/0022-0663.95.4.667

[96] X. Wang, "Influences of learning emotion on learning outcome in online teaching mode," *International Journal of Emerging Technologies in Learning (iJET)*, vol. 17, no. 8, pp. 126–139, 2022. https://doi.org/10.3991/ijet.v17i08.30459

[97] Y. Georgiou and E. A. Kyza, "Relations between student motivation, immersion and learning outcomes in location-based augmented reality settings," *Computers in Human Behavior*, vol. 89, pp. 173–181, 2018. https://doi.org/10.1016/j.chb.2018.08.011

[98] Z. Yu, W. Xu, and P. Sukjairungwattana, "Motivation, learning strategies, and outcomes in mobile English language learning," *The Asia-Pacific Education Researcher*, vol. 32, pp. 545–560, 2022. https://doi.org/10.1007/s40299-022-00675-0
[99] R. K. Mallya and B. Srinivasan, "Impact of mobile learning in the cloud on learning competencies of engineering students," *International Journal of Online and Biomedical Engineering (iJOE)*, vol. 15, no. 9, pp. 80–87, 2019. https://doi.org/10.3991/ijoe.v15i09.10671
[100] S. Bolkan, A. K. Goodboy, and D. M. Kelsey, "Instructor clarity and student motivation: Academic performance as a product of students' ability and motivation to process instructional material," *Communication Education*, vol. 65, no. 2, pp. 129–148, 2015. https://doi.org/10.1080/03634523.2015.1079329
[101] E. N. O'Reilly, "Correlations among perceived autonomy support, intrinsic motivation, and learning outcomes in an intensive foreign language program," *Theory and Practice in Language Studies*, vol. 4, no. 7, pp. 1313–1318, 2014. https://doi.org/10.4304/tpls.4.7.1313-1318
[102] S. S. Asih and Renggani, "Intensity attention of parents and communication in families to learning outcomes," in *Proceedings of the International Conference Primary Education Research Pivotal Literature and Research UNNES 2018 (IC PEOPLE UNNES 2018)*, 2019. https://doi.org/10.2991/icpeopleunnes-18.2019.36
[103] D. M. Palfreyman, "Family, friends, and learning beyond the classroom: Social networks and social capital in language learning," in *Palgrave Macmillan UK eBooks*, 2011, pp. 17–34. https://doi.org/10.1057/9780230306790_3
[104] R. Brooks, "Young people's higher education choices: The role of family and friends," *British Journal of Sociology of Education*, vol. 24, no. 3, pp. 283–297, 2003. https://doi.org/10.1080/01425690301896
[105] B. P. Mallory, D. J. Fisher, A. R. Witham, and A. D. Gultice, "With a little help from my friends: How faculty peer review can transform mediocre teaching methods into powerful learning experiences," 2014.
[106] H. Maldonado, S. R. Klemmer, and R. D. Pea, "When is collaborating with friends a good idea? Insights from design education," in *Proceedings of the 9th International Conference on Computer Supported Collaborative Learning (CSCL'09)*, 2009, vol. 1, pp. 227–231. https://doi.org/10.3115/1600053.1600087
[107] S. M. Martin, "Are public school teacher salaries paid compensating wage differentials for student racial and ethnic characteristics?" *Education Economics*, vol. 18, no. 3, pp. 349–370, 2008. https://doi.org/10.1080/09645290802470228
[108] I. Buil, S. Catalán, and E. Martínez, "The influence of flow on learning outcomes: An empirical study on the use of clickers," *British Journal of Educational Technology*, vol. 50, no. 1, pp. 428–439, 2017. https://doi.org/10.1111/bjet.12561
[109] Y. Guo *et al.*, "The impact of flow on learning outcomes in a graduate-level information management course," *Journal of Global Business Issues,* vol. 1, no. 2, pp. 31–39, 2007.
[110] S. Rochani, "Enhancement of concentration and mathematics learning outcomes using discovery learning method on transformation topic," *Indonesian Journal of Mathematics Education*, vol. 2, no. 2, p. 89, 2019. https://doi.org/10.31002/ijome.v2i2.1666
[111] K. Litchfield, A. Javernick-Will, and A. Maul, "Technical and professional skills of engineers involved and not involved in engineering service," *Journal of Engineering Education*, vol. 105, no. 1, pp. 70–92, 2015. https://doi.org/10.1002/jee.20109
[112] A. Abu-Al-Aish and S. Love, "Factors influencing students' acceptance of m-learning: An investigation in higher education," *The International Review of Research in Open and Distributed Learning*, vol. 14, no. 5, 2013. https://doi.org/10.19173/irrodl.v14i5.1631

[113] J. Currey, S. K. Sprogis, G. Burdeu, J. Considine, J. A. Allen, and E. Oldland, "Students perceive team-based learning facilitates development of graduate learning outcomes and professional skills," *Journal of Teaching and Learning for Graduate Employability*, vol. 9, no. 1, pp. 93–113, 2018. https://doi.org/10.21153/jtlge2018vol9no1art759

[114] D. F. Dansereau, "The nuts and bolts of cooperative learning," *PsycCRITIQUES*, vol. 40, no. 7, pp. 678–679, 1995. https://doi.org/10.1037/003814

[115] J.-W. Lin, "Examining the factors that influence students' science learning processes and their learning outcomes: 30 years of conceptual change research," *EURASIA Journal of Mathematics, Science & Technology Education*, vol. 12, no. 9, pp. 2617–2646, 2016. https://doi.org/10.12973/eurasia.2016.000600a

[116] Y. S. Nasution and E. Surya, "Application of TPS type cooperative learning in improving students' mathematics learning outcome," 2017.

[117] K. D. Strang, "Does cooperative e-learning improve graduate student project outcomes?" *International Journal of Technology Enhanced Learning*, vol. 5, no. 1, pp. 42–55, 2013. https://doi.org/10.1504/IJTEL.2013.055947

[118] A. Rahman, A. S. Ahmar, and R. Rusli, "The influence of cooperative learning models on learning outcomes based on students' learning styles," *World Transactions on Engineering and Technology Education*, vol. 14, no. 3, pp. 425–430, 2016. https://doi.org/10.26858/wtetev14i3y2016p6425430

[119] J. C. Sweeney and D. Ingram, "A comparison of traditional and web-based tutorials in marketing education: An exploratory study," *Journal of Marketing Education*, vol. 23, no. 1, pp. 55–62, 2001. https://doi.org/10.1177/0273475301231007

[120] L. C. Duque, "A framework for analysing higher education performance: Students' satisfaction, perceived learning outcomes, and dropout intentions," *Total Quality Management & Business Excellence*, vol. 25, nos. 1–2, pp. 1–21, 2014. https://doi.org/10.1080/14783363.2013.807677

[121] S. B. Eom and N. Ashill, "The determinants of students' perceived learning outcomes and satisfaction in university online education: An update," *Decision Sciences Journal of Innovative Education*, vol. 14, no. 2, pp. 185–215, 2016. https://doi.org/10.1111/dsji.12097

[122] M. Muzammil, A. Sutawijaya, and M. Harsasi, "Investigating student satisfaction in online learning: The role of student interaction and engagement in distance learning university," *Turkish Online Journal of Distance Education*, vol. 21, Issue: Special Issue-IODL, pp. 88–96, 2020. https://doi.org/10.17718/tojde.770928

[123] A. B. Bernardo, C. Galve-González, J. C. Núñez, and L. S. Almeida, "A path model of university dropout predictors: The role of satisfaction, the use of self-regulation learning strategies and students' engagement," *Sustainability*, vol. 14, no. 3, p. 1057, 2022. https://doi.org/10.3390/su14031057

[124] S. A. Myers and A. K. Goodboy, "College student learning, motivation, and satisfaction as a function of effective instructor communication behaviors," *The Southern Communication Journal*, vol. 79, no. 1, pp. 14–26, 2014. https://doi.org/10.1080/1041794x.2013.815266

[125] J. Nielsen, "Usability inspection methods," in *Conference Companion on Human Factors in Computing Systems – CHI '94*, 1994, pp. 413–414. https://doi.org/10.1145/259963.260531

[126] T. L. Saaty, "The analytic hierarchy and analytic network processes for the measurement of intangible criteria and for decision-making," in *International Series in Operations Research and Management Science*, 2016, vol. 233, pp. 363–419. https://doi.org/10.1007/978-1-4939-3094-4_10

[127] N. Bhushan and K. Rai, *Strategic Decision Making: Applying the Analytic Hierarchy Process.* London: Springer, 2004. https://doi.org/10.1007/b97668

[128] M. Benaida, "Developing and extending usability heuristics evaluation for user interface design via AHP," *Soft Computing*, vol. 27, pp. 9693–9707, 2023. https://doi.org/10.1007/s00500-022-07803-4

[129] M. Brunelli, *Introduction to the Analytic Hierarchy Process.* Springer, 2015. https://doi.org/10.1007/978-3-319-12502-2

[130] K. Schmidt, I. Aumann, I. Hollander, K. Damm, and J.-M. G. von der Schulenburg, "Applying the analytic hierarchy process in healthcare research: A systematic literature review and evaluation of reporting," *BMC Medical Informatics and Decision Making*, vol. 15, 2015. https://doi.org/10.1186/s12911-015-0234-7

[131] T. L. Saaty, "Decision making with the analytic hierarchy process," *International Journal of Services Sciences (IJSSCI)*, vol. 1, no. 1, pp. 83–98, 2008. https://doi.org/10.1504/IJSSCI.2008.017590

[132] N. Bhushan and K. Rai, *Strategic Decision Making: Applying the Analytic Hierarchy Process*. London: Springer, 2004. https://doi.org/10.1007/b97668

[133] H.-C. Yeh, Y.-C. Chen, and C. Wei, "A new approach to selecting a regionalized design hyetograph by principal component analysis and analytic hierarchy process," *Paddy and Water Environment*, vol. 11, pp. 73–85, 2013. https://doi.org/10.1007/s10333-011-0294-y

[134] E. J. T. Hamilton and E. T. Dorgu, "Curriculum and indigenous education for technological advancement," *British Journal of Education,* vol. 3, no. 11, pp. 32–39, 2015.

[135] J. D. Nisbet and J. Shucksmith, *Learning Strategies*. London, New York: Routledge, Taylor & Franscis Group, 2018.

[136] S. L. Zorluoğlu and Ç. Güven, "Analysis of 5th grade science learning outcomes and exam questions according to revised bloom taxonomy," *Journal of Educational Issues*, vol. 6, no. 1, 2020. https://doi.org/10.5296/jei.v6i1.16197

[137] C. Husbands and J. Pearce, "What makes great pedagogy? Nine claims from research," 2012.

[138] P. Mete, "The views of students in an inclusive classroom environment in high school on the course learning process," *İlköğretim Online*, pp. 552–564, 2020. https://doi.org/10.17051/ilkonline.2020.689692

[139] I. Abualrub, B. Karseth, and B. Stensaker, "The various understandings of learning environment in higher education and its quality implications," *Quality in Higher Education*, vol. 19, no. 1, pp. 90–110, 2013. https://doi.org/10.1080/13538322.2013.772464

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