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Effective Blended Learning Model Selection Based on Student Learning Style using Analytic Hierarchy Process for an Undergraduate Engineering Course

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ABSTRACT

Blended learning is a flexible method conducted through face-to-face and online learning. It requires students to learn by attempting the classes physically and allows them to learn virtually at different times and places. It has become more evident and common after the Movement Control Order (MCO) as most of the lectures at the university are carried out in hybrid mode. The blended learning models create problems and opportunities for students as they need to explore and adapt to different lecturers' different blended learning methods in terms of teaching styles, planning, and timing. Therefore, the objective of this research is to investigate the best-blended learning models for an undergraduate engineering course based on student learning style by using the Analytic Hierarchy Process (AHP) method, as it is a big challenge to select the most effective approach for universities to educate, tutor and bring out quality students according to their learning styles. The AHP method is used to aid the students in finding the best-blended learning model based on their learning style. AHP analysis is then conducted to validate and verify its accuracy by comparing it with Visual, Auditory, Read/write, and Kinesthetic (VARK) models. As a result, most students are kinaesthetic learners (72%) based on VARK results, and the face-to-face driver model is the most preferred blended learning model with the priority vector at 31.33% through the AHP analysis. The accuracy of the AHP result is 74% by comparing it with the VARK result. In summary, the data can be deployed in the UTeM blended learning system to improve the course design and student learning experience.

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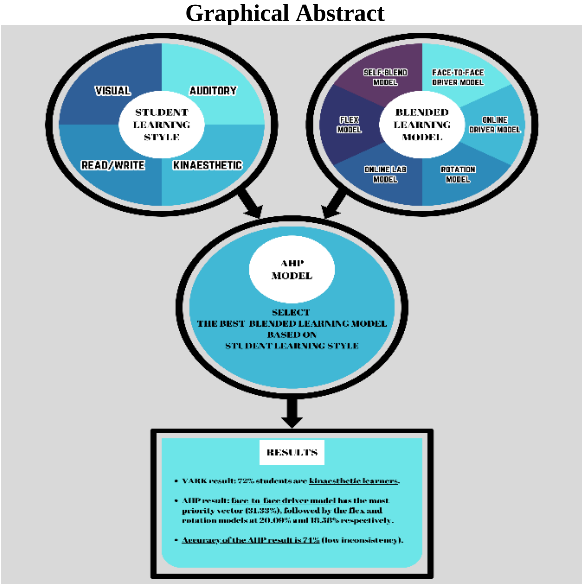
Graphical Abstract



NOMENCLATURE

AHP	Analytic Hierarchy Process	MCO	Movement Control Order
AR	Augmented Reality	MODM	Multi-objective Decision-making
C.I.	Consistency Index	PCM	Pairwise Comparison Matrix
COVID-19	CoronavirusDisease 2019	R.I.	Random Index
C.R.	Consistency Ratio	TOPSIS	Technique for Order of Preference by Similarity to Ideal Solution
FKP	Fakulti Kejuruteraan Pembuatan (Faculty of Manufacturing Engineering)	UTeM	Universiti Teknikal Malaysia Melaka
HCI	Human-Computer Interaction	VARK	Visual, Auditory, Read/Write, Kinaesthetic
MADM	Multi-attribute Decision-making	VIKOR	VIseKriterijumska Optimizacija I Kompromisno Resenje
MCDM	Multi-criteria Decision-making		

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1. INTRODUCTION

Blended learning is a new educational methodology in 21st-century education. Its primary purpose is to create and provide an integrated classroom involving all learners from different places. There are six main blended learning models to explore and choose from face-to-face driver, online driver, rotation, flex, online lab, and self-blend to stimulate and engage students to have more significant gains innovatively. Students are more likely to succeed when face-to-face learning is combined with online learning options [1]. Blended learning can be an effective learning method as it enhances the teaching-learning experiences, especially for students facing various blended learning models [2]. Also, the students can identify their learning needs in terms of knowledge and skills through blended learning [3]. It improves students' brainstorming outcomes by exposing them to a more flexible environment that can propose more ideas and solutions [4].

However, blended learning comes with several limitations. Various types of blended learning models have been designed due to no standard for integrating the blended learning concept [5]. As different lecturers have designed different blended learning models based on their understanding of the concept, it challenges students to habituate to the blended learning style and its planning [6]. For example, learning technology and technology for teaching and training are the challenges that need to be faced by the students and lecturers, respectively [7]. Each model has its concept and characteristics that may affect the student’s understanding and learning outcome [8]. Compared to fully online learning, blended learning is ineffective due to external factors like environment, knowledge, and skills [9]. To ensure that engineering students can stand a chance in competing in the industrial fields with the knowledge and skills required in management, planning, problem-solving and decision-making, blended learning models in the universities significantly impact the students. By referring to the available blended learning models, universities face the challenges of selecting the appropriate ones as it impacts the student’s learning effectiveness and the university’s reputation.

The COVID-19 pandemic forced most education institutions worldwide to switch to online learning as a substitute method of ensuring that the offered content is workable for student growth. As a result of this situation, a significant quantity of online education began. To offer knowledge, this utilized a variety of formats and interfaces and a misperception that students should be responsible for their learning results. Although most students concur that online learning offers a positive learning environment and better professional prospects through improved teamwork, students with special needs and budgetary constraints face technical difficulties and may not be given equal access to technology [10]. Also, online-based learning would lead to social isolation as it decreases engagement between the lecturer and friends. Several technical and communication skills can only develop effectively during face-to-face interaction [11].

As one of the core elements of multimedia applications is education technology, the teaching and learning process in the education system is greatly improved by interactive multimedia [12]. Numerous alternative e-learning options are available nowadays, some of which are free. Design preservation and utilization can be accelerated using Human-Computer Interaction (HCI) design rationales as a learning resource [13]. Due to students in the higher education field differing in age, it is crucial to consider all of the HCI principles to ensure that the proper e-learning solution is integrated with a suitable interface design, especially in an HCI classroom [14].

The education system has undergone significant change due to technology's rapidly expanding use, and students and lecturers now have better digital abilities [15]. The metaverse has been designed as a learning environment with immense potential. As a result, compared to existing approaches that currently use technology, such as flipped learning and e-learning, the metaverse's immersion possibilities grow [16]. Additionally, technology can affect how people think, learn, and communicate. Technological improvements push lecturers and students to comprehend and apply technology in teaching and learning activities to provide a flexible learning environment. The aspects that increase student analytical thinking skills are studied by flipping the classroom and combining digital storytelling and inquiry-based learning (IBL) [17]. The students agreed with the development of augmented reality (AR) in blended learning since it provided students freedom in learning time and period [18]. It also improved their self-discipline, integrity, and accountability.

Moreover, student learning styles in terms of personalities and characteristics are also crucial in leading the blended learning model to succession [19]. It cannot develop students’ communication skills to interact with others during the online seminar if they hide behind the screen [20]. Students who cannot provide instant and concrete responses during blended learning will become passive participants [21]. Besides, technical issues related to the devices’ hardware and software, like weak internet connection and bad sound delivery, will affect the quality of blended learning models that require online seminars [22]. Hence, educators need to learn a new skill in understanding blended learning models and select a suitable model to implement a delivery system that works well for their students.

There are four main student learning styles in the VARK model: Visual, Auditory, Reading/Writing, and Kinaesthetic. The VARK inventory provides metrics in each of the four perceptual modes, with individuals having preferences for anywhere from one to all four. The students have relative preferences along the four perceptual modes but can learn to function in the other modes. It focuses on classifying how the students receive and gather the information [23]. It helps the students identify their learning styles and understand their personalities [24]. A study compares the impact of the conceptual map and conventional lecture approaches on students' learning based on the VARK learning styles model [8]. The results have shown that implementing the VARK model can effectively identify the student’s preferred learning styles to enhance the standard of education and promote deeper learning. Through the VARK models, the students can improve their performance and enhance their study skills precisely as they understand their strengths in learning style and habit. There are also differences in learning approaches for the four VARK learning styles. Visual learners prefer videos, pictures, graphs and colours as they can remember what they have seen the most [25]. Auditory learners like to explain new ideas to others; hence, open discussion to discuss topics with others will suit them well [19]. Read/Write learners have a habit of taking notes based on reading materials like essays, reports, textbooks, printed handouts, readings, manuals, and web pages to improve their learning [26]. Kinaesthetic learners prefer hands-on approaches that link the material to reality, like doing things to understand them and finding solutions to problems [27].

Nevertheless, there are several limitations to the VARK models. The model does not consider external factors or other variables like student aspiration and abnormalities in learning. The models can be inaccurate as the student may apply different learning styles depending on different situations. Students are not limited to one learning style only in their studies [28]. Most students may have multimodal learning styles depending on the course and subject. Besides, the result data collected from VARK questionnaires can also be inaccurate if students answer them dishonestly. Students may expect their learning style and lead the VARK questionnaire into the results they would like to see. Hence, applying the VARK models to the students may be a dilemma. A good strategy for behaviours and development can be planned for the students so that their learning process and experiences can be benefited to the maximum.

Next, the multi-criteria decision-making (MCDM) method is a decision-making process with multiple criteria to consider. These methods can help decision-makers choose between different options, rank options or allocate resources [29]. In MCDM, many tools and methods can be used, ranging from simple methods like weighted sum models to more complex methods such as Analytic Hierarchy Process (AHP), VIseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR) and Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS). The MCDM method of choice is determined by the specific decision-making problem. Some factors included are the number of criteria, the type of data available, and the decision maker's preferences. MCDM is widely implemented in various fields, including finance, engineering design, agriculture, and environmental management. MCDM is an effective decision-making method that may result in more information and better conclusions by properly organizing complicated situations and openly evaluating many factors [29]. MCDM methods can be classified into two main categories. The first is multi-attribute decision making (MADM), used to choose a single option from various possibilities. The options are scored against a set of criteria, and the option with the greatest overall rating is picked. The second one is multi-objective decision-making (MODM), which is used to identify the approach that provides the best potential trade-off among the objectives.

In this research, the AHP model is focused as the engineering tool to conduct multi-criteria decision-making. It is categorized as a MADM method and helps analyse complex decisions to identify the best decision using math and psychology knowledge [30]. It is an inclusive system as it can quickly structure problems from different aspects and backgrounds into a hierarchy to represent them [31]. The AHP method can be used for highly diversified input data [32]. Also, the AHP method can handle the bigger issues and make it ideal for planning, analysis, and decision-making purposes among many alternatives [33]. The AHP evaluates the outcomes of each pairwise comparison using linear algebra. Linear algebra is a mathematical concept that aids in using matrices to determine the weight of criteria. Each criterion is given its weight in terms of importance. The more significant a criterion is to the final judgement, the larger its weight. Numerous decisions can be made using this comparing technique [34]. However, AHP only allows use in triangular fuzzy numbers and not all linear equations will come with a solution [35]. As the handling issues become more extensive, the level number of hierarchy increases [36]. This led to the number of pairs increasing and more effort and time are required for analysis. AHP can be applied in various fields like engineering, science, and mathematics for analysis purposes, but the final decision made from the modeling method is not pledged.

This research will explore the student learning styles for undergraduate manufacturing engineering course students by using VARK models at the Faculty of Manufacturing Engineering at Universiti Teknikal Malaysia Melaka (UTeM). VARK questionnaire will be used for data collection. From the VARK questionnaire results, students' preferred blended learning models are classified. Then, the AHP model is developed to select the best blended learning model based on student learning style. The generated AHP model is compared with the VARK model results to validate its accuracy. It is essential to investigate in terms of theoretical preparation and experimental expertise with blended learning to identify the suitable blended learning model for universities to educate, tutor and bring out quality students.

2. METHODOLOGY

2. 1. Overview of the Study The research is focused on exploring the students' preferred blended learning model based on their learning style with the application of VARK and AHP models. Figure 1 shows the research process flow chart procedure. The methods and equipment used are also listed for data collection and analysis.

2. 2. Data Collection A total of fifty year-four students have been chosen from the Faculty of Manufacturing Engineering at UTeM to be involved in the data collection as they have experienced all six types of blended learning models throughout their university life in UTeM. UTeM has implemented these six types of models in the blended learning system for the degree courses. So, their feedback is more practical and accurate than students from the other years and whoever only theoretically knows the blended learning models.

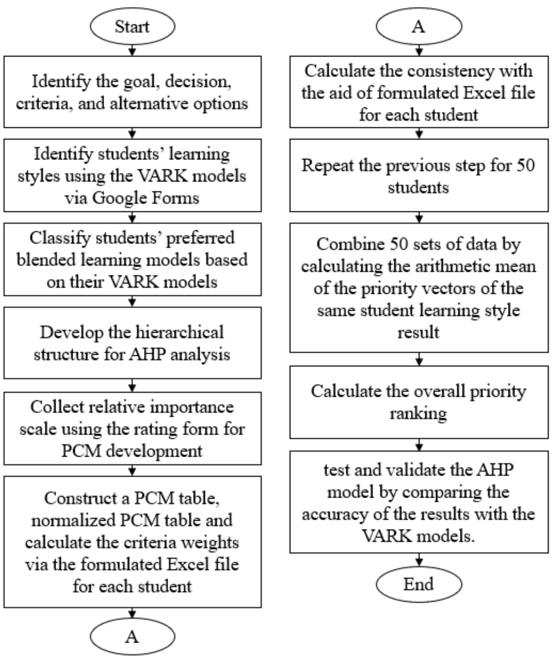

Figure 1. Research Process Flow Chart

Specifically, these students are selected from the undergraduate engineering course. The faculty has nearly 1000 students, meaning 5% of the sample population is randomly picked to participate in the survey. A simple random sample is applied in this research as this technique is the easiest probability sampling technique to use. Based on the literature review, the sample population is between 3 – 10%. Since randomization is included, this method has high internal and external validity and is less likely to be biased by factors like sampling and selection bias. There are several other feasible alternatives to simple random sampling, such as stratified sampling, cluster sampling and systematic sampling. These methods might introduce more variability compared to simple random sampling.

There are several tools and equipment are used to complete the research. To conduct the literature review, the research is done through journals, research papers and articles from physical and online publications. The main websites used for research included Google Scholar, Scopus and ScienceDirect. The reviewed topics are related to the research in terms of VARK, blended learning and AHP models. Besides, an online questionnaire is used to collect data from the 50 selected students in UTeM via Google Forms. The contents are a VARK questionnaire retrieved from VARK Learn Limited 2023, version 8.01, and a short survey on the students' preferred blended learning model. To conduct quantitative analysis for complex data, the software program Microsoft Excel is utilized for statistical analysis purposes. The Excel framework, fundamental data presentation and management, descriptive statistics, and common statistical analysis are all provided in Excel.

2. 3. AHP Model Development The AHP model is used to identify the best-blended learning model based on student learning style. The AHP relate the student learning styles determined by VARK models with the six blended learning models to form 24 possible combinations. The following steps show the procedure of applying AHP for decision-making in this research.

1. The problem and objective are defined. The problem is that various types of blended learning models have been designed because there is no standard for integrating the blended learning concept and each model has its concept and characteristics that may affect the student's understanding and learning outcome. So, the objective is to identify the best blended learning model based on student learning style.

2. The hierarchical structure is developed by identifying the criteria and alternative options for this research as shown in Figure 2. The top tier is the objective, the second tier is the criteria and the third tier is the alternative options. In this research , the VARK model is the criteria while the blended learning models are the alternative options.

3. A pairwise comparison matrix is constructed. The pairwise comparison matrix is used to determine the relative importance of different criteria with respect to the objective. The value can be determined by comparing two elements based on the relative importance scale (row element divided by column element). Table 1 shows the relative importance scale used for rating the PCM. Then, the normalized pairwise comparison matrix is calculated by summing the total value for each column element, and then each column value is divided by the total value for each column element. Next, the criteria weights are calculated. Equation (1) shows the formula for calculating the priority vectors from the normalized pairwise comparison matrix. Figure 3 shows the formulated Excel template used to develop the AHP model. The relative importance scale is keyed into the green column, and it will calculate the priority vectors for the blended learning models.

$$\text{Priority vector for each row} = \frac{\text{Sum of row elements}}{\text{Number of criteria}} \quad (1)$$

4. The consistency is calculated. The weighted value is calculated by multiplying the not normalized pairwise matrix value with the criteria weights in column sequence. Then, the weighted sum value is calculated by summing up the weighted value in the row sequence. The weighted sum value and criteria weights ratio are calculated for each row. After that, the average ratio of weighted sum value and criteria weights, λ_{max} is calculated as shown in Equation (2). After λ_{max} is determined, the consistency index (C.I.) and consistency ratio (C.R.) are determined as shown in Equations (3) and (4). When calculating C.R., the random index (R.I.) is involved and its value is determined based on the number of compared elements. Table 2 shows the random index.

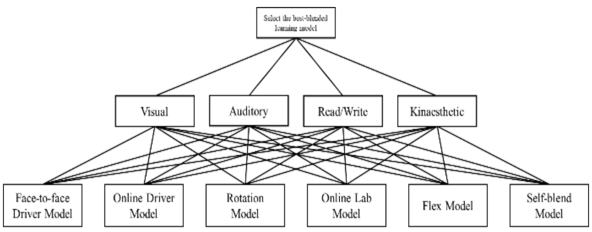

Figure 2. Hierarchical Structure of the AHP Model

TABLE 1. Relative Importance Scale

Verbal Judgement of Preference	Numerical Rating
Extremely Preferred	9
Very Strongly Preferred	7
Strongly Preferred	5
Moderately Preferred	3
Equally Preferred	1
Intermediate Values	2, 4, 6, 8

Pairwise Comparison Matrix	Face-to-face Driver	Online Driver	Rotation	Online Lab	Flex	Self-Blend
Face-to-face Driver	1	3	7	8	5	9
Online Driver	1/3	1	5	7	3	7
Rotation	1/7	1/5	1	3	0.333	4
Online Lab	1/8	1/7	1/3	1	0.2	3
Flex	1/5	1/3	3	5	1	5
Self-Blend	1/9	1/7	1/4	1/3	1/5	1
SUM	1.9123	4.8190	16.5863	24.3333	9.7330	29.0000

Normalized PCM	Face-to-face Driver	Online Driver	Rotation	Online Lab	Flex	Self-Blend	Criteria Weights	Priority Vector
Face-to-face Driver	0.5229	0.6225	0.4220	0.3288	0.5137	0.3103	0.4534	45.34%
Online Driver	0.1743	0.2075	0.3015	0.2877	0.3082	0.2414	0.2534	25.34%
Rotation	0.0747	0.0415	0.0603	0.1233	0.0342	0.1379	0.0787	7.87%
Online Lab	0.0654	0.0296	0.0201	0.0411	0.0205	0.1034	0.0467	4.67%
Flex	0.1046	0.0692	0.1811	0.2055	0.1027	0.1724	0.1392	13.92%
Self-Blend	0.0581	0.0296	0.0151	0.0137	0.0205	0.0345	0.0286	2.86%
SUM	1	1	1	1	1	1		

Figure 3. PCM and Normalized PCM Tables in the Formulated Excel

If C.R. is less than 0.1 (10%), the system is considered standard and reasonably consistent. Instead, the system is considered as not consistent and the criteria weights have to be recalculated to get it consistent. Figure 4 shows the consistency analysis tables used in the formulated Excel. If C.R. is less than 0.1, the indicator column will show VALID in green. Instead, it will show INVALID in red.

$$\lambda_{max} = \frac{\text{Sum of the ratio of weighted sum value and criteria weights}}{\text{Number of criteria}} \quad (2)$$

$$C.I. = \frac{\lambda_{max} - n}{n - 1} \quad (3)$$

$$C.R. = \frac{C.I.}{R.I.} \quad (4)$$

5. Steps 3 to 4 are repeated to develop the pairwise comparison matrix, priority vectors, and consistency ratio for the 50 sets of data collected from the students.
6. The overall priority vector is calculated by calculating the arithmetic mean of the priority vectors of the same student learning style result, as shown in Equation (5).

TABLE 2. Random Index

n	1	2	3	4	5	6	7	8	9	10
R.I.	0.00	0.00	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49

Consistency Analysis	Face-to-face Driver	Online Driver	Rotation	Online Lab	Flex	Self-Blend	Weighted Sum Value	WSV/CW
Face-to-face Driver	0.4534	0.7603	0.5506	0.3736	0.6962	0.2573	3.0914	6.818
Online Driver	0.1511	0.2534	0.3933	0.3269	0.4177	0.2001	1.7426	6.876
Rotation	0.0648	0.0507	0.0787	0.1401	0.0464	0.1144	0.4949	6.293
Online Lab	0.0567	0.0362	0.0262	0.0467	0.0278	0.0858	0.2794	5.983
Flex	0.0907	0.0845	0.2362	0.2335	0.1392	0.1430	0.9271	6.658
Self-Blend	0.0504	0.0362	0.0197	0.0156	0.0278	0.0286	0.1783	6.234

λmax	6.4771	
Consistency Index (C.I.)	0.0954	
Random Index (R.I.)	1.24	
Consistency Ratio	0.0770	VALID

Figure 4. Consistency Analysis Table in the Formulated Excel

Then, the overall priority vectors are ranked by the combination of multiplication between weight and priority vector from each student's learning style result. The AHP ranking of alternative options is finalized by sorting the overall priority ranking result calculated from the previous step based on a higher priority in table format. The alternative option with the highest priority vector will be selected as the best option.

$$Arithmetic\ mean = \frac{N_1 + N_2 + N_3 + \cdots + N_n}{n} \tag{5}$$

7. The AHP result is compared with the VARK result from the questionnaire to test and validate its accuracy regarding the number of students correctly identified in the AHP model based on the VARK model. Only the number of students correctly identified in the AHP model based on the VARK model is included.

3. RESULTS AND DISCUSSION

3. 1. VARK Model Analysis

The first objective of this research is to identify students learning styles by using the VARK models. Hence, the VARK questionnaire determines a person's preferred learning style. After the data is collected, it is analyzed via the formulated Excel by pasting the results of each student into specific columns to show the students' learning styles. However, cases are being found that several students have multimodal learning styles in which they get the same highest number for two or more learning styles in the VARK questionnaire. This demonstrates that these students can remember more information when learning through various senses. Interviews with the specific students are made to identify their most dominant learning style in the manufacturing engineering course to prevent miscellaneous results in the VARK model. Table 3 shows the number of students based on their learning styles. The majority of engineering students are kinaesthetic learners.

Next, VARK analysis proceeded to achieve this research's second objective: to classify students' preferred blended learning models based on their VARK models. The VARK questionnaire created in Google Forms is used to identify students' preferred blended learning models. Six types of models are explained in short and the students must select the most preferred blended learning model. Then, they must also mention the reason for preferring that model. Table 4 shows the number of students with their preferred blended learning models, while Figure 5 shows the stacked bar graph of students' preferred blended learning models based on their VARK models.

Based on the results, 50% of the students preferred the face-to-face driver model. Most students mentioned that the face-to-face driver model is easier to understand the lesson during the learning process than other learning models. They can directly communicate with the lecturer face-to-face when they find questions in learning. It is an easier and more effective model, especially in engineering courses that require lots of practice and skills development. This has shown that these students prefer a blended learning model that can learn affordably in terms of efficiency and effectiveness, although more time and energy are required compared to other models.

Then, 12 students preferred the rotation model. They believed this model can reduce the frequency of attending classes physically. They claimed that the theoretical lesson can be conducted online, and they would like to attend physical classes only when there is a requirement

TABLE 3. Number of Students Based on Their Learning Style in the VARK Model

Student Learning Style	Number of Students
Visual	5
Auditory	8
Read/Write	1
Kinaesthetic	36
TOTAL	**50**

TABLE 4. Number of Students with Their Preferred Blended Learning Models

Blended Learning Models	Number of Students				TOTAL
	V	A	R	K	
Face-to-face Driver Model	4	4	1	16	25
Online Driver Model	0	0	0	1	1
Rotation Model	0	3	0	9	12
Online Lab Model	0	0	0	0	0
Flex Model	1	1	0	9	11
Self-blend Model	0	0	0	1	1
TOTAL	5	8	1	36	50

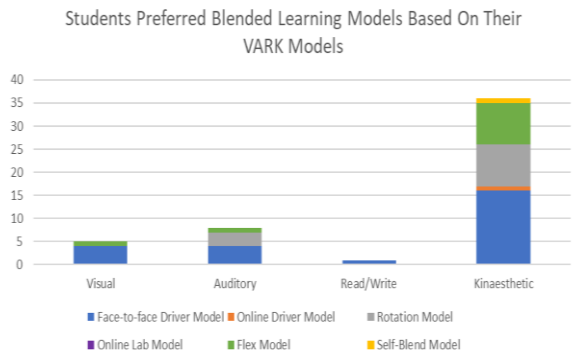

Figure 5. Students Preferred Blended Learning Models Based on Their VARK Models

for hands-on activities such as skill practices and lab sessions. It is an efficient model for students and lecturers as it reduces the time wasted in preparing themselves to attend a physical class for simple theoretical lessons. Furthermore, 11 students preferred the flex model. The students indicated that the flex model is better as it provides options for them to attend the class physically or remotely. It is a flexible learning model for the students because it allows them to manage at their own pace and time to study and brings comfort to them in terms of mood. However, several of them mentioned that this model depends on the subject. If the subject is required hands-on practice, then face-to-face is required. Instead, online learning is enough for them to study theoretical lessons.

Besides, only one student prefers the online driver model and the self-blend model. The student who preferred the online driver model stated that it is a simple and easy blended learning model for him, while the student who preferred the self-blend model stated that it enables him to study anytime and anywhere. Although both of these blended learning models get only 1 student preferred, they have provided essential data and feedback for the research as it shows that some students have their own thoughts and styles to prefer these blended learning models in their learning.

However, no students preferred the online lab model in their learning. Based on the literature review, students may not prefer this blended learning model due to limited interaction and communication between students and lecturers [37]. It might also provide poor learning experiences for the students as they are only guided and supervised by the paraprofessionali. Students are free to explore themselves in this blended learning model and sometimes they might be lost in the learning process if the guidance provided is not clear enough [38]. This blended learning model is only suitable in some specific cases like pandemics or severe cases, as several limitations are implemented in terms of quota accepted in the physical class. Hence, these possible reasons lead to no students preferring it as a practicable blended learning model in their learning.

3. 2. AHP Analysis To achieve objective three of this research, the AHP model is designed and developed to select the best blended learning model based on student learning style. As mentioned in the methodology, several steps are required to get the final result in ranking based on the priority vectors to identify the best-blended learning model. Consistency analysis is required to ensure the data collected are valid and consistent. After developing the priority vector for 50 students, the data are combined based on the VARK model using Equation (5). Table 5 shows the priority vector for the blended learning models in terms of VARK.

TABLE 5. Priority Vector for the Blended Learning Models in terms of VARK

Blended Learning Models	**Priority Vector**			
	V	**A**	**R**	**K**
Face-to-face Driver Model	37.62%	28.65%	41.16%	30.07%
Online Driver Model	15.42%	15.65%	17.44%	15.46%
Rotation Model	10.81%	28.51%	5.01%	17.84%
Online Lab Model	9.04%	6.75%	9.68%	6.30%
Flex Model	18.44%	13.51%	24.01%	22.60%
Self-blend Model	8.66%	6.93%	2.71%	7.73%
TOTAL	100.00%	100.00%	100.00%	100.00%

Later, the VARK criteria in the second tier of the hierarchical structure are also required to construct PCM to get its priority vector to complete the AHP results. To get the importance relative scale for the VARK PCM, the answers from the VARK questionnaire are referred. There are 16 questions in a VARK questionnaire and 800 answers for the 50 sets of the VARK questionnaires. The percentage difference is calculated in terms of VARK for the different VARK combinations. The values are 90% normalized to get the relative importance scale for VARK PCM. Figure 6 shows the VARK PCM, normalized VARK PCM and consistency analysis for VARK PCM in formulated Excel. The priority vector for visual, auditory, read/write and kinaesthetic are 14.41%, 21.65%, 4.31% and 59.63%, respectively. The C.R. is 0.0594, which is less than 0.1 (valid).

VARK PCM	Visual	Auditory	Read/Write	Kinaesthetic
Visual	1	0.50	5.00	0.20
Auditory	2.00	1	6.00	0.25
Read/Write	0.20	0.17	1	0.11
Kinaesthetic	5.00	4.00	9.01	1
SUM	8.200	5.667	21.009	1.561

Normalized PCM	Visual	Auditory	Read/Write	Kinaesthetic	Criteria Weights	Priority Vector
Visual	0.1220	0.0882	0.2380	0.1281	0.1441	14.41%
Auditory	0.2439	0.1765	0.2856	0.1602	0.2165	21.65%
Read/Write	0.0244	0.0294	0.0476	0.0711	0.0431	4.31%
Kinaesthetic	0.6098	0.7059	0.4288	0.6406	0.5963	59.63%
SUM	1	1	1	1		

Consistency Analysis	Visual	Auditory	Read/Write	Kinaesthetic	Weighted Sum Value	WSV/CW
Visual	0.1441	0.1083	0.2156	0.1193	0.5872	4.076
Auditory	0.2882	0.2165	0.2588	0.1491	0.9125	4.214
Read/Write	0.0288	0.0361	0.0431	0.0662	0.1742	4.040
Kinaesthetic	0.7204	0.8661	0.3885	0.5963	2.5713	4.312

λmax	4.1605	
Consistency Index (C.I.)	0.0535	
Random Index (R.I.)	0.9	
Consistency Ratio	0.0594	VALID

Figure 6. VARK PCM, Normalized VARK PCM and Consistency Analysis for VARK PCM in Formulated Excel

Then, the combination of the priority vectors calculated from Table 5 and Figure 6 is done to get the overall priority ranking for the blended learning model. Table 6 shows the overall priority ranking of the AHP model.

According to Table 6, the face-to-face driver model is engineering students' most preferred blended learning model. It is tallied with the finding of Zafirah et al. [39], as most students are interested in the face-to-face driver model due to its effectiveness. Students can get a better understanding through the lecture in the physical class and be able to discuss the questions they found with the lecturers directly. So, two-way communication via face-to-face sessions is an effective learning method as the students feel stable enough to have a learning session at a fixed time and place.

For the online lab model which is the least preferred blended learning model by the engineering students. There are a few possible reasons why students have not preferred it. First, the students are limited to interacting with the virtual environment [38]. This led to students having difficulty observing and manipulating physical objects and limiting their development of practical skills to connect theoretical knowledge. Also, the online lab model is less effective as the students might be isolated due to the difficulty of getting the lecturer's support [11]. This can also cause the loss of learning time and interest. Thus, this model becomes the least preferred model is reasonable. For the same possible reasons, the online driver model is not what many students prefer. Although a more flexible model allows students to learn at their own pace, it depends on their motivation to learn. Sometimes, the equipment required for online learning is more expensive, creating difficulty for students with limited budgets [40].

Besides, the self-blend model is not preferred by many students. Other than the student isolation issue, it lacks structure as it allows students to learn whatever they want [41]. It is effective for highly self-motivated students who can manage their time properly, while less effective for students who need support and guidance. Moreover, this model makes it difficult to track student progress if they apply for many online courses from different providers [42]. It leads to lecturers taking time to evaluate the student learning progress.

TABLE 6. Overall Priority Ranking of the AHP Model

Blended Learning Models	Priority Vector
Face-to-face Driver Model	31.33%
Online Driver Model	15.58%
Rotation Model	18.58%
Online Lab Model	6.94%
Flex Model	20.09%
Self-blend Model	7.47%

3. 3. Comparison Accuracy To achieve objective four of this research, the AHP results are compared with the VARK results in accuracy to test and validate the AHP model. The VARK results are defined as the actual results, while the AHP results are defined as the calculated results. The overall VARK and AHP results are converted from the percentage values into the number of students for evaluation to calculate the accuracy. Table 7 shows the number of students who preferred the blended learning models in terms of VARK and AHP. The number of students correctly identified for the face-to-face driver model, online driver model, rotation model, online lab model, flex model, and self-blend model are 16, 1, 9, 0, 10, and 1, respectively. The accuracy of the AHP result is 74%.

It is believed that from the analysis, 74% accuracy is considered a good result due to the AHP model being good at consistency (low inconsistency). This can be justified through the method in the AHP model as it has ensured the C.R. is less than 0.1 during the consistency analysis. However, there might be inconsistent results that occurred due to the judgment of the decision-maker and it led to the accuracy dropping [43]. Besides, the factor that might affect the accuracy is the students' personality. The students do not understand their preference for the blended learning model. For example, the student claimed that the most preferred blended learning model for him is the face-to-face driver model, but after evaluating through the AHP analysis, his preferred blended learning model is the flex model. This can lead to the accuracy dropped as VARK results are directly applied and assumed as the actual result.

TABLE 7. Number of Students that Preferred the Blended Learning Models in terms of VARK and AHP Results

Blended Learning Models	Number of Students	
	VARK	AHP
Face-to-face Driver Model	25	16
Online Driver Model	1	8
Rotation Model	12	9
Online Lab Model	0	3
Flex Model	11	10
Self-blend Model	1	4

4. CONCLUSION

In summary, this research has aimed to utilize the AHP model to aid in identifying the best blended learning model for engineering students based on their learning styles. Blended learning, VARK, and AHP models are studied in this research. Based on the VARK result, most students are kinaesthetic learners (72%). After classifying the students for the blended learning model based on the VARK model, 50% of the students prefer the face-to-face driver model as the top blended learning model. Then, the AHP model is designed and developed to identify the best blended learning model. According to the AHP result, the face-to-face driver model has the highest priority vector (31.33%), followed by the flex and rotation models at 20.09% and 18.58%, respectively. AHP analysis is conducted to the results in terms of consistency to ensure the data is valid and consistent. Afterward, the AHP results are compared with the VARK results to test and validate in terms of accuracy. The accuracy of the AHP result is 74%, which is considered as low inconsistency.

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Persian Abstract

چکیده

یادگیری ترکیبی روشی انعطاف‌پذیر است که از طریق یادگیری حضوری و آنلاین انجام می‌شود. دانش آموزان را ملزم به یادگیری با تلاش فیزیکی در کلاس ها می کند و به آنها امکان می دهد در زمان ها و مکان های مختلف به طور مجازی یاد بگیرند. این امر پس از دستور کنترل حرکت (MCO) مشهودتر و رایج‌تر شده است زیرا اکثر سخنرانی‌ها در دانشگاه به صورت ترکیبی انجام می‌شوند. مدل‌های یادگیری ترکیبی مشکلات و فرصت‌هایی را برای دانش‌آموزان ایجاد می‌کنند، زیرا آنها باید روش‌های مختلف یادگیری ترکیبی اساتید مختلف را از نظر سبک‌های تدریس، برنامه‌ریزی و زمان‌بندی کشف و سازگار کنند. بنابراین، هدف این تحقیق بررسی بهترین مدل‌های یادگیری ترکیبی برای دوره کارشناسی مهندسی بر اساس سبک یادگیری دانشجویان با استفاده از روش فرآیند تحلیل سلسله مراتبی (AHP) است، زیرا انتخاب مؤثرترین رویکرد برای آن چالش بزرگی است. دانشگاه ها برای آموزش، تعلیم و تربیت دانش آموزان با کیفیت با توجه به سبک های یادگیری آنها. روش AHP برای کمک به دانش آموزان در یافتن بهترین مدل یادگیری تلفیقی بر اساس سبک یادگیری استفاده می شود. سپس تجزیه و تحلیل AHP برای اعتبارسنجی و تأیید صحت آن با مقایسه آن با مدل‌های دیداری، شنیداری، خواندن/نوشتن و جنبشی (VARK) انجام می‌شود. در نتیجه، بیشتر دانش‌آموزان بر اساس نتایج VARK، یادگیرنده‌های حرکتی هستند (۷۲٪)، و مدل محرک چهره به چهره ترجیح داده‌شده‌ترین مدل یادگیری ترکیبی با بردار اولویت در ۳۱.۳۳٪ از طریق تحلیل AHP است. دقت نتیجه AHP با مقایسه آن با نتیجه VARK 74 درصد است. به طور خلاصه، داده ها را می توان در سیستم یادگیری ترکیبی UTeM برای بهبود طراحی دوره و تجربه یادگیری دانش آموز مستقر کرد.