TOPSIS AND VIKOR INTEGRATED MODEL TO ANALYSE THE ACCURACY OF AHP VARK MODEL BLENDED LEARNING DATA

This report is submitted in accordance with requirement of the University Teknikal Malaysia Melaka (UTeM) for Bachelor Degree of Manufacturing Engineering (Hons.)

by

MUHAMMAD FARHAN BIN IBRAHIM

FACULTY OF INDUSTRIAL AND MANUFACTURING TECHNOLOGY AND ENGINEERING

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DECLARATION

I hereby, declared this report entitled "TOPSIS AND VIKOR INTEGRATED MODEL TO ANALYSE THE ACCURACY OF AHP VARK MODEL BLENDED LEARNING DATA." is the result of my own research except as cited in references.

Signature : ……………………………………………

Author's Name : MUHAMMAD FARHAN BIN IBRAHIM

Date : 14 July 2024

APPROVAL

This report is submitted to the Faculty of Industrial and Manufacturing technology Engineering of Universiti Teknikal Malaysia Melaka as a partial fulfilment of the requirement for Degree of Manufacturing Engineering (Hons). The member of the supervisory committee is as follow:

PROF. MADYA IR. TS. DR. SHAJAHAN BIN MAIDIN
Fakulti Teknologi & Kejuruteraan Industri & Pembuatan
Universiti Teknikal Malaysia Melaka

………………………………………………………

ASSOCIATE PROF. IR. TS. DR. SHAJAHAN BIN MAIDIN

ABSTRACT

Blended learning integrates face-to-face and online education, requiring students to attend physical classes and engage in virtual learning at their convenience. This approach became prevalent post-Movement Control Order (MCO) as universities adopted hybrid teaching methods. However, blended learning presents challenges and opportunities as students must adapt to varying teaching styles, planning, and timing from different lecturers. Higher education institutions face the challenge of selecting the most effective approach to cater to diverse learning styles and produce quality graduates. The research objectives include studying AHP VARK model data from previous student projects, applying the integrated TOPSIS VIKOR model, and testing the accuracy of AHP blended learning data. Methodologically, the study involves a comprehensive review of multi-criteria decision-making techniques, detailed analysis using TOPSIS and VIKOR models, and a focus on evaluating the accuracy of blended learning data through these integrated methods. The result shows that TOPSIS and VIKOR method with 88.6% accuracy surpass AHP VARK model with 74% accuracy, these results indicate that the TOPSIS and VIKOR models provide a good method for assessing the accuracy of the AHP VARK model, offering insights into the effectiveness of different blended learning models. Future recommendations include expanding the dataset to include a more diverse student population and different educational contexts. The findings of this study can contribute to the enhancement of decision analysis methodologies in blended learning contexts, providing deeper insights into the effectiveness of the AHP-VARK model.

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CHAPTER 1

INTRODUCTION

1.1 Background study

In recent years, the educational landscape is experiencing transformative changes, especially in undergraduate engineering education. Traditional methods of teaching and learning are slowly giving way to friendlier and more personalized approaches, driven by the advancement in technology. Thanks to virtual platforms, cloud computing, and online learning management systems (LMS), a significant proportion of educational materials and teachings tools have become available to students outside the classroom(Vodovozov et al., 2022).

The idea of combining traditional classroom work with online resources to create a more flexible and personalized approach is an important part of the education revolution. Especially in an undergraduate engineering course, it is important to have varied learning styles and preferences of the students. This learning approach is driven by the recognition that not all students learn in the same way, and educational practices should reflect this diversity. One big challenge is about how users can successfully use the technology and ensuring participants' commitment given the individual learner characteristics and encounters with technology (Hofmann, 2014)

It is crucial to prioritize the development and implementation of blended learning models that are finely tuned to the individual learning styles of students. This is where multicriteria decision making techniques like Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS) and VlseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR) step in. Furthermore, the methodologies provide a more structured approach for rating and assessing several blended learning models with respect to different competing assessment criteria in such a way that it is guaranteed to select the most suited model for each student.

In 1981, Hwang and Yoon developed the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) method (Hwang & Yoon, 1981) for solving multiple criteria decision making (MCDM) problems based upon the concept that the chosen alternative should have the shortest distance to the positive ideal solution (A*) and the longest distance from the negative ideal solution (A−)(Hanine et al., 2016). This approach is frequently used in the Multiple Criteria Decision-Making process to choose the best option from a group of alternatives. The TOPSIS approach presumes that each criterion tends toward a monotonically decreasing or increasing utility (Ding, 2 011).

VIKOR method determines the compromise ranking-list, the compromise solution, and the weight stability intervals for preferences stability of the compromise solution obtained with the initial (given) weights (Opricovic & Tzeng, 2004). The advantage of the VIKOR model is to rank and choose the alternatives with multiple criteria (Tzeng et al., 2005). By utilizing VIKOR, the project ensures that the selected blended learning model successfully navigates and sets a delicate balance between the various learning styles of the students, in addition to aligning with their unique learning preferences.

This study attempts to provide an in-depth and systematic approach to decision-making, taking into consideration both qualitative and quantitative factors, by combining TOPSIS, and VIKOR. The project will investigate how the Blended Learning Model's interest is affected by various learning styles, including kinesthetic, auditory, and visual. The primary focus is on evaluating the accuracy and sensitivity of the AHP-VARK model, a sophisticated decision-making model that combines Analytical Hierarchy Process (AHP) principles with the Visual, Auditory, Reading/Writing, and Kinesthetic (VARK) learning styles. By applying this integrated model to blended learning data, the research aims to provide valuable insights into the effectiveness of the AHP-VARK approach. This endeavor contributes to the enhancement of decision analysis methodologies in the dynamic context of blended learning, fostering a deeper understanding of accuracy and sensitivity within the framework of multi-criteria decision analysis.

1.2 Problem statement

Since the outbreaks of COVID-19 disease and the movement control order (MCO) started, students are forced to adopt new learning methods following the limitations they face in the MCO. Some students struggle to adapt and follow the new learning methods that are different from the traditional methods they used. According to (Gherheș et al., 2021) face-to-face learning requires the lecturers' attendance in the classroom, and the students are engaged in a continuous physical environment. The problem lies in the need to determine the ideal blended learning model for each student, considering various criteria that define effectiveness, such as student performance, satisfaction, and adaptability. Designing a one-size-fits-all blended learning approach is insufficient, as it fails to address the unique needs and preferences of individual learners. Generally, research has found that Blended Learning results in improvement in student success and satisfaction, (Means et al., 2013) as well as an improvement in students' sense of community(Rovai & Jordan, 2004) when compared with face-to-face courses.

In the ever-changing landscape of blended learning environments, where educational content and learning styles constantly evolve, the efficacy and adaptability of decision-making models become paramount. The AHP-VARK model, a sophisticated fusion of AHP and VARK learning styles, is employed to navigate this complex educational terrain. However, the dynamic nature of blended learning environments necessitates a comprehensive examination of the model's ability to adapt to ongoing changes. Moreover, the accuracy of the AHP data, a foundational component of the AHP-VARK model, comes under critical observation. The authors of the book concluded that, despite its popularity, AHP is incapable of solving complex problems (Munier & Hontoria, 2021). Recognizing potential inaccuracies, the study proposes the utilization of the TOPSIS and VIKOR methodologies to rigorously analyze the accuracy and sensitivity of the AHP data. This strategic integration of TOPSIS and VIKOR aims to provide a more robust and reliable evaluation of the AHP-VARK model, ensuring that decisions derived from the model are grounded in accurate and dependable data.

1.3 Objectives

The objectives of this project are as follows:

a) To study AHP VARK model data.

b) To apply the TOPSIS VIKOR integrated model.

c) To test the accuracy of AHP blended learning model data

1.4 Scope of study

This research project embarks on an exploration of two widely employed methodologies in the domain of multi-criteria decision analysis, namely, the TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) and VIKOR (VlseKriterijumska Optimizacija I Kompromisno Resenje) methods. In the introductory phase, the focus lies on explaining the principles and objectives that underpin these decision-making tools. TOPSIS is characterized by its approach of determining the ideal and worst solutions based on criteria, while VIKOR is adept at striking a balance among conflicting objectives to derive compromise solutions. The overarching goals of these methods include offering a systematic decision-making approach and a robust framework for evaluating alternatives that involve multiple criteria.

In the scope of this project, the primary data source will be derived from a previous FYP student report. This existing dataset serves as a foundational resource for the subsequent analysis. The central focus of the study lies in detailing the integration of TOPSIS and VIKOR methodologies. This framework is specifically designed to evaluate the accuracy and sensitivity of the AHP-VARK model. By combining these decision-making techniques, the project aims to contribute to a more robust understanding of multi-criteria decision analysis, providing valuable insights into the complex relationships between different evaluation criteria within the context of the AHP-VARK model.

CHAPTER 2

LITERATURE REVIEW

This chapter explores the existing literature related to the integration of TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) and VIKOR (VlseKriterijumska Optimizacija I Kompromisno Resenje) models to evaluate the accuracy and sensitivity of the AHP VARK model in analyzing blended learning data. The review will cover current studies, theories, and practical applications related to the subject. It aims to establish the foundation for the present study by summarizing key findings and identifying gaps that warrant further investigation.

2.1 Multi criteria Decision Making Method

Multi Criteria Decision Making is a methodology that aids in the decision-making process when there are multiple criteria to consider (Rustandi & Shilul Imaroh, 2021). Previous sources state that multi-criteria decision-making techniques have proven useful in numerous fields of research and applications. The literature highlights the importance of using multi-criteria decision-making methodologies to find the best or most appropriate solution among alternatives (Alakaş et al., 2020). This methodology allows multi-criteria decision-making of options and constraints, providing a holistic approach to decision-making.

Several studies have utilized multi-criteria decision-making methods in different decision-making processes. Additionally, multi-criteria decision-making can help balance the three aspects of sustainability - economic, social, and environmental. Furthermore, the literature suggests that multi-criteria decision-making methods can handle both qualitative and quantitative criteria, allowing decision-makers to make informed choices based on a combination of different types of criteria (Alakaş et al., 2020). In summary, multi-criteria decision-making is a versatile methodology that assists decision-makers in considering multiple criteria and reaching the most appropriate solution among alternatives (Rustandi & Shilul Imaroh, 2021).

2.2 TOPSIS Model

The Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) is a versatile multi-criteria decision-making (MCDM) methodology that has found applications in various fields, including education. This section explores the applicability and relevance of TOPSIS in educational contexts, focusing on its benefits, guiding principles, and real-world examples of its use. In general, TOPSIS provides criteria that help researchers rank alternative items. TOPSIS is a useful multi-attribute decision making (MADM) method that deals with real decision problems in human lives by analyzing, comparing, and ranking the alternatives to choose the best and the most suitable option considering the criteria of the problem (Madanchian & Taherdoost, 2023). The TOPSIS method takes into consideration all kinds of criteria and provides a rational and understandable ranking of alternatives. According to this technique, the best alternative would be one that is closest to the positive-ideal solution and farthest from the negative-ideal (Krohling & Pacheco, 2015). Furthermore, TOPSIS is known for its simple calculation process and flexible application.

In summary, the TOPSIS method is a multi-criteria decision-making model that provides a rational and understandable ranking of alternatives. Its simplicity, consideration of all criteria, and clear calculation process make it a valuable tool for decision-making in various industries and contexts. In general, the TOPSIS algorithm's procedure begins with creating a decision matrix that shows the degree to which each criterion is satisfied with each option. Next, the matrix is normalized with a desired normalizing scheme, and the values are multiplied by the criteria weights.

2.2.1 Advantages of TOPSIS

The Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) offers distinct advantages. Known for its objectivity and adaptability, the advantages of TOPSIS, its versatility and the ability to classify results into individual groups also suggests the possibility of its wider use (Galik et al., 2022). The literature demonstrates the extensive application of TOPSIS in diverse decision-making scenarios, such as the prioritization of performance indicators to assist paper manufacturing plants in achieving higher sustainable manufacturing performance and increasing their competitiveness. Moreover, (Alqahtani & Rajkhan, 2020) discusses the application of TOPSIS in combination with AHP for analyzing

E-learning critical success factors, this article examines eight different criteria across instructor characteristics, student characteristics, technology support, and course design. TOPSIS's ability to handle multiple criteria allows for a comprehensive evaluation of e-learning effectiveness, considering various factors that contribute to its success.

In conclusion, a literature review on the advantages of TOPSIS reveals that it offers several benefits, including its simplicity in calculation, reliability with fewer rank reversals, ability to handle many alternatives and criteria, and its applicability in qualitative and quantitative research. TOPSIS offers several advantages over other methods, making it a popular choice in the research and industrial communities (Tang et al., 2018).

2.2.2 Disadvantages of TOPSIS

These are the disadvantage highlighted by (Madanchian & Taherdoost, 2023). Firstly, is the use of Euclidean Distance in TOPSIS, which does not account for the correlation between attributes. This limitation can lead to information overlap, potentially impacting the accuracy of the results. Moreover, the process of weighing in TOPSIS is often considered a challenging and uncertain task. Assigning appropriate weights to criteria requires subjective judgment and can introduce ambiguity into the decision-making process.

TOPSIS method has a high dependence on the weight of each index to be evaluated (Liu et al., 2023). Another drawback is the possibility of encountering alternatives that are close to both positive and negative ideal points simultaneously. This scenario can make it difficult for TOPSIS to clearly distinguish between alternatives, posing a challenge in decision-making situations. Additionally, when faced with uncertain or insufficient data, TOPSIS may struggle to provide precise determinations due to the potential for vague human judgments.

Despite these limitations, the widespread adoption of TOPSIS underscores its practical utility in decision-making scenarios. Researchers in the field are actively engaged in exploring enhancements and modifications to address these drawbacks. Continuous efforts aim to refine TOPSIS and make it more robust, ensuring its continued relevance in the dynamic landscape of Multi-Criteria Decision Making. By acknowledging its limitations and actively seeking improvements, researchers aim to maximize the benefits of TOPSIS while minimizing its potential shortcomings.

2.2.3 Application of TOPSIS

TOPSIS has found its applications in diverse educational contexts, enriching decision-making processes. In curriculum design, TOPSIS aids in the selection of the most suitable curriculum design by balancing factors such as course content, student engagement, and resource allocation (Triantaphyllou, 2000). Furthermore, it helps with faculty performance evaluation by considering a variety of factors, such as research output, teaching effectiveness, and institutional service. A methodical approach to assessing academic achievement, TOPSIS considers a few variables, including research output, teaching effectiveness, and institutional service. The method's ability to handle complex decision scenarios and adapt to both quantitative and qualitative criteria make it a valuable tool in the education sector.

TOPSIS has been extensively applied in the field of personnel selection (Nabeeh et al., 2019). Other areas where TOPSIS has found application include supply chain management, where it has been used to optimize supplier selection and evaluation. TOPSIS has also been used in the assessment of financial performance, where it helps in comparing and ranking companies based on their financial indicators (Chakraborty, 2022). In addition, TOPSIS has been utilized in manufacturing decision-making processes to select suppliers or evaluate the performance of different products. Researchers have used TOPSIS to make decisions related to university admissions, student performance evaluation, and faculty selection. Overall, the literature review highlights that TOPSIS has inspired the development of numerous methods and comparative analysis approaches. Furthermore, TOPSIS has shown promising results in other areas such as purchase decisions and outsource provider selection, where it helps in selecting the best supplier based on multiple criteria (Chakraborty, 2022).

In summary, the literature review reveals that TOPSIS is widely used and applied in various fields including supply chain management, design, mechanical engineering, airline industry, automobile industry, finance and banking industry, food industry, information technology industry, and manufacturing industry (Parveen & Kamble, 2021). This literature review demonstrates the extensive and diverse applications of TOPSIS in different industries and domains.

2.3 VIKOR Model

The VIKOR method, developed by Opricovic and Tzeng, stands as a robust approach to address multicriteria decision-making challenges, particularly in scenarios where discrete decision problems involve non-commensurable and conflicting criteria (Opricovic & Tzeng, 2007). The methodology offers a systematic way for decision-makers to navigate through complex decision landscapes. The method provides decision-makers with the flexibility to consider multiple scenarios and find a solution that is not only optimal but also resilient to potential challenges or setbacks. It specifies the compromise order list, solution, and the weight stability range for the chosen stability in the achieved compromise solution with the original weights (Türegün, 2022). A distinctive feature of VIKOR is its incorporation of a decision mechanism coefficient, offering decision-makers the option to adopt either radical or conservative decision strategies. This flexibility is especially valuable in situations where the decision-makers need to balance risk and reward, allowing them to tailor their approach based on the specific context of the decision problem.

The multicriteria ranking index, a key component of VIKOR, is based on the concept of 'closeness' to the 'ideal' solution. This measure assists decision-makers in quantifying how well each alternative aligns with the desired criteria. By using this index, VIKOR enables decision-makers to rank alternatives systematically, providing a clear and objective basis for decision-making (Opricovic & Tzeng, 2004). It's important to note that the results obtained from the VIKOR ranking can be sensitive to the inclusion or removal of alternatives. This highlights the method's responsiveness to changes in the decision space and emphasizes the need for careful consideration when modifying the set of alternatives under evaluation. Furthermore, VIKOR's interactivity is a notable feature, allowing decision-makers to actively participate in and control the decision-making process. This is facilitated through the incorporation of weights, as discussed by (Zolfani et al., 2020). The ability to assign weights to different criteria empowers decision-makers to emphasize the importance of certain factors over others, reflecting their preferences and priorities in the decision-making process.

2.3.1 Advantages of VIKOR

(Kastratović et al., 2017) provides a comprehensive exploration of the advantageous features inherent in the VIKOR method, particularly in the context of decision-making related to investment projects. The method's primary strength lies in its capacity to address the intricate nature of decision scenarios where diverse and conflicting criteria must be considered. By focusing on identifying the best compromise solution, VIKOR offers a systematic approach to handling incommensurable factors, allowing decision makers to arrive at solutions that strike an optimal balance. A notable characteristic of the VIKOR method highlighted in the document is its simplicity and practicality. Unlike some other multi-criteria decision-making techniques, VIKOR is characterized by a straightforward implementation and interpretation process. This simplicity is a valuable attribute, making the method accessible to a broader range of decision makers, including those who may not possess advanced expertise in complex mathematical or computational methodologies.

The document emphasizes the efficiency gained from fewer computational steps, expediting the decision-making process. The versatility of the VIKOR method is underscored, as it finds application across various decision-making problems in different fields, including engineering, economics, and management. This adaptability enhances its appeal for decision makers operating in diverse domains where a multitude of criteria must be considered simultaneously. Another key advantage highlighted in the document is the method's ability to aggregate both maximum group utility and minimum individual regret. This dual consideration ensures that decisions not only benefit the collective group but also consider the satisfaction and concerns of individual decision makers. This feature contributes to a more equitable and balanced outcome, fostering collaboration and buy-in from all stakeholders involved in the decision-making process. Furthermore, the document draws attention to the inclusion of sensitivity analysis within the VIKOR method. This analytical tool allows decision makers to assess the impact of different weights assigned to criteria, providing insights into the stability and robustness of the chosen solution. The ability to conduct sensitivity analysis enhances the method's adaptability, enabling decision makers to account for changing conditions, preferences, or uncertainties.

The article "Susceptibility of deforestation hotspots in Terai-Dooars belt of Himalayan Foothills: A comparative analysis of VIKOR and TOPSIS models (Bera et al.,

2022) explores deforestation in the Himalayan Foothills, comparing AHP, TOPSIS, and VIKOR methods. The authors state that VIKOR offers "rationality, simplicity, better computational proficiency and high efficiency to measure the performance of every alternative in a simple mathematical way."(Bera et al., 2022)

2.3.2 Disadvantages of VIKOR

(Huang et al., 2009) critically assess the limitations of the VIKOR model and propose modifications to enhance its efficacy. VIKOR may yield inaccurate preference rankings of alternatives. The authors assert that in some instances, VIKOR's results are clearly incorrect, as demonstrated with their house selection example. The paper highlights issues with the way S (maximum group utility) and R (minimum individual regret) values are calculated in VIKOR. The method normalizes these values, which affects the level of regret based on both the best and worst values of each criterion, while according to regret theory, it should be influenced only by the best values.

VIKOR defines regret based on the difference between alternatives and the best value of each criterion referred to as the discontent utility in this paper. However, this approach ignores the choiceless utility, which is the utility that an individual would derive if he/she experienced the outcome without having chosen it. The authors propose that VIKOR does not fully encapsulate emotional factors such as regret and rejoicing, which are part of decision making according to regret theory. The original VIKOR model does not consider anticipated feelings that can influence decision makers. To address these issues, the authors propose a revised VIKOR model that incorporates the perspective of regret theory, measuring both choiceless and discontent utilities. This revised model aims to reflect realistic MCDM problems and decision-makers' choice behavior more accurately.

The article "VIKOR multi-criteria decision making with AHP reliable weighting for article acceptance recommendation"(Wibawa et al., 2019) discusses the integration of AHP and VIKOR methods for building a more robust decision support system for recommending article acceptance. The authors acknowledge a key limitation of VIKOR: its reliance on subjective weighting. The paper explains that VIKOR's initial weights, which determine the relative importance of different criteria, are often assigned subjectively. This subjectivity can introduce bias and potentially lead to less reliable outcomes. To address this, the authors propose using AHP to establish more reliable weights for the VIKOR method, ultimately aiming for a more objective and accurate article acceptance recommendation system.

2.3.3 Applications of VIKOR

(Kastratović et al., 2017) employs the VIKOR method, a widely recognized multi-criteria decision-making approach, to tackle the common challenge of allocating capital among multiple investment projects. The methodology initiates with the creation of a decision matrix, detailing various potential projects and assessing them against dynamic financial indicators like net present value and internal rate of return. Significantly, each criterion is assigned a weight, reflecting its relative importance to the decision-making entity, and accommodating the diverse significance enterprises may attribute to specific financial measures.

Subsequently, the method progresses to normalize the decision matrix and compute utility measures (Si and Ri), designed to quantify how each project approaches the ideal solution from positive and negative perspectives. A composite measure (Qi) is then derived, striking a balance between utility and regret associated with each investment option. The introduction of parameter 'v' allows for fine-tuning the strategy, adjusting the weight between maximizing group utility, and minimizing individual regret based on the decision-maker's preferences. The calculated Qi values lead to a systematic ranking of investment projects, providing decision-makers with an empirical basis for selecting the optimal alternative. The VIKOR method stands out as a structured and comprehensive approach to multi-criteria decision-making, addressing complex investment decisions by incorporating a broad array of financial indicators.

The article "VIKOR multi-criteria decision making with AHP reliable weighting for article acceptance recommendation"(Wibawa et al., 2019) presents a novel application of the VIKOR method in the academic publishing domain. Recognizing the multi-faceted nature of article evaluation, the authors utilize VIKOR to develop a decision support system for recommending articles for publication. The article highlights that acceptance decisions are rarely based on a single factor; instead, reviewers consider a range of criteria, including originality, quality, clarity, significance, and relevance. The authors leverage VIKOR's strength in handling such multi-criteria decision-making scenarios to create a system that ranks articles based on their overall merit, considering the trade-offs and potential conflicts between these criteria. This approach aims to provide a more comprehensive and objective assessment of articles compared to relying solely on subjective judgments or a single evaluation factor.

2.3.4 Summary Table of Literature Review

Table 2.1: Summary Table

Author	Year	Sample	Title	Source	Findings
Alakaş et al.	2020	Industrial symbiosis applications based on ANP	Ranking of sustainability criteria for industrial symbiosis applications based on ANP	Journal of Environmental Engineering and Landscape Management	the study provides strategic insights into the criteria affecting the sustainability of industrial symbiosis, the importance of management systems.
Alqahtani & Rajkhan	2020	consisted of 69 e-learning managers from various educational institutions.	E-Learning Critical Success Factors during the COVID-19 Pandemic: A Comprehensive Analysis of E-Learning Managerial Perspectives	Department of Industrial Engineering, King Abdulaziz University	The study highlights blended learning as the most effective approach and emphasizes that technological advancement alone is insufficient without robust e-learning strategies, skilled instructors, and engaged, self-motivated students.
Chakraborty	2022	top 20 world university rankings from Times Higher Education in 2020	TOPSIS and Modified TOPSIS: A comparative analysis	Decision Analytics Journal	the paper finds that while both TOPSIS and modified TOPSIS are derived from the same mathematical origin and are structurally similar, they produce different rankings due to the way attribute weight is incorporated.
Galik et al.	2022	labor market flexibility in 15 European Union Member States. The data covers a period from 2009 to 2018.	Evaluating Labour Market Flexibility Using the TOPSIS Method: Sustainable Industrial Relations	journal Sustainability.	The study found that the TOPSIS method is a suitable approach for measuring and comparing labour market flexibility across different countries and over time.
Guitouni & Martel	1998	Choosing an appropriate MCDA method	Tentative guidelines to help choosing an appropriate MCDA method	European Journal of Operational Research	This paper demonstrates how crucial it is for any decision aid methodology to include steps

					related to structuring and modelling.
Huang et al.	2009	Multiple criteria decision making - The perspective of regret theory	A revised VIKOR model for multiple criteria decision making - The perspective of regret theory	Communications in Computer and Information Science	The paper finds that the revised VIKOR model, provides a more accurate reflection of decision-makers' unlike the original VIKOR model which can produce incorrect preference rankings.
Hwang & Yoon	1981	Multiple Attributes Decision Making Methods	Multiple Attributes Decision Making Methods and Applications	Multiple Attributes Decision Making	Introduction to multiple attributes decision-making methods
Kastratović et al.	2017	Investment Projects	Application of Vikor Method in Ranking the Investment Projects	Journal of Economics and Law	The findings of the research document is that the VIKOR method effectively ranks investment projects by evaluating them against multiple criteria, resulting in the identification of an investment alternative
Krohling & Pacheco	2015	Ranking evolutionary algorithms	A-TOPSIS - An approach based on TOPSIS for ranking evolutionary algorithms	Procedia Computer Science	The study presents the A-TOPSIS method as an effective tool for ranking evolutionary algorithms by considering both their mean values and standard deviations.
Liu et al	2023	discusses the advantages and disadvantages of AHP, Entropy value, TOPSIS, Fuzzy comprehensive evaluation.	Analysis of the Advantages and Disadvantages of Four Comprehensive Evaluation Methods	School of Quality Management and Standardization, Foshan University	The article concludes by suggesting that combining these methods, instead of relying on just one, can lead to more robust and reliable evaluations.
Madanchian & Taherdoost	2023	Multi-criteria decision making	A comprehensive guide to the TOPSIS method for multi-criteria decision making	Sustainable Social Development	This study has examined the main advantages and disadvantages of TOPSIS and given an overview of its development and applications.
Nabeeh et al.	2019	Personnel Selection	An Integrated Neutrosophic-TOPSIS Approach and Its Application to Personnel Selection: A New Trend in Brain Processing and Analysis	IEEE Access	The study found that integrating neutrosophic sets with the AHP and TOPSIS methodologies enhances traditional personnel selection processes

Opricovic & Tzeng	2004	VIKOR and TOPSIS	Compromise solution by MCDM methods: A comparative analysis of VIKOR and TOPSIS	European Journal of Operational Research	The paper finds that VIKOR and TOPSIS MCDM methods both aim for a solution close to the ideal but differ in their approach to normalization, aggregation, and the relative importance of distances in their ranking processes.
Opricovic & Tzeng	2007	Outranking methods	Extended VIKOR method in comparison with outranking methods	European Journal of Operational Research	The study's findings indicate that alternative A5 is the best compromise solution for the multicriteria optimization of the hydropower systems on the Drina River,
Parveen & Kamble	2021	Group decision making in intuitionistic fuzzy environment	An extension of TOPSIS for group decision making in intuitionistic fuzzy environment	Mathematical Foundations of Computing	Extension of TOPSIS for group decision making in intuitionistic fuzzy environment
Rustandi & Shilul Imaroh	2021	Optimization Contractor Selection	Analysis fuzzy AHP for optimization contractor selection using multi-criteria in determining the best alternative contractor	Dinasti International Journal of Management Science	The findings of this study shows that it can be utilised to advise TSI management that all contractor selection procedures should be conducted objectively, with the use of techniques that reduce bias or uncertainty.
Tang et al.	2018	Logistics Service Quality	Research on Taguchi TOPSIS Method in Logistics Service Quality	Advances in Social Science, Education and Humanities Research	The study found that the hesitant fuzzy Taguchi TOPSIS method provides an effective multi-attribute decision-making approach, concluding that the service quality of the third logistics enterprise is superior to the other three evaluated companies.
Triantaphyllou	2000	Comparative Study	Multi-Criteria Decision-Making Methods: A Comparative Study	Applied Optimization (APOP, volume 44)	The book presents an extensive comparative study of the Multi-Criteria Decision-Making methods, highlighting various abnormalities in some methods and addressing critical aspects like quantification of qualitative

					data, deriving weights, and sensitivity analysis.
Türegün	2022	analyses the financial performance of companies in the tourism sector that are publicly traded on the Borsa Istanbul.	Financial performance evaluation by multi-criteria decision-making technique	Ozyegin University, School of Applied Sciences, Turkey	The findings reveal similar company rankings in 2018 and 2019, with AVTUR consistently ranked highest and MARTI lowest. However, slight ranking variations emerged in 2020, highlighting the influence of market conditions on evaluation outcome
Wibawa et al	2019	This study focused on a review of 18 articles	VIKOR multi-criteria decision making with AHP reliable weighting for article acceptance recommendation	International Journal of Advances in Intelligent Informatics	The authors found that the AHP-VIKOR method outperforms the traditional VIKOR method in terms of reliability and accuracy when ranking articles for acceptance
Zolfani et al.	2020	Reanalysis of the MADM methods based on logarithmic normalization	A VIKOR and TOPSIS focused reanalysis of the MADM methods based on logarithmic normalization	Facta Universitatis, Series: Mechanical Engineering	The study found that logarithmic normalization offers more stable results and is resistant to the rank reversal problem in multi-attribute decision-making methods when compared to conventional normalization models.

CHAPTER 3

METHODOLOGY

This chapter provides a detailed explanation of the steps that were taken to finish this project successfully. Ensuring transparency and replicability, the objective is to present a thorough and comprehensible understanding of the study's methodology. Achieving the research goals and answering the research questions highlighted in Chapter 1 depend heavily on the methodology used in this study.

3.1 Overview of the Study

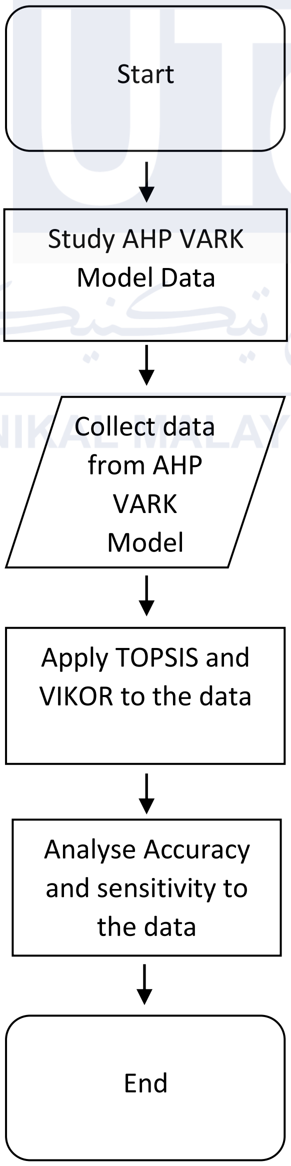


Figure 3.1: Project Flow Chart

This study outlines the systematic approach used in conducting the research to test the accuracy and sensitivity of the (AHP) in prioritizing the blended learning model based on the VARK model using (TOPSIS) and (VIKOR). The research methodology encompasses overview of the study, data statistic investigation period, equipment used, construction of questionnaire, software used, TOPSIS AND VIKOR methods, and Comparison of the data. Figure1 shows a flow chart that illustrates the methodical implementation of processes and procedures.

3.2 AHP VARK Model Data research study

The research will conduct a comprehensive investigation into the data derived from previous student Final Year Report (FYP) that have implemented the Analytic Hierarchy Process (AHP) in conjunction with the VARK (Visual, Auditory, Reading/Writing, Kinesthetic) model. The primary focus is on analyzing and understanding the patterns, trends, and outcomes associated with the application of the AHP VARK model in diverse educational settings, with particular emphasis on blended learning environments. This study serves as the foundational step in building insights and informing subsequent stages of the research, providing a robust basis for the integration of the TOPSIS and VIKOR models in the later phases of the project.

3.3 Data collection

In this comprehensive project, the primary focus revolves around gathering and analyzing data derived from previous student PSM project. The first data is the survey taken from 50 Year 4 undergraduate engineering course students from UTeM about their Preferred Blended Learning Models and their preferred VARK model. The survey likely encompassed questions that delved into the students' experiences, preferences, and expectations regarding the integration of various learning methodologies. The second data is AHP model analysis result. AHP is a decision-making tool that helps in systematically evaluating and prioritizing different criteria and alternatives. The data provided will be used to conduct accuracy and sensitivity to the results.

3.4 TOPSIS Model

TOPSIS model will use a data survey from 50 Year 4 undergraduate engineering course students from UTeM about their Preferred Blended Learning Models and their preferred VARK model conducted by previous PSM student. The standard operating procedure of TOPSIS for decision-making in this project and the TOPSIS flow chart are shown below.

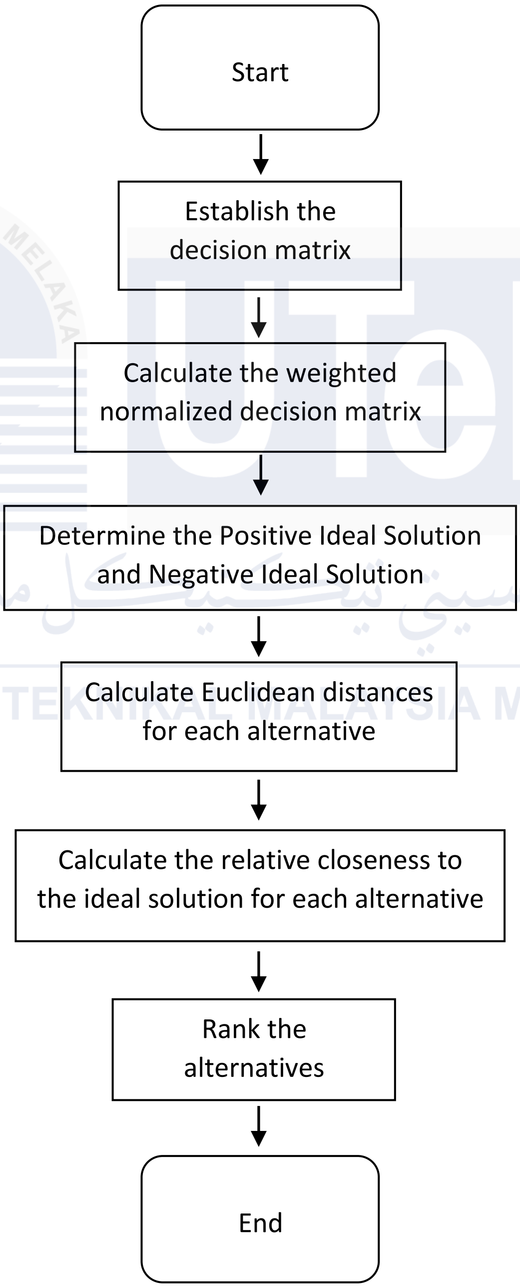


Figure 3.2: TOPSIS Flow Chart

In this project, the VARK model is the criteria while the blended learning models are the alternative options. The decision matrix with m alternatives and n criteria is represented as $X = (x_{ij})_{mxn}$.

Step 1: Calculate and normalize the decision matrix.

Normalize the decision matrix by dividing each element by the square root of the sum of squares of all elements in the corresponding column. This step ensures that all criteria are on the same scale.

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} {x_{ij}}^2}}$$

Step 2: Calculate weight normalized matrix.

Firstly, calculate the weights by dividing the sum of each criterion by the total sum of all criteria.

$$\text{Weight } w_j = \frac{Total\ sum\ of\ each\ criteria}{Total\ sum\ of\ all\ criteria}$$

after calculating the weightage, multiply each column of the normalized decision matrix by its respective weight.

$$v_{ij} = w_j$$

Step 3: Determine the positive ideal and negative ideal solutions.

$$v_j^+ = \{v_j^+, v_j^+, \ldots, v_n^+\} = \{max_j(v_{ij})\} \qquad v_j^- = \{v_j^-, v_j^-, \ldots, v_n^-\} = \{min_j(v_{ij})\}$$

Step 4: Calculate Euclidean distances for each alternative.

Euclidean distances quantify the similarity or dissimilarity of each alternative to the ideal and anti-ideal solutions. By computing the distance between each alternative and these reference points, we obtain a measure of how well each alternative performs relative to the best and worst possible outcomes. Alternatives with shorter distances to the ideal solution and longer distances to the anti-ideal solution are considered more favorable.

$$D_i^+ = \sqrt{\sum_{j=1}^{n}\left(v_{ij} - v_j^+\right)^2} \quad D_i^- = \sqrt{\sum_{j=1}^{n}\left(v_{ij} - v_j^-\right)^2}$$

Step 5: Calculate relative closeness.

This value is always between 0 and 1, and the alternatives which got values closer to 1 are better.

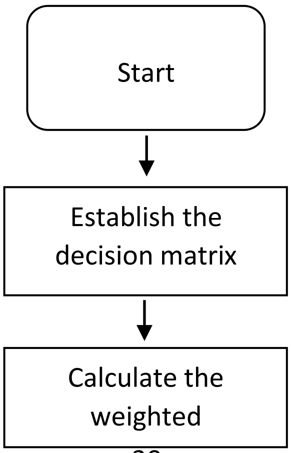
$$C_i = \frac{D_i^-}{D_i^- + D_i^+}$$

Step 6: Rank the alternatives.

In the final step of TOPSIS, the alternatives are ranked from the best with the biggest to the worst alternative, with the lowest. The top alternative in the list, that is the alternative with the biggest value is the solution.

3.5 VIKOR Model

VIKOR model will use a data survey from 50 Year 4 undergraduate engineering course students from UTeM about their Preferred Blended Learning Models and their preferred VARK model conducted by previous PSM student. The standard operating procedure of VIKOR for decision-making in this project and the VIKOR flow chart are shown below.



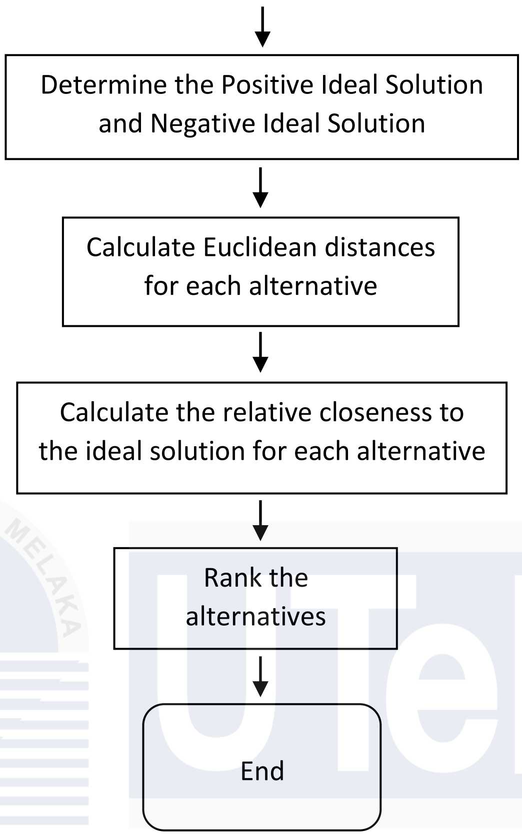


Figure 3.3: VIKOR Flow Chart

<u>Step 1: Determines the best f_i^x and the f_i^{x-} worst values.</u>

Before normalization, identify the best and worst values for each criterion across all alternatives. The best number indicates the most ideal performance, and the lowest value is the worst possible performance for each criterion.

$$f_i^x = \max f_{ij} \qquad\qquad f_i^- = \min f_{ij}$$

Best **Worst**

<u>Step 2: Calculate the weight.</u>

Firstly, calculate the weights by dividing the sum of each criterion by the total sum of all criteria.

$$\text{Weight } w_j = \frac{Total\ sum\ of\ each\ criteria}{Total\ sum\ of\ all\ criteria}$$

Step 3: Calculate and normalize the S_i and R_i values.

After weighting the decision matrix, the next step is to calculate the S_i and R_i for each alternative based on the normalized and weighted decision matrix. S_i represents the distance from the best value, while R_i represents the distance from the worst value for each alternative value to help assess how well each alternative performs relative to the best and worst outcomes across all criteria.

$$S_i = \sum_{j=1}^{m} \left(W_j \frac{x_i^+ - x_{ij}}{x_i^+ - x_i^-} \right)$$

$$R_i = max \left(W_j \frac{x_i^+ - x_{ij}}{x_i^+ - x_i^-} \right)$$

Step 4: Calculate the Q_i

Calculate the Q_i values, which represent the total compromise for every alternative. These numbers quantify the balance between getting the best performance for each criterion and minimizing the difference from the poorest performance.

$$Q_i = v * \frac{S_i - S^*}{S^- - S^*} + (1 - v) * \frac{R_i - R^*}{R^- - R^*}$$

$$S^* = \min S_i \,, \qquad S^- = max\ S_i \,, \qquad R^* = \min R_i \,, \qquad R^- = \max S_i$$

Step 5: Rank the alternatives.

Rank the alternatives based on their $Q_i$values. The alternative with the lowest $Q_i$value is considered the best compromise solution, offering the most balanced performance across all criteria.

Step 6: Propose as a compromise solution.

Propose as a compromise solution the alternatives, which is the best ranked by the measure Q (minimum), if the following two conditions are satisfied.

Condition 1:

The first requirement is an acceptable advantage, meaning that the difference in Q between the best and second-best options must be less than the given DQ value.

$$Q(A^2) - Q(A^1) \geq DQ$$

$$DQ = \frac{1}{J-1}$$

Condition 2:

Acceptable stability in decision making. The alternative Not satisfied must be the best ranked by S or/and R.

3.6 Accuracy analysis

Upon completion of the TOPSIS and VIKOR model evaluations, statistical analyses will be employed to validate and interpret the obtained results. These analyses aimed at assessing the reliability and robustness of the rankings derived from AHP, TOPSIS and VIKOR Model. The result will be interpreted to evaluate and compare rankings from AHP, TOPSIS, and VIKOR models. Discussion of the implication on the findings and their significance in assessing the accuracy and sensitivity of the AHP blended learning model will be conducted. Comparing these rankings allows for a thorough evaluation of the AHP model's accuracy and sensitivity in reflecting preferences and priorities. Differences in rankings between the models may highlight areas where the AHP model excels or falls short, providing insights into its effectiveness in differentiating and prioritizing blended learning models.

CHAPTER 4

RESULT AND DISCUSSION

This chapter presents and discusses the results of using the TOPSIS and VIKOR integrated models to evaluate the accuracy and sensitivity of the AHP-VARK model in blended learning data. Evaluation process includes forming decision matrix, calculation of normalized decision matrices, determination of ideal solutions and final ranking of alternatives. The accuracy of these results is further validated using Spearman's Rank Correlation Coefficient. The purpose of this chapter is to provide a thorough understanding of the results achieved using the proposed methodology.

4.1 Data Overview

The dataset used in this study was gathered from several blended learning approaches, including Face to Face Driver, Online Driver, Rotation, Online Lab, Flex, and Self-blend models. Each model is assessed based on VARK (Visual, Auditory, Read/Write, and Kinesthetic) learning preferences.

Table 4.1: Number of Students with Their Preferred Blended Learning Models

Blended Learning Models	**Number of Students in terms of VARK**				**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

The dataset obtained from a previous FYP student includes data gathered via a survey designed to assess students' preferences for the VARK (Visual, Auditory, Read/Write, and Kinesthetic) model across several blended learning models. The data contains the number of students that prefer each learning style within the various blended learning contexts.

Table 4.2 Overall Priority Ranking of the AHP Model

Blended Learning Model	Calculation	Overall Priority Ranking
Face-to-face Driver Model	(0.3762*0.1441) + (0.2865*0.2165) + (0.4116*0.0431) + (0.3007*0.5963)	31.33%
Online Driver Model	(0.1542*0.1441) + (0.1565*0.2165) + (0.1744*0.0431) + (0.1546*0.5963)	15.58%
Rotation Model	(0.1081*0.1441) + (0.2851*0.2165) + (0.0501*0.0431) + (0.1784*0.5963)	18.58%
Flex Model	(0.0904*0.1441) + (0.0675*0.2165) + (0.0968*0.0431) + (0.0630*0.5963)	6.94%
Online Lab Model	(0.1844*0.1441) + (0.1351*0.2165) + (0.2401*0.0431) + (0.2260*0.5963)	20.09%
Self-blend Model	(0.0866*0.1441) + (0.0693*0.2165) + (0.0271*0.0431) + (0.0773*0.5963)	7.47%

The Analytic Hierarchy Process (AHP) was employed to rank various blended learning models based on the VARK learning styles Visual, Auditory, Read/Write, and Kinaesthetic. Table 3 shows that the face-to-face driver model had a higher priority vector of 31.33%, as determined using AHP analysis, was used to calculate weights by pairwise comparison. The flex model and the rotation model followed, having priority vectors of 20.09% and 18.58%, the ranking process included survey data from students about various learning experiences and preferences. The AHP analysis also revealed overall accuracy of 74% which reveals significant consistency between predictions provided by AHP VARK model and the individual's preferences. Such information would not only serve as an essential base to continuation with evaluation of the accuracy and reliability validation on AHP-VARK Model using integrated TOPSIS & VIKOR methods, but also guarantees fitting evaluation practice for blended learning strategies.

4.2 TOPSIS Analysis

Step 1: Calculate and normalize the decision matrix.

Normalize the decision matrix by dividing each element by the square root of the sum of squares of all elements in the corresponding column. This step ensures that all criteria are on the same scale.

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} {x_{ij}}^2}}$$

Table 4.3 Normalize Decision Matrix

Vark Model	V	A	R	K
Face to Face driver Model	0.970143	0.784465	1	0.78072
Online Driver Model	0	0	0	0.048795
Rotation Model	0	0.588348	0	0.439155
Online Lab Model	0	0	0	0
Flex Model	0.242536	0.196116	0	0.439155
Self-blend Model	0	0	0	0.048795

The normalized decision matrix for the TOPSIS analysis is presented in Table 4.1. This table shows the normalized values for each criterion (V, A, R, K) across the different blended learning models. For instance, the Face-to-Face Driver Model, which initially had high values across most criteria, retained its relative superiority in the normalized matrix. Specifically, the normalized values for the Face-to-Face Driver Model are 0.970 for Visual (V), 0.784 for Auditory (A), 1 for Read/Write (R), and 0.781 for Kinaesthetic (K). These values indicate that this model performs consistently well across all VARK criteria, which is expected given its comprehensive approach to blended learning. On the other hand, the Online Driver Model, which had lower initial values, shows normalized values of 0 for V, A, and R, and a small value of 0.049 for K. This suggests that the Online Driver Model performs poorly compared to other models, particularly in the Visual, Auditory, and Read/Write criteria. Similarly, the Online Lab Model has normalized values of 0 across all criteria, indicating the least favourable performance among the alternatives.

The Rotation Model and the Flex Model show intermediate performance. The Rotation Model has normalized values of 0 for V and R, 0.588 for A, and 0.439 for K, reflecting a moderate performance particularly in the Auditory and Kinaesthetic criteria. The Flex Model, with normalized values of 0.243 for V, 0.196 for A, and 0.439 for K, shows a balanced yet not outstanding performance across the criteria. Lastly, the Self-blend Model, like the Online Driver Model, has normalized values of 0 for V, A, and R, and a small value of 0.049 for K, indicating it is not a strong performer in any of the criteria. Overall, the normalized decision matrix highlights the relative strengths and weaknesses of each blended learning model across the VARK criteria

Step 2: Calculate weight normalized matrix.

Firstly, calculate the weights by dividing the sum of each criterion by the total sum of all criteria.

$$\text{Weight } w_j = \frac{Total\ sum\ of\ each\ criteria}{Total\ sum\ of\ all\ criteria}$$

after calculating the weightage, multiply each column of the normalized decision matrix by its respective weight. The weights for the criteria V, A, R, and K are 0.1, 0.16, 0.02, and 0.72, respectively. These weights indicate that the K criterion (Kinaesthetic) holds the highest importance among the criteria, followed by A (Auditory), V (Visual), and R (Read/Write), which has the least importance.

$$v_{ij} = w_j r_{ij}$$

Table 4.4 Weight Normalized Matrix

Vark Model	V	A	R	K
Face to Face driver Model	0.097014	0.125514	0.02	0.562118
Online Driver Model	0	0	0	0.035132
Rotation Model	0	0.094136	0	0.316192
Online Lab Model	0	0	0	0
Flex Model	0.024254	0.031379	0	0.316192
Self-blend Model	0	0	0	0.035132

These values highlight the dominance of the Kinaesthetic (K) criterion across the models, particularly for the Face to Face Driver Model, which scores the highest in this category. This indicates that this model is particularly strong in delivering content that aligns well with kinaesthetic learning preferences. The Online Lab Model, on the other hand, has zero values across all criteria, suggesting it is not favoured in any of the VARK categories based on the weightings used.

Step 3: Determine the positive ideal and negative ideal solutions.

In the third step of the TOPSIS analysis, positive ideal solution and the negative ideal solution for each criterion need to be calculated. These solutions represent the best and worst possible outcomes and serve as benchmarks for evaluating each alternative. The positive ideal solution is calculated by taking the maximum value for each criterion across all alternatives. Conversely, the negative ideal solution is determined by taking the minimum value for each criterion across all alternatives. The positive and negative ideal solutions for this analysis are as follows:

$$v_j^+ = \{v_j^+, v_j^+, \ldots, v_n^+\} = \{max_j(v_{ij})\} \qquad v_j^- = \{v_j^-, v_j^-, \ldots, v_n^-\} = \{min_j(v_{ij})\}$$

Table 4.5: Positive ideal and negative ideal solutions

Vark Model	V	A	R	K
Face to Face driver Model	0.097014	0.125514	0.02	0.562118
Online Driver Model	0	0	0	0.035132
Rotation Model	0	0.094136	0	0.316192
Online Lab Model	0	0	0	0
Flex Model	0.024254	0.031379	0	0.316192
Self-blend Model	0	0	0	0.035132

V+	0.097014	0.125514	0.02	0.562118
V-	0	0	0	0

Step 4: Calculate Euclidean distances for each alternative.

Euclidean distances quantify the similarity or dissimilarity of each alternative to the ideal and anti-ideal solutions. By computing the distance between each alternative and these reference points, we obtain a measure of how well each alternative performs relative to the best and worst possible outcomes. Alternatives with shorter distances to the ideal solution and longer distances to the anti-ideal solution are considered more favorable.

$$D_i^+ = \sqrt{\sum_{j=1}^{n}\left(v_{ij} - v_j^+\right)^2} \quad D_i^- = \sqrt{\sum_{j=1}^{n}\left(v_{ij} - v_j^-\right)^2}$$

Table 4.6: Euclidean distances

Vark Model	V	A	R	K	Di+	Di-
Face to Face driver Model	0.097014	0.125514	0.02	0.562118	0	0.584417
Online Driver Model	0	0	0	0.035132	0.550709	0.035132
Rotation Model	0	0.094136	0	0.316192	0.266976	0.329907
Online Lab Model	0	0	0	0	0.584417	0
Flex Model	0.024254	0.031379	0	0.316192	0.273926	0.318669
Self-blend Model	0	0	0	0.035132	0.550709	0.035132

The Euclidean distances reveal how close each alternative is to the ideal and anti-ideal solutions. The Face-to-Face Driver Model has a D_i^+ value of 0 and a D_i^- value of 0.588603, indicating that it is the closest to the positive ideal solution and the farthest from the negative ideal solution, thus making it the most favourable alternative. In contrast, the Online Lab Model, with a D_i^+ value of 0.579489 and a D_i^- value of 0, is the least favorable as it is the closest to the negative ideal solution and the farthest from the positive ideal solution. Other models like the Rotation Model and Flex Model have intermediate D_i^+ and D_i^- values, reflecting their moderate performance compared to the ideal and anti-ideal solutions. The Online Driver Model and Self-blend Model, with similar distance values, also show poor performance relative to the ideal solution.

Step 5: Calculate relative closeness.

This value is always between 0 and 1, and the alternatives which got values closer to 1 are better.

$$C_i = \frac{D_i^-}{D_i^- + D_i^+}$$

Table 4.7: Relative Closeness

Vark Model	Di+	Di-	Ci
Face to Face driver Model	0	0.584417	1
Online Driver Model	0.550709	0.035132	0.059969
Rotation Model	0.266976	0.329907	0.552716
Online Lab Model	0.584417	0	0
Flex Model	0.273926	0.318669	0.537751
Self-blend Model	0.550709	0.035132	0.059969

on the results, the Face to Face Driver model has the highest relative closeness (Ci = 1), indicating it is the best alternative among those evaluated. It is the closest to the positive ideal solution, making it the most preferred model. The Rotation Model and Flex Model follow with Ci values of 0.552716 and 0.537751, respectively. These models are also relatively close to the ideal but not as much as the Face to Face Driver model. The Online Driver and Self-blend Models have the same relative closeness value of 0.059969, making them less favourable compared to the top alternatives. The Online Lab model has a Ci value of 0, indicating it is the least preferred alternative in this analysis.

<u>Step 6: Rank the alternatives.</u>

In the final step of TOPSIS, the alternatives are ranked from the best with the biggest to the worst alternative, with the lowest. The top alternative in the list that is the alternative with the biggest value is the solution.

Table 4.8: Alternatives Ranking

Vark Model	Ci	Rank
Face to Face driver Model	1	1
Online Driver Model	0.059969	4
Rotation Model	0.552716	2
Online Lab Model	0	5
Flex Model	0.537751	3
Self-blend Model	0.059969	4

The Face to Face Driver model ranks first with a Ci value of 1, making it the most preferred alternative. This model's strong performance across all criteria and its proximity to the ideal solution highlight its effectiveness in addressing the needs of different learning styles (VARK). The Rotation Model and Flex Model, with Ci values of 0.552716 and 0.537751, respectively, are the next best alternatives. They perform relatively well but not as strongly as the Face to Face Driver model. Their intermediate ranking suggests that they are viable options, though they do not fully meet the criteria as effectively as the top-ranked model. The Online Driver and Self-blend Models both have a Ci value of 0.059969, placing them in a tie for the fourth position. Their lower rankings indicate that they are less favourable compared to the other models, especially in terms of meeting the ideal solution criteria. The Online Lab model, with a Ci value of 0, ranks last. This indicates that it is the least preferred alternative, performing poorly across the criteria and being the farthest from the ideal solution.

4.3 VIKOR Analysis

Step 1: Determines the best f_i^x and the f_i^{x-} worst values.

Before normalization, identify the best and worst values for each criterion across all alternatives. The best number indicates the most ideal performance, and the lowest value is the worst possible performance for each criterion.

$$f_i^x = \max f_{ij} \qquad\qquad f_i^- = \min f_{ij}$$

Best **Worst**

The table shows the best $f_i^x$and worst f_i^{x-}values for each criterion.

Table 4.9: Best and Worse Value

Vark Model	V	A	R	K	Total
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
Best	4	4	1	16	
Worst	0	0	0	0	

These values are derived from the performance data of each blended learning model in addressing the different VARK criteria. The Face-to-Face Driver Model consistently shows high values, indicating its strong performance across the criteria. In contrast, models like the Online Lab Model and Self-blend Model display lower values, reflecting their less favourable performance. By establishing these benchmarks, the VIKOR analysis can proceed to evaluate each alternative's relative performance in subsequent steps. This step is foundational as it provides the reference points for normalization and subsequent calculations in the VIKOR method.

<u>Step 2: Calculate the weight.</u>

Firstly, calculate the weights by dividing the sum of each criterion by the total sum of all criteria.

$$\text{Weight } w_j = \frac{Total\ sum\ of\ each\ criteria}{Total\ sum\ of\ all\ criteria}$$

Table 4.10: The Data Weight

Weightage	0.1	0.16	0.02	0.72	
Vark Model	V	A	R	K	Total
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

These weights reflect the prioritization of criteria for the blended learning models. Kinaesthetic learning (K) is given the highest weight, indicating it is the most significant criterion in this analysis. This is followed by Auditory (A), Visual (V), and Read/Write (R) criteria. The high weight for kinaesthetic learning suggests that the blended learning models that perform well in this criterion will have a substantial impact on the overall ranking.

Step 3: Calculate and normalize the S_i and R_i values.

After weighting the decision matrix, the next step is to calculate the S_i and R_i for each alternative based on the normalized and weighted decision matrix. S_i represents the distance from the best value, while R_i represents the distance from the worst value for each alternative value to help assess how well each alternative performs relative to the best and worst outcomes across all criteria. The criteria weights, derived in Step 2, are as follows: Visual (V) at 0.1, Auditory (A) at 0.16, Read/Write (R) at 0.02, and kinaesthetic (K) at 0.72.

$$S_i = \sum_{j=1}^{m} \left(W_j \frac{x_i^+ - x_{ij}}{x_i^+ - x_i^-} \right)$$

$$R_i = max \left(W_j \frac{x_i^+ - x_{ij}}{x_i^+ - x_i^-} \right)$$

Table 4.11: The S_i and R_i values

Weightage	0.1	0.16	0.02	0.72		
Vark Model	V	A	R	K	S_i	R_i
Face to Face driver Model	0	0	0	0	0	0
Online Driver Model	0.1	0.16	0.02	0.675	0.955	0.675
Rotation Model	0.1	0.04	0.02	0.315	0.475	0.315
Online Lab Model	0.1	0.16	0.02	0.72	1	0.72
Flex Model	0.075	0.12	0.02	0.315	0.53	0.315
Self-blend Model	0.1	0.16	0.02	0.675	0.955	0.675

The results show that the Face-to-Face Driver Model has the lowest Si and Ri values, both being zero, indicating that it is the closest to the ideal solution and farthest from the worst scenario. This suggests that this model performs optimally across all VARK criteria, particularly excelling in the kinaesthetic domain, which holds the highest weight. On the other hand, the Online Driver, Online Lab, and Self-blend Models exhibit high Si and Ri values, implying they are less favourable as they are closer to the worst-case scenario and farther from the ideal. The Rotation and Flex Models display intermediate Si and Ri values, suggesting moderate performance. The significance of Step 3 lies in its ability to quantify how well each alternative aligns with the ideal and deviates from the worst scenarios, providing a clear picture of their relative performances.

Step 4: Calculate the Q_i

Calculate the Q_i values, which represent the total compromise for every alternative. These numbers quantify the balance between getting the best performance for each criterion and minimizing the difference from the poorest performance.

$$Q_i = v * \frac{S_i - S^*}{S^- - S^*} + (1 - v) * \frac{R_i - R^*}{R^- - R^*}$$

$$S^* = \min S_i\,, \qquad S^- = max\ S_i\,, \qquad R^* = \min R_i\,, \qquad R^- = \max S_i$$

Table 4.12: The Q_i, S_i and R_i values

	S_i	R_i	Q_i
Face to Face driver Model	0	0	0
Online Driver Model	0.955	0.675	0.94625
Rotation Model	0.475	0.315	0.45625
Online Lab Model	1	0.72	1
Flex Model	0.53	0.315	0.48375
Self-blend Model	0.955	0.675	0.94625

These Q_i values reflect the compromise solution rankings. The Face-to-Face Driver Model, with the lowest Q_i value of 0, is considered the best alternative, offering the most balanced performance across all criteria. The Online Driver and Self-blend Models have the highest Q_i values, indicating they are the least favourable. The Rotation and Flex Models, with intermediate Q_i values, suggest moderate performance. Step 4 thus finalizes the ranking by quantifying the balance between achieving the best overall performance and minimizing individual regret.

<u>Step 5: Rank the alternatives.</u>

Rank the alternatives based on their $Q_i$values. The alternative with the lowest $Q_i$value is considered the best compromise solution, offering the most balanced performance across all criteria.

Table 4.13: Alternatives Ranking

	S_i	R_i	Q_i	Rank
Face to Face driver Model	0	0	0	1
Online Driver Model	0.955	0.675	0.94625	4
Rotation Model	0.475	0.315	0.45625	2
Online Lab Model	1	0.72	1	5
Flex Model	0.53	0.315	0.48375	3
Self-blend Model	0.955	0.675	0.94625	4
S+, R+	0	0		
S-, R-	1	0.72		

The Face to Face Driver Model has the lowest Q_i value of 0, making it the most preferred alternative. This indicates that this model is the closest to the ideal solution and farthest from the worst scenario, balancing both the collective utility and individual regret optimally. Its top rank signifies its effectiveness in meeting the criteria set for the blended learning models. The Rotation Model, with a Q_i value of 0.45625, is ranked second. This model performs well across the criteria but not as strongly as the Face to Face Driver Model. It is a viable alternative, showing moderate compromise between the best and worst performances. The Flex Model follows closely with a Q_i value of 0.48375, placing it third. It demonstrates a relatively balanced performance across the evaluated criteria, making it another strong option for blended learning approaches. Both the Online Driver Model and the Self-blend Model have a Q_i value of 0.9775, tying them at the fourth position. These models are less favourable compared to the top three alternatives, as their higher Q_i values indicate a greater distance from the ideal solution and closer proximity to the worst scenario. The Online Lab Model has the highest $Q_i$value of 1, placing it last in the ranking. This model is the least preferred alternative due to its poor performance across the criteria, being farthest from the ideal solution and closest to the worst-case scenario.

Step 6: Propose as a compromise solution.

Propose as a compromise solution the alternatives, which is the best ranked by the measure Q (minimum), if the following two conditions are satisfied.

Condition 1: Acceptable Advantage

The first requirement is an acceptable advantage, meaning that the difference in Q between the best and second-best options must be less than the given DQ value. In this context, J represents the number of alternatives. The acceptable advantage condition confirms that the top-ranked alternative is distinctively better than the others.

$$Q(A^2) - Q(A^1) \geq DQ$$

$$DQ = \frac{1}{J-1}$$

$$Q(A^2) - Q(A^1) = 0.45625 - 0.00000 = 0.45625$$

$DQ = \frac{1}{6-1} = 0.2$ Satisfied

Condition 2: Acceptable Stability

The second condition checks the stability of the decision by ensuring that the proposed best alternative is also the best when evaluated by either the S (maximum group utility) or R (minimum individual regret) criteria, or both. This condition guarantees that the proposed compromise solution is good across different evaluation measures. The Face to Face Driver model also be the best in terms of S or R. From the data, it is evident that the Face to Face Driver model ranks best in terms of both criteria. Given that both conditions are satisfied, the Face to Face Driver model can be proposed as the compromise solution.

4.4 Accuracy Analysis

Table 4.14: Spearmen's Rank Correlation Coefficient Data

Alternative	AHP Ranking	TOPSIS-VIKOR Ranking	Difference (d)	Squared Difference (d^2)
Face to Face driver Model	1	1	0	0
Online Driver Model	4	4	0	0
Rotation Model	3	2	1	1
Online Lab Model	6	5	1	1
Flex Model	2	3	-1	1
Self-blend Model	5	4	1	1
Sum				4
p	0.885714			

Spearmen's rank correlation coefficient is used to test the consistency and accuracy of the multi criteria decision making method which is AHP VARK model and TOPSIS and VIKOR model. This non-parametric measure assesses the strength and direction of the association between two ranked variables. It is a measurement of the level to which rankings produced by various means agree with each other. In case of high Spearman's rho values, it implies that the ranking is closer meaning consistency or accuracy in ranking. The coefficient value ranges between -1 and +1 where +1 indicates perfect positive correlation, 0 signifies no correlation while -1 indicates perfect negative correlation. Spearman's Rank Correlation Coefficient measures the strength and direction of the association between two ranked variables where di is the difference between the ranks of each alternative in two different methods and n is the number of alternatives as formula shown below:

$$\rho = 1 - \frac{6\sum d_i^2}{n(n^2-1)}$$

The face-to-face driver model was ranked the highest by both AHP and the integrated TOPSIS-VIKOR models with a Ci=1.000 in TOPSIS and Qi=0.000 in VIKOR. Next came flex and rotation models which were highly ranked in both methods. The high level of agreement between these models is further supported by their computed Spearman's ρ value of 0.886.

This strong positive correlation means there is a great deal of overlap between the rankings produced by AHP and those of the combined TOPSIS-VIKOR approach, which suggests that both methods have similar views regarding ranking of alternatives hence making this decision-making process more reliable for future use. It also suggests that both techniques are consistent on how they rank the assessment criteria, thus enhancing trustworthiness of decision-making process. In addition to this, combination accuracy at 88.6% far exceeds what has ever been reported using AHP alone at 74%, thereby confirming integration model's robustness.

Face-to-face driver model appeared prominently among top-ranked options as an appropriate blended learning approach for engineering students. This enhances credibility beyond doubt as shown by Spearman's rho hence creating a dependable basis upon which educational institutions can review their blended learning strategies leading to enhanced student outcomes to improved course design. Spearman's rank correlation has been used to validate the rankings generated by different decision-making models. This method aids in ensuring that the chosen model aligns well with real-world data and expert assessments, thereby enhancing the reliability of the decision-making process (Paradowski et al., 2021).

4.5 Summary

In short, Chapter 4 presents the evaluation and ranking of blended learning models using the TOPSIS and VIKOR integrated with the AHP-VARK model. The analysis identified the Face-to-Face Driver Model as the best option, followed by the Rotation and Flex Models. Using the TOPSIS method, the Face-to-Face Driver Model showed the highest relative closeness to the ideal solution, while VIKOR analysis confirmed its analysis by providing the lowest Q_i value. The results demonstrated high consistency and accuracy, validating the integrated model's effectiveness in reflecting student learning styles and preferences. All the objectives in the project are achieved and the results are fulfilled by the objectives and scope requirements.

CHAPTER 5

CONCLUSION

This study aimed to evaluate the accuracy and sensitivity of the AHP-VARK model in the context of blended learning data using the TOPSIS and VIKOR integrated models. The comprehensive analysis presented in the previous chapters demonstrates that the integrated approach of utilizing TOPSIS and VIKOR models significantly enhances the decision-making process. The study's key findings indicate a high correlation and consistency, as evidenced by the Spearman's Rank Correlation Coefficient (ρ) value of 0.886, reflecting a strong positive correlation between the rankings produced by the AHP model and the integrated TOPSIS-VIKOR model. This high level of agreement ensures reliability and consistency in the decision-making process. Furthermore, the combined accuracy of the TOPSIS and VIKOR models, which stands at 88.6%, surpasses the AHP model's accuracy of 74%, underscoring the robustness and reliability of the integrated model in evaluating blended learning approaches. The face-to-face driver model emerged as the top-ranked blended learning approach for engineering students, consistently appearing at the top of the rankings in both the AHP and the integrated models, reinforcing its credibility as an effective blended learning strategy. Additionally, the use of VARK (Visual, Auditory, Read/Write, and kinaesthetic) learning preferences as evaluation criteria proved effective in differentiating and prioritizing blended learning models, enabling a more tailored and student-centric approach to education.

Based on these findings, several recommendations can be made to further improve the evaluation and implementation of blended learning models. Educational institutions should consider adopting integrated decision-making models like TOPSIS and VIKOR in conjunction with the AHP model to enhance the accuracy and reliability of their evaluations. This approach can provide a more comprehensive understanding of the effectiveness of different learning strategies. Given the consistent high ranking of the face-to-face driver model, institutions should prioritize this approach in their blended learning strategies, allocating additional resources and support to optimize this model and address any potential areas for improvement. Continuous data collection and analysis are crucial; ongoing surveys and assessments can provide updated data that can be used to refine and adjust the evaluation models, ensuring they remain relevant and effective. While VARK preferences have proven useful, additional criteria such as technological readiness, student engagement, and accessibility should be incorporated into the evaluation process to provide a more holistic view of the effectiveness of blended learning models. Educators and administrators should receive training on the use of multi-criteria decision-making tools and the interpretation of their results to make more informed decisions and effectively implement the recommended strategies. Lastly, policymakers should develop frameworks that support the integration of robust decision-making models in educational planning, providing guidelines and best practices for institutions to follow, ensuring consistency and quality in blended learning implementations.

In conclusion, the integration of TOPSIS and VIKOR models with the AHP-VARK model offers a powerful tool for evaluating blended learning approaches. By adopting these recommendations, educational institutions can enhance their decision-making processes, leading to improved student outcomes and more effective learning environments.

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