Faculty of Computer Science and Information Technology

Recommendation for Product Selling Opportunity using Hybrid-MCDM in E-commerce Marketplace

Christopher Chee Chin Fung

Master of Science
2025

Recommendation for Product Selling Opportunity using Hybrid-MCDM in E-commerce Marketplace

Christopher Chee Chin Fung

A thesis submitted

In fulfillment of the requirements for the degree of Master of Science

(Data Mining)

Faculty of Computer Science and Information Technology
UNIVERSITI MALAYSIA SARAWAK
2025

DECLARATION

I declare that the work in this thesis was carried out in accordance with the regulations of Universiti Malaysia Sarawak. Except where due acknowledgements have been made, the work is that of the author alone. The thesis has not been accepted for any degree and is not concurrently submitted in candidature of any other degree.

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Signature

Name: Christopher Chee Chin Fung

Matric No.: 21020289

Faculty of Computer Science and Information Technology

Universiti Malaysia Sarawak

Date : 18-05-2025

ACKNOWLEDGEMENT

I would like to take this opportunity to express special thanks of gratitude to those who have contributed directly or indirectly in the completion of this thesis.

First of all, I would like to thank my supervisor, Dr. Chiew Kang Leng for his supervision, encouragement and guidance. Besides, I would like to thank my co-supervisor, Dr. Izzatul too. I am appreciated that my supervisor is patient and always spare their time for idea discussion and online meetings with me in order to have a clearer understanding of the direction during the completion of this study.

Secondly, I would like to thank post-graduate coordinator, Dr. Azman Bin Bujang Masli for guiding and providing useful information throughout the period.

Last but not least, I would like to extend my gratitude towards my family and friends, who supports me all the time. Support and encouragement given during my period of study in Universiti Malaysia Sarawak making it possible for me to complete my study. Thank you all.

ABSTRACT

The rapid growth of E-commerce platform has attracted both consumers and sellers, yet it presents significant challenges for sellers due to intensifying competition. This heightened competition may result in market losses for sellers. To mitigate these challenges, sellers must enhance their competitiveness in the marketplace. Thus, a data analytic approach to identify potential products through product selling recommendation for sellers within the E-commerce marketplace was proposed. By leveraging these recommendations, sellers can make informed decisions and saves time on complex decision-making processes. The Multi-Criteria Decision-Making (MCDM) method is applied to identify potential products, utilizing Analytic Hierarchy Process (AHP) and Technique for Order Preference by Similarity to Ideal Solution (TOPSIS). AHP uses pairwise comparison to derive weights, while TOPSIS focuses on proximity to the ideal solution. These methods have been selected for ranking alternatives in MCDM. In order to apply MCDM, various product feature such as Estimated Sales Volume (ESV), Net Promoter Rating (NPR), Sales Rate (SR) and Price (P) are proposed. These features serve as the key metrics for evaluating the potential of a product in the marketplace. The hybrid-based MCDM method (AHP-TOPSIS) is evaluated using Ranking Evaluation Value (REV). REV is used as a quantitative metric to compare the appropriateness of the ranking outcomes under a consistent set of criteria weights. In this evaluation, higher REV values indicate better-aligned recommendations with the decision-making objectives. To ensure the consistency of the hybrid-based ranking model, further experiment is conducted to evaluate its overall performance. To test the consistency of the model over time, different datasets were used to imitate the data from various timelines. Additionally, different product categories were included to evaluate the performance of the model across diverse types of products. The results demonstrated that AHP-TOPSIS offers

superior identification of potential products based on the product features (ESV, NPR, SR and P). Therefore, the application of AHP-TOPSIS to identify potential products is able to help sellers to overcome competitiveness in the E-commerce marketplace.

Keywords: E-commerce, MCDM, sales recommendation, market trend analysis, selling opportunity, product performance analytics

Pendekatan Analitik Data untuk Menemui Peluang Jualan Produk dalam Pasaran E-Dagang

ABSTRAK

Pengembangan pesat platform E-dagang telah menarik perhatian konsumer and peniaga, namun ia turut memberikan cabaran besar kepada peniaga disebabkan persaingan yang semakin sengit. Persaingan sengit ini boleh mengakibatkan kerugian pasaran bagi peniaga. Untuk mengurangkan masalah ini, peniaga perlu meningkatkan daya saingan mereka dalam pasaran. Oleh itu, pendekatan analitik data telah dicadangkan bagi mengenal pasti produk berpotensi melalui cadangan penjualan produk untuk peniaga dalam pasaran E-dagang. Dengan memanfaatkan cadangan ini, peniaga dapat membuat keputusan yang lebih bijak dan menjimatkan masa dalam proses yang kompleks. Bagi mengenal pasti produk berpotensi, kaedah Multi-Kriteria Pembuatan Keputusan (MCDM) telah digunakan dengan memanfaatkan pendekatan Proses Hirarki Analitik (AHP) dan Teknik untuk Keutamaan Susunan Berdasarkan Persamaan dengan Penyelesaian Ideal (TOPSIS). AHP menggunakan perbandingan berpasangan untuk menentukan pemberat manakala TOPSIS menumpukan kepada pendekatan yang menghampiri penyelesaian ideal. Kaedah-kaedah tersebut telah dipilih untuk menilai kedudukan alternatif dalam MCDM. Dalam aplikasi MCDM, pelbagai ciri produk seperti Anggaran Jumlah Jualan (ESV), Penarafan Promoter Bersih (NPR), Kadar Jualan (SR) dan Harga (P) telah dicadangkan. Ciri-ciri ini berfungsi sebagai metrik utama dalam penilaian potensi produk di pasaran. Kaedah MCDM berasaskan hybrid (AHP-TOPSIS) dinilai dengan menggunakan Nilai Penilaian Kedudukan (REV). REV digunakan sebagai metrik kuantitatif untuk membandingkan kesesuaian hasil kedudukan dengan syarat set kriteria pemberat yang konsisten. Dalam penilaian ini, nilai REV yang lebih tinggi menunjukkan cadangan yang lebih selaras dengan objektif membuat keputusan.

Untuk memastikan konsistensi model kedudukan berasaskan hybrid, eksperimen lanjut dilakukan untuk menilai prestasi keseluruhannya. Untuk menguji konsistensi model dari masa ke masa, set-set data berlainan digunakan untuk mewakili data dalam tempoh masa yang berbeza. Selain itu, kategori produk yang berbeza digunakan untuk menilai prestasi model dalam pelbagai jenis kategori produk. Hasil keputusan menunjukkan bahawa AHP-TOPSIS menawarkan pengenalpastian produk berpotensi yang lebih baik berdasarkan ciri-ciri produk (ESV, NPR, SR dan P). Oleh itu, aplikasi AHP-TOPSIS untuk mengenal pasti produk berpotensi dapat membantu peniaga untuk mengatasi persaingan dalam pasaran E-dagang.

Kata kunci: *E-dagang, MCDM, cadangan jualan, analisis tren pasaran, peluang penjualan, analitik prestasi produk*

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LIST OF ABBREVIATIONS

MCDM	Multi-criteria Decision-making
AHP	Analytic Hierarchy Process
BWM	Best Worst Method
TOPSIS	Technique for Order of Preference by Similarity to Ideal Solution
WASPAS	Weighted Aggregated Sum Product Assessment
ESV	Estimated Sales Volume
SR	Sales Rate
P	Price
NPR	Net Promoter Score
NPS	Net Promoter Rating
ALP	Average Lifespan in Percentage
LET	Last Engagement Timestamp
TLET	Total Last Engagement Timestamp
TEET	Total Expected Engagement Timestamp
REV	Ranking Evaluation Value

CHAPTER 1

INTRODUCTION

1.1 Study background

E-commerce marketplace has changed the lifestyle of people nowadays, especially on the shopping method. Anything purchasable can be purchased online by using a few fingers tap. The convenience of E-commerce platform has raised more consumers' attention to practice online shopping. Therefore, business owner seeks this as the business opportunity to setup their business on E-commerce marketplace. Besides benefiting the consumers, it is also convenience for sellers to setup the B2C (business-to-consumer) business. B2C business is a type of business model where sellers can sell products directly to customers and bypassing third-party retailers, wholesalers and middleman (Baczkiewicz, MCDM based e-commerce consumer decision support tool, 2021). Since the invention of E-commerce has benefits both sellers and consumers, it is undoubtedly experiencing rapid growth in the E-commerce industry.

The rapid growth of E-commerce marketplace has attracted both sellers and consumers. The increase in the number of consumers is good for the E-commerce marketplace as sellers can gain more sales. The increase in the number of sellers is also good for the E-commerce marketplace as consumers can have many choices of product to choose from. However, the overcrowded number of sellers in the marketplace may not necessarily healthy. This is because price war is often happening among sellers. For example, China E-commerce firms such as JD.com, Suning, DangDang and Gome have experienced great losses in 2012 due to competitive price war (Liu, 2021). Price war happens when a seller reduces the price of product to subdue other competitors and to gain market share. When facing such situation, competitor may also further slash down their product price to gain back the market share or customers while suppressing other sellers. Consumers may benefit from the price war in a short term. Consumers can enjoy the benefits of purchasing high quality products at a reasonable fair price due to the price competition among the sellers. On the other hand, sellers who relates in the market share will experience lower profit than expected. Sellers may source for low-cost product just to compete with the price. If the price war gets more competitive, small businesses may experience close down. In a long run, consumers will be left with less selection when shopping because only larger firms are able to survive in the price war.

In order to reduce price competition, sellers or business owners need to understand and maintain their product core characteristics, value and competitiveness of the product instead of only lowering the product price to gain market share until great loss is experienced. In today's market, price is not the only factor that affects the sales rate. Baczkiewicz, et al. (2021) stated that product's quality, service and innovation also have greater impact. Product characteristics (product features) such as price, quality and service are considered by the consumers. Recommending a right product at the right time with good customer service can also lead to gain in sales. Therefore, sellers should sell products that suits the consumer's consideration by understanding from their perspective.

1.2 Problem statement

Crowded sellers in the E-commerce marketplace selling similar products may resulted in highly competitive price war. On the other hand, selling random product without proper consideration can avoid price war but it may result in another situation such as selling low demand product.

Before consumer deciding to purchase a product, many features of the product are considered (Hatta et al., 2018). Nowadays, a single feature of the product cannot be used to determine the product selling recommendation. There are many similar products to select in the E-commerce marketplace. In order to satisfy the consumers' purchase intention, product with more than one outstanding feature need to be prioritized by the sellers. Otherwise, sellers may experience poor business performance by selling low competitive product in the market. Hence, product with multiple good features need to be prioritized by the sellers.

Besides, it is difficult to compare the products based on multiple product features of a product to form product selling recommendation. Comparing in such method is time-consuming and not systematic. In order to overcome such multi decision problem, popular method such as MCDM can be applied. MCDM can compare and rank the products based on their product features respectively.

1.3 Objectives

Objectives of the study is as below:

i. To develop multi-criteria decision-making (MCDM) method that provides product selling recommendation

ii. To identify product features to form criteria for product selling recommendation

iii. To evaluate the performance of the multi-criteria decision-making (MCDM) method for product selling recommendation

1.4 Research scope

Product selling recommendation is the suggestion of a product from a list of products based on product's selling opportunity in the market. The higher the product's selling opportunity, the higher its selling potential. Research has shown that products with greater market opportunities often experience enhanced sales performance due to increased consumer interest and demand. For example, a study by Sudirjo (2023) on marketing strategies emphasized how leveraging market opportunities can significantly improve product competitiveness, leading to higher sales potential. Additionally, digitalization in the B2B customer journey highlights that understanding and exploiting digital opportunities can enhance a product's market potential, aligning with the idea that a product's selling opportunity directly impacts its sales performance (Andersson et al., 2024). Hence, product with high selling opportunity tended to be suggested by the product selling recommendation. Product features had to be studied in order to understand product selling opportunity for the computation of the product selling recommendation. In this study, computed numerical value of product feature was focused to form the product selling recommendation.

Recommendation is the main focus of this study. Forecasting or prediction on the outcome was beyond the research scope. There was difference between recommendation and forecasting. Forecasting focuses on generating the 'future' outcome by using the value of history records. Whereas recommendation focuses on the potential of a product selling by studying the comparison difference of the history records.

Product selected for the research study on product selling recommendation was the products on E-commerce platform. Shopee Malaysia was the E-commerce platform chosen for this study. Since there was no exact data and API for the details of product on the platform, data scraping was required for the data collection process. An automated data scraping tool was developed and used throughout the data collection process.

1.5 Research significance

MCDM is a tool that assist decision-makers to select alternative products based on the criteria. By using MCDM, irrelevant product can be filtered when selecting suitable product to sell in the E-commerce marketplace. MCDM is an approach for overall assessment of a product when dealing with complex decisive problems that involves more than one variable. MCDM can be applied to provide product selling recommendation.

Besides, this study aims to determine product features or characteristics that can be used as the criteria for product selling recommendation. Importance weight of criteria can be identified and help sellers to understand the performance of products in the marketplace.

Evaluation on the method applied in E-commerce marketplace can help to understand the benefits and limitations of MCDM method. Proper evaluation on method ensures that product selling recommendation is relevant and accurate. The result from evaluation can produce appropriate product selling recommendation that can help sellers to find potential product and reduce risks.

1.6 Thesis organisation

This thesis is organized into five distinct chapters, apart from references and appendices. The contents of the chapters are summarized as follows:

Chapter 1: Introduction provides understanding on the background of this research. This chapters also describes the key problems identified in existing E-commerce marketplace, followed by objectives and scope of this research.

Chapter 2: Literature Review introduces the application of MCDM to solve daily life problems. Related works on the application of MCDM and product features are elaborated. Different type of MCDM methods is discussed in this chapter. Product features are studied to form the criteria for the application of MCDM.

Chapter 3: Methodology explains the step-by-step phases to design the methodology. These phases include criteria selection, weight computation and hybrid-based ranking.

Chapter 4: Experimental Results discusses the preliminary experiment and the application of methodology. Discussion and findings on the methodology are discussed. Last but not least, results and evaluation are carried out to further determine the application of methodology in different situation.

Chapter 5: Conclusion and Future Works concludes the project achievement and project limitations. Future works elaborate the improvement of the project that can be done to minimize the limitations in the future.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

The purpose of this chapter is to elaborate on the literature review. There are 2 main components to be studied. First of all, product feature is the product attribute factor that affects the priority of criteria. Investigation on product feature is required to determine applicability of product feature. After that, priority of product feature will be studied based on the purpose of investigation. Secondly, ranking of different products based on their prioritised product features is another complex problem. Different priority of product feature will result in different ranking of products. The approach that fulfilled the ranking of products based on their product features is investigated to help the sellers in the E-commerce marketplace.

2.2 Related works

Decision-making is a common action, but it is very important as it impacts our daily life. A lot of choices have been made to select the most suitable option among many options. For example, people do consider the price and specifications of the car when they purchase a new car. With various brands, types and specifications available for cars, decision-makers often need significant time to carefully weigh their options before reaching a decision. A notable approach used in many published works is MCDM which can help the decision makers to make an efficient decision.

Published work by Stopka et al. (2022) stated that MCDM can help to select an appropriate electric car. In the research, six variants of similar electric vehicles are compared using MCDM technique. Criteria such as price, mileage, power, energy, maximum speed and trunk volume of the electric cars are considered to select the most suitable electric car.

The life insurance recommender system study by Rani et al. (2021) also applied MCDM approach. The life insurance recommender system can recommend suitable life insurance products based on personal preference. This system can save the time of decision makers by filtering out irrelevant product. So, MCDM plays an important role in choosing life insurance product for future financial planning.

The application of MCDM techniques is pervasive in daily life, particularly when navigating complex decision-making scenarios. Various decisions require specific MCDM approaches customised to their unique characteristics. Given the diverse array of MCDM techniques available, it represents a compelling area of research within the dynamic landscape of the E-commerce marketplace.

2.3 Multi-criteria decision-making

When it comes to choosing the suitable product for sell, there are many alternative products, especially in the E-commerce marketplace. Although we know that the product feature is important, but choosing suitable product based on multiple product features is another topic to cover. So, selecting the optimal alternative from a set of alternatives is considered a simple approach when MCDM is applied as the problem-solving technique (Bafail & Abdulaal, 2022). MCDM is a set of methods used to compare, rank and select optimal selection among complex alternatives. MCDM can compare several criteria at once to rank the optimal alternative instead of comparing single criterion to another criterion in order to determine the optimal alternative. Therefore, MCDM can help decision makers to make more informed and structured decisions when dealing with complex choices.

MCDM provides a robust method for evaluating and ranking products based on a comprehensive set of criteria. To select the most suitable product for a seller, product features are identified and used to form criteria for product selling recommendations. Next, these criteria are weighted based on defined goals. The process of selecting and weighting criteria is crucial in the MCDM process, as it directly impacts the final ranking results. In the final step, product alternatives are ranked according to the criteria weights and the product features. Hence, MCDM is an effective approach for selecting the most suitable product for sellers based on product features. In order to make the optimal ranking of alternatives, Bafail & Abdullal (2022) stated that different requirements of alternatives need to be studied and differentiate by decision makers. Therefore, we need a tool that can evaluate the products based on product features and select the optimal product for the sellers. When a decision is needed, MCDM is the tool that can be used to examine and select the optimal choice when dealing multiple choices (Bafail & Abdulaal, 2022). Multiple selection issue that involves quantitative and qualitative criteria can be solved effectively using MCDM model (Rani et al., 2021). Another study stated that the MCDM method can help to make decisions when buying products that have different factors and options to consider (Wang et al., 2019). The main function of MCDM method is to help decision-makers to overcome complicated tasks such as evaluating, selecting and prioritising (Baczkiewicz, MCDM based e-commerce consumer decision support tool, 2021). So, it is helpful to apply MCDM model in the E-commerce marketplace.

AHP is a MCDM technique which is widely used in decision-making (Bafail & Abdulaal, 2022). AHP is popular because it is a comprehensive and rational framework that evaluates complex decision problems based on tenets of psychology and mathematics (Bafail & Abdulaal, 2022). It is simple and intuitive as decision-making problem can be structured into a hierarchy tree using AHP approach (Alsalem, et al., 2018). Since AHP relies heavily on pairwise comparison, it could be a trouble when the criteria involve in the problem is high in number. This is because more computation is needed for each criterion to compare to other criterion.

BWM is a new MCDM technique (Bafail & Abdulaal, 2022). The advantage of BWM is that it has fewer calculations for pairwise comparison. Since BWM only compares the best and worst criteria for pairwise comparison, it is more effective to evaluate criteria priority. BWM only compare best and worst criteria for pairwise comparison. Hence, it has reduced complexity when compared to AHP. However, it depends heavily on the selected best and worst criteria. Nuance may happen if the best and worst criteria selected is not suitable.

Another popular MCDM technique that is widely used in decision-making is TOPSIS (Amudha et al., 2021). TOPSIS evaluates complex decisions based on the selection of distances from positive and negative ideal solution (Abdulvahitoglu & Kilic, 2022). TOPSIS applies geometrical point by using Euclidean distance to determine the relative distance of a selection to the optimal solution. The selection is ideal if it has the nearest distance to the positive ideal distance and has the farthest distance from negative ideal solution. Due to its simplicity to measure distance of positive and negative ideal solutions, it is widely used in solving multi-criteria problems (Baczkiewicz, MCDM based e-commerce consumer decision support tool, 2021). However, relative importance of the distances between each point is not considered (Alsalem, et al., 2018). Therefore, TOPSIS is sensitive to the scale of the data used for computation. In order to solve this issue, proper normalization and standardization is required to carry out. Alternatively, integration of other MCDMs method that have the normalization or standardization approach with TOPSIS is another approach.

WASPAS is a combination of MCDM techniques of WSM (Weighted Sum Model) and WPM (Weighted Product Model) (Wang et al., 2021). According to Wang et al. (2021), the improved version of WSM and WPM to form WASPAS is more stable and precise. WASPAS is widely used in daily life as it can simplifies complex calculation operations for ranking alternatives (Zavadskar et al., 2012). It is flexible and stable to use but it requires proper weight determination. This is because WASPAS only applies simple mathematics approach to compute the rankings. When the criteria have different units of measurement, WASPAS may struggle and provide inaccurate ranking. To overcome this issue, proper normalization and transformation of data, need to be carry out. Alternatively, integration of other MCDMs method that have the normalization or standardization approach with WASPAS is another approach.

Table 2.1: Summary of MCDMs

MCDM	Strength	Weakness
AHP	Simple and decomposes problem into smaller parts	High computation when dealing with large number of criteria and alternatives
BWM	Reduced complexity and less computation due to minimal comparison	Highly rely on the best and worst criteria selected which may causes nuances
TOPSIS	Simple and emphasizes positive and negative ideal solution	Sensitive to scale of the data, which may require normalization or standardization
WASPAS	Flexible because it is combination of weighted sum and product model	Requires proper weight determination

To evaluate alternatives when dealing with selection problems, different MCDM methods are often integrated. Problems that involve MDAM (Multiple Attribute Decision Making) and MODM (Multiple Objective Decision Making) problems can be solved using MCDM (Norouziyan, 2022). MDAM often helps to evaluate multiple alternatives in decision problems and MODM focuses on finding the optimal solution among conflicting criteria. Meanwhile, MCDM helps to choose the best alternative among optimal weighted criteria in a decision problem. So, integrated MCDMs can solve the ranking problem in terms of a set of products and their product features at different stages when integration is applied.

The application of MCDM methods in integrated form is widely used in daily life. Such integration approaches are like combining 2 tools. Weighting MCDM helps to examine which criteria of a product is important towards defined goals. Meanwhile, ranking MCDM helps to pick the overall best product from a list of products based on defined goals. Therefore, combining both MCDM methods helps to find product alternatives that fulfilled the desired factors. A study from Turkey applied AHP-TOPSIS for foreign direct investment investigation (Çalık et al., 2019). According to Çalık et al. (2019) AHP is used to select priority of criteria for foreign direct investment and TOPSIS is used to rank the sectors in accordance with evaluation criteria. Another study claiming that AHP-TOPSIS is applied to select the most suitable oilseed for biodiesel production (Abdulvahitoglu & Kilic, 2022). The approach for the application of AHP-TOPSIS in oilseed is similar as in the application of foreign direct investment. So, the integration of multiple MCDMs can be applied to solve selection problem in daily life.

2.4 Product feature

To identify a product with high demand potential, product features need to be studied. According to Hatta et al. (2018), factors that affect the purchasing decision includes product quality, price and promotion. Although these factors are the main reason for consumers to consider the purchasing decision, but these factors cannot be used directly to determine a good selling product for the sellers on the E-commerce marketplace. For example, offering a discount price promotion of a product can attract a lot of customers and gain sales, but it is not ideal for sellers. This is because discounted price promotion is reducing the profit margin of expected profit. If done incorrectly, sellers may experience business loss. Therefore, the alternative approach is to study the sales performance of a product instead of promotion. Sales performance is measured based on the product's selling activities.

Sales performance of a product is an essential factor. Sales performance is a measurement used to evaluate the ability of a product to reach targeted goals in a certain period. Different companies have different goals as they need different measurement to evaluate their strategies based on business need (Budiono et al., 2022). In order to understand the effect of sales performance towards a product, sales volume and sales rate trend of product on E-commerce marketplace are investigated. Sales volume indicates that amount of sales gain in a certain period while sales rate indicates the rate of sales gain in a certain period. The approach to investigate product sales rate trend is similar to the study on cancer risk (Qiu et al., 2021). According to Qiu et al. (2021), cancer risk can be controlled by investigating the differences in cancer patterns. Hence, we can identify the sales performance of a product by investigating the differences in sales volume and sales rate pattern.

Price is the unit of measurement for the cost spent in exchange of goods or services. Product price affects the purchasing decisions of consumers (Hatta et al., 2018). Different consumers have different willingness to spend certain cost in order to exchange goods or services. This is because consumers are sensitive to the price of products (Carvalho et al., 2020). Besides purchasing decision, product price also does affect the customer loyalty and satisfaction due to the fact that consumers are price sensitive (Wantara & Tambrin, 2019). Consumers may not be willing to pay and seek for cheaper alternative if the product price is higher than expected price. Reasonable price also has a direct positive effect on consumers' perception toward quality (Zhong & Moon, 2020). Therefore, a fair, reasonable and acceptable product price is an important product feature to investigate in this study. Although product price is essential, but it cannot be the only factor to make consumers satisfied and loyal (Yusuf et al., 2019).

Other than price, quality is another important product feature to look into. Quality is the measurement of satisfaction of goods or services based on certain standards. Product quality affects the purchasing intentions of consumers (Hatta et al., 2018). Another study supported that good product quality results in high purchasing intentions (Mirabi et al., 2015). Besides good product quality, good customer service quality also has a positive impact on purchasing intention (Carvalho et al., 2020). Therefore, high quality is preferred by consumers regardless of products or service provided. In this study, our focus is the product quality in E-commerce marketplace. So, product quality on the E-commerce platform is often determined based on the star ratings and reviews given by other consumers. A study by Helversen et al. (2018) stated that purchasing intention in E-commerce platform is affected by ratings and reviews Many online consumers will refer to the product reviews before purchasing, and it helps online sellers to estimate product sales performance based on reviews (Park et al., 2019). Another study found that star rating has a significant impact on product sales (Li et al., 2019). Therefore, star ratings and reviews can be considered as the measurement towards the product quality in E-commerce marketplace.

Besides, packaging is also another essential product feature. Proper packaging can create a visual effect that attracts the purchasing intention of customers when they compared the packaging of similar products. Proper packaging includes the size, design, colour and functionality of the packaging. Packaging can help to establish relationship with the customers. Proper packaging can help customers to choose their product if they are familiar with the packaging. Thus, this can help to improve the purchasing intention when they are more familiar with the product. A study shows that visual effect of a proper packaging can create unplanned purchases due to the appearance aspects of the product (Mirabi, Akbariyeh, & Tahmasebifard, 2015).

2.5 Summary

Numerous studies shown that MCDM can help in complex decision problem. In this study, MCDM can be applied to help sellers to select appropriate product to sell in the E-commerce marketplace. MCDM methods can be applied include AHP, BWM, TOPSIS and WASPAS. These MCDM methods can be integrated and used effectively. To form the criteria for MCDM, product features such as sales performance, price and quality need to be studied.

CHAPTER 3

METHODOLOGY

3.1 Introduction

The purpose of this chapter is to focus on the methodology. The methodology involves 3 main phases: criteria selection, weight computation and hybrid-based ranking. First, we select the criteria of recommendation for product selling in the E-commerce platform. After that, the relative importance of each criterion is determined to obtain the respective weight. Finally, the respective criteria weight obtained are used for hybrid-based ranking. Besides, experiment design and experiment environment are discussed in depth. Figure 3.1 shows the overview of the methodology. Besides, dataset and method used for data analysis are elaborated in brief.

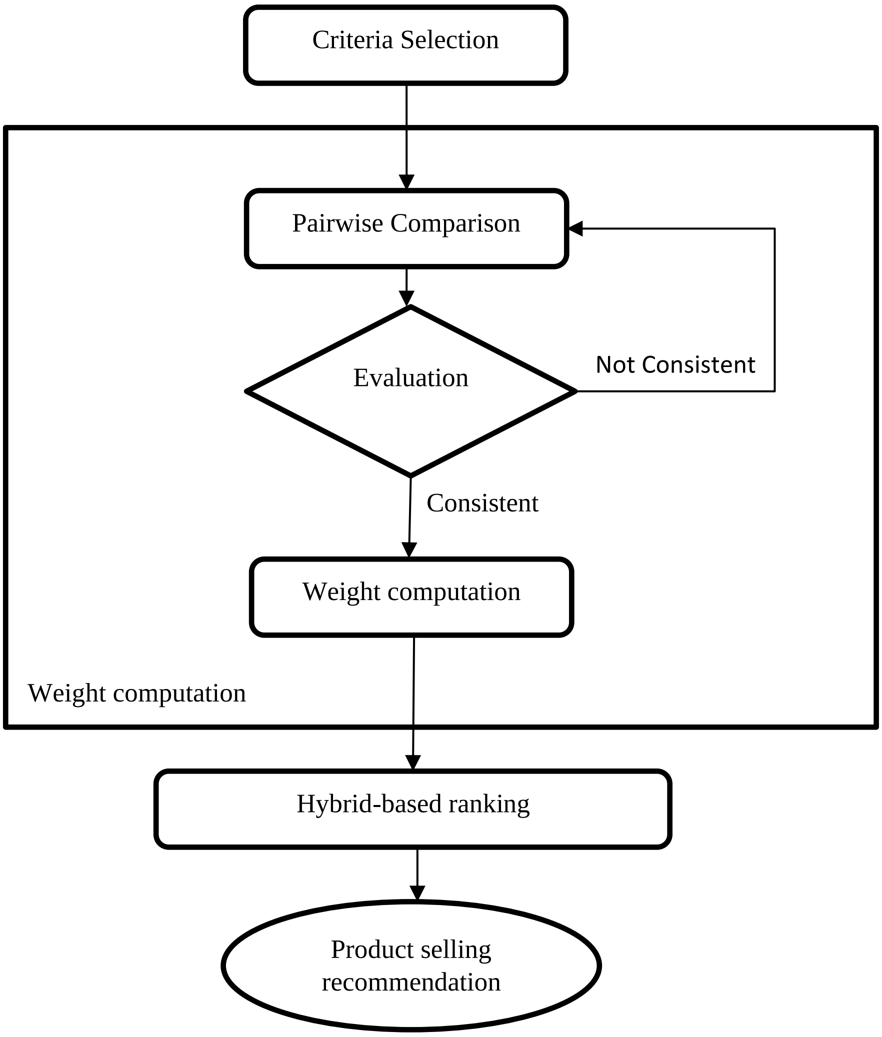

Figure 3.1: Overview of the methodology.

3.2 Criteria selection

In order to recommend a product for sellers in the E-commerce marketplace, it was essential to identify the criteria of recommendation in product selling. To evaluate the product selling recommendation, more than one criterion is required because a single criterion is not comprehensive and cannot represent the overall result (Baydas & Elma, 2021). Therefore, the criteria of product selling recommendation needed to be selected.

Selected criteria for product selling recommendation were estimated sales volume, sales rate, price and net promoter rating. Figure 3.3 shows the hierarchical model for product selling recommendation.

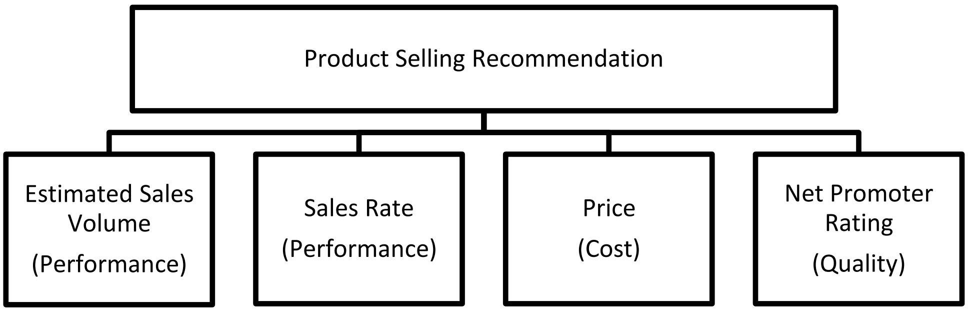

Figure 3.2: Hierarchical model for product selling recommendation.

In this study, packaging was not selected as the criteria for product selling recommendation. This is because customer cannot observe the packaging of the product directly. Therefore, the visual effect of the packaging cannot be applied for product on the E-commerce platform.

3.2.1 Estimated sales volume

ESV was an important criterion that belonged to the performance aspect of the product selling recommendation. ESV is made up of sales volume and sales rate. Sales volume refers to the amount of product sold at a given time. In this study, the accumulation of daily sales was used to determine sales volume at a given time. The formula to calculate sales volume is as follows:

$$Sales\ volume = \sum_{t=t_i}^{t_f} S_t \qquad \text{Equation 3.1}$$

where t is the time, t_i is the initial time, t_f is the final time and S_t is the daily sales at a given time. Although we knew that the sales volume is an important criterion, solely focusing on the sales volume does not provide a decisive approach. This was because sales volume will change from time to time. Therefore, sales rate of a product also needed to be taken into consideration. The formula to calculate ESV is as follows:

$$ESV = Sales\ Volume \times Sales\ Rate \qquad \text{Equation 3.2}$$

3.2.2 Sales rate

Besides ESV, SR was another important criterion that indicated the performance of a product in the E-commerce marketplace. SR determined the rate of a product being sold at a given time. Therefore, SR can be understood as the trending status of a product in the market. If the SR of actual sales is higher than the SR of estimated sales, it means that the product is getting more sales than expected. It is noteworthy to mention that the rate of change is perceived as a feature that represents some characteristic and not to be viewed as a complete forecasting result. The formula to calculate sale rate is as follows:

$$Sales\ Rate\ (SR) = \frac{\Delta Actual}{\Delta Estimated} \qquad \text{Equation 3.3}$$

where $\Delta Actual$ is the rate of change of actual sales rate and $\Delta Estimated$ is the rate of change of estimated sales rate. The calculation of SR will be discussed in depth under section 4.3.2.

3.2.3 Price

Price, P was a criterion that relates to cost aspect of a recommended selling product. Price needed to be considered although it is a non-beneficial criterion, especially in the E-commerce marketplace. Non-beneficial criterion is a criterion that lower values are preferred in order to maximize the benefit. Another common example of a non-beneficial criterion is time, where lower values are preferred to maximize efficiency. On the other hand, beneficial criterion is a criterion that higher values are preferred in order to maximize the benefit. The online product pricing strategy was as important as the traditional market pricing strategy (Altay et al., 2022). This is because customers picked the cheaper product if both products were of similar quality. In this study, the latest price of a product was taken.

3.2.4 Net promoter rating

Quality of product in E-commerce platforms often relied on the reviews. Having more reviews, especially positive reviews meaned that the product was having positive impressions and tends to attract potential customers. However, the impression of the product cannot be determined by using the number of product reviews alone. Therefore, NPS was introduced to determine the product review based on customer rating. NPS was a benchmarking tool for customer satisfaction and having a scale of 0 to 10. The formula of NPS is as follows:

$$NPS = \frac{\sum Promoters - \sum Detractors}{Sample\ size} \qquad \text{Equation 3.4}$$

where $Promoters$ is the scale of 9 to 10 and $Detractors$ is the scale of 0 to 6 (Baehre et al., 2021). The scale of 7 to 8 (Passive) was not taken into consideration in NPS because NPS focuses on extreme opinions that provide more meaningful insights. Since Passive represent a neutral opinion, they do not contribute to understanding strong customer loyalty or dissatisfaction. When the NPS of the product is high, it indicated that the customer is satisfied with the product and tends to recommend the product to others. Therefore, customers are more likely to perceive the product as high-quality as the NPS increases (Mirabi, Akbariyeh, & Tahmasebifard, 2015). In this study, the scale of NPS was adjusted into 1 to 5 which matched the rating score in the E-commerce marketplace instead of 0 to 10. The rating score of 4 in the E-commerce marketplace was the Passive for NPS and it was not taken into accountable. The formula to calculate NPS in the E-commerce marketplace is as follows:

$$NPS = \frac{\sum r_5 - \sum r_3 - \sum r_2 - \sum r_1}{Number\ of\ reviews} \qquad \text{Equation 3.5}$$

where $r_5$is the rating score of 5, r_3 is the rating score of 3, r_2 is the rating score of 2 and r_1 is the rating score of 1. Although NPS was sufficient to be used as a metric to indicate the quality of a product based on reviews, not every buyer rated the product after their purchased in the E-commerce marketplace. Therefore, NPS was formatted into NPR by multiplied the rating rate. The application of NPR will be discussed in depth under section 4.3.3. The formula to calculate NPR is as follows:

$$NPR = NPS \times \frac{Number\ of\ reviews}{Sold\ quantity} \qquad \text{Equation 3.6}$$

3.3 Weight computation

After the criteria of product selling recommendation has been analysed, MCDM method need to be applied for multi-criteria decision support. Considered that the different weight of each criterion plays an important role, and it will impact the ranking result. Therefore, MCDM methods applied for weight computation had to be chosen carefully. MCDM method applied in this study only focused on the pairwise comparison-based methods. This is because such methods represented the relative importance of each criterion with respect to other criteria. Pairwise comparison allows decision-makers to evaluate the importance level of each criterion based on their desired goals. Besides, pairwise comparison can ensure consistency and reduce chances of bias as it is a systematic method to compare criteria. Hence, MCDM methods such as AHP and BWM that fitted the pairwise comparison-based requirement are used.

3.3.1 Analytic hierarchy process

AHP is a MCDM method that determines the relative importance of criteria among other criteria in a decision problem. The step-by-step procedure to carry out AHP is described as follows:

Step 1: Construct a hierarchy model of a problem that contain criteria (see Figure 3.3).

Step 2: Determine the relative importance of different criteria with respect to the goal and form a pairwise comparison matrix using the preference scale. Table 3.1 shows the preference scale used to represent the relative importance of criteria in the pairwise comparison matrix.

Table 3.1: Preference scale and definition (Ishizaka & Labib, 2011)

Scale	Relative importance
1	Equal
3	Moderate
5	Strong
7	Very strong
9	Extreme
2, 4, 6, 8	Intermediate

Step 3: Normalise the pairwise comparison matrix by dividing each data to the sum in each respective column.

Step 4: Obtain the criteria weight by calculating the average of each row in the normalised pairwise comparison matrix.

Step 5: Evaluate the consistency using consistency test. If the consistency result obtained is less than 0.1, consistent data is achieved. Otherwise, pairwise comparison matrix should be revised.

3.3.2 Best worst method

BWM is another MCDM method that determines the relative importance of criteria among other criteria in a decision problem. Study shown that BWM is alternative to AHP because it has fewer pairwise comparison computation. The step-by-step procedure to carry out BWM is described as follows

Step 1: Construct a hierarchy model of a problem that contains criteria (see Figure 3.3).

Step 2: Determine the most important and the least important criteria.

Step 3: Determine the relative importance of the most important criteria over other criteria using a scale of 1 to 9 (see Table 3.1).

Step 4: Determine the relative importance of other criteria over the least important criteria using a scale of 1 to 9 (see Table 3.1.).

Step 5: Obtain the criteria weight by solving the linear equation using the BWM solver[1].

Step 6: Evaluate the consistency using consistency test provided in BWM solver. BWM solver is a tool to ensure that the pairwise comparison formed is consistent. The tool automates the calculation process. Therefore, manual calculation is not necessary. If the consistency result obtained is less than the threshold value provided by the BWM solver, consistent data is achieved. Otherwise, pairwise comparison matrix should be revised.

3.4 Hybrid-based ranking

After determining the weight of criteria in a decision problem using AHP and BWM, the combination of AHP or BWM as the criteria weight with other MCDM method that is primary focuses on alternative ranking is further studied for product selling recommendation. The integration of two or more MCDM methods is the hybrid method that

[1] https://bestworstmethod.com/software/

has proposed by many researchers (Emovon & Oghenenyerovwho, 2020). Additional MCDM methods that focus on ranking such as TOPSIS and WASPAS are applied for the integration of weighted ranking as the hybrid approach. Ranking MCDM allows decision-makers to sort alternatives from the best to the least favourable. Without a ranking system, it would be challenging to compare and determine the most optimal alternatives among different choices. By combining both weighting and ranking MCDM methods, it can compare several criteria at once to rank the optimal alternative. Therefore, a combination of hybrid-based ranking such as AHP-TOPSIS, BWM-TOPSIS, AHP-WASPAS and BWM-WAPSAS will be formed and evaluated for the purpose of product selling recommendation. All concepts and procedures of hybrid-based ranking methods are explained using three criteria as the example. The implementation of hybrid-based ranking will be discussed in depth under Section 4.5. The matrix shows the sample value (x) of the 3-crietria decision matrix using variables.

$$\begin{bmatrix} x_{11} & x_{12} & x_{13} \\ x_{21} & x_{22} & x_{23} \\ x_{31} & x_{32} & x_{33} \end{bmatrix} \qquad \text{Equation 3.7}$$

3.4.1 TOPSIS

TOPSIS is a MCDM method that ranks the decision based on the Euclidean distance between each decision. The step-by-step procedure to compute TOPSIS is as follows:

Step 1: Normalise the decision matrix. After that, compute weighted normalised decision matrix by multiplying the weight of each criterion to the respective column. The formula to calculate weighted normalised decision matrix in each table cell of decision matrix is as follows:

$$V_{ij} = \frac{x_{ij}}{\sqrt{\sum_{j=1}^{n} x_{ij}^2}} \times w_j$$ Equation 3.8

where i is the row number, j is the column number, x is the value in each cell of decision matrix, n is the number of criteria and w is the weightage.

Step 2: Find ideal best (V_j^+) and ideal worst (V_j^-).

For beneficial criteria: Obtain V_j^+ by getting the maximum value in the respective column and obtain V_j^- by getting the minimum value in the respective column.

For non-beneficial criteria: Obtain V_j^+ by getting the minimum value in the respective column and obtain V_j^- by getting the maximum value in the respective column.

Step 3: Find Euclidean distance from ideal best (S_i^+) and Euclidean distance from ideal worst (S_i^-). The formula for S_i^+ and S_i^- are as follows:

$$S_i^+ = \sqrt{\sum_{j=1}^{m} (V_{ij} - V_j^+)^2}$$ Equation 3.9

$$S_i^- = \sqrt{\sum_{j=1}^{m} (V_{ij} - V_j^-)^2}$$ Equation 3.10

where i is the row number, j is the column number, V_{ij} is the value in each cell of weighted normalised decision matrix obtained in Equation 3.8 and m is the number of criteria.

Step 4: Calculate the performance score (P_i).

$$P_i = S_i^+ + S_i^- \qquad \text{Equation 3.11}$$

where S_i^+ is the Euclidean distance from ideal best obtained in Equation 3.9 and S_i^- is the Euclidean distance from ideal worst obtained in Equation 3.10.

Step 5: Rank alternatives based on Pi. The higher Pi indicates the better alternative.

3.4.2 WASPAS

WASPAS is a MCDM method consisting of weighted sum model (WSM) and weighted product model (WPM). The step-by-step procedure to carry out WASPAS is as follows:

Step 1: Normalised the decision matrix.

For beneficial criteria: Divide the value in the normalised decision matrix by maximum value in the respective column.

For non-beneficial criteria: Divide the minimum value in the respective column by the value in the normalised decision matrix.

Step 2: Calculate the WSM performance score (P_i^{WSM}) using the normalised decision matrix. The formula to calculate P_i^{WSM} is as follows:

$$P_i^{WSM} = \sum_{j=1}^{n} x_{ij} w_j \qquad \text{Equation 3.12}$$

where i is the row number, j is the column number, x is the value in each cell of decision matrix, n is the number of criteria and w is the weightage.

Step 3: Calculate the WPM performance score (P_i^{WPM}) using the normalised decision matrix. The formula to calculate the P_i^{WPM} is as follows:

$$P_i^{WPM} = \prod_{j=1}^{n} x_{ij}^{w_j} \qquad \text{Equation 3.13}$$

where i is the row number, j is the column number, x is the value in each cell of decision matrix, n is the number of criteria and w is the weightage.

Step 4: Calculate the WASPAS performance score (P_i^{WASPAS}). The formula to calculate P_i^{WASPAS} is as follows:

$$P_i^{WASPAS} = \lambda P_i^{WSM} + (1 - \lambda) P_i^{WPM} \qquad \text{Equation 3.14}$$

where λ is the WSM ratio, P_i^{WSM} is the WSM performance score obtained in Equation 3.12 and P_i^{WPM} is the WPM performance score obtained in Equation 3.13.

Step 5: Rank alternatives based on P_i^{WASPAS}. The higher P_i^{WASPAS} indicates the better alternative.

3.5 Experiment design

3.5.1 Dataset

A total of 600 products from Shopee Malaysia[2] were scraped daily using an automated scraping module named as Selenium Automation. Selenium has a popular web scraping tool called Selenium WebDriver (Naing et al., 2024). It is the main tool for browser automation and interaction. To run Selenium WebDriver, command script is pre-defined for it to navigate web pages via web browser to collect large amount of data from Shopee Malaysia. This scraping tool scraped product data based on the HTML tag appeared in the web page. After the locaters has been assigned to each of the specific HTML tag, Selenium Automation will interact with the locaters to collect specific data when it runs across the web page. It scrapes raw product details from web page to web page according to the URL of the product stored in the 600-product list. The scraping work started from 10 January 2022 to 5 November 2022. Shopee platform was chosen as it has meaningful raw data for study purposes. In this context, meaningful raw data is raw data that can be used directly without re-construct the data to make it meaningful. These 600 products are from the Mobile & Accessories category of Shopee platform. Each 100 products are selected randomly from the sub-categories of Mobile & Accessories category as suggested by Cheriyan & Tamilarasi (2019). These sub-categories include Audio, Cables & Chargers, Cases & Covers, Powerbanks & Batteries, Screen Protectors and Selfie Accessories. Due to the anti-crawling

[2] https://shopee.com.my/

mechanism and the large volume of product on Shopee platform, only 100 products are randomly selected from each sub-category.

In this study, sub-categories such as Screen Protectors and Selfie Accessories are excluded as the products categorized under these sub-categories are ambiguous. There are no clear boundaries in these sub-categories as there are many irrelevant products are categorized under such sub-category. For example, selfie accessories such as tripods, lighting equipment or even smartphone lenses are categorized under the same group, making it challenging to create a clear distinction among these products. Data involving Audio category are used as training dataset while data involving Cables & Chargers, Cases & Covers and Powerbanks & Batteries are used as validation dataset. Training dataset is used to build model while validation datasets are used to validate the behaviour of the model built.

Both datasets are further split into Dataset A and Dataset B based on their time range. Dataset A ranges from Day 1 to Day 60 and Dataset B ranges from Day 61 to Day 120. The purpose of splitting the dataset based on time range is to study its behaviour over time. The data collected has an accumulation of 300 days, but we only used the first 120 days. This is because our aim is to study the model that can provide the output within a short period of time. These data are not removed but will be used for other investigation if required.

3.5.2 Data analysis

To examine the accuracy of ranking result, REV is used to estimate the weighted value of a product. Products with higher REV are to be ranked higher. REV can only be applied for comparison of different ranking model, provided that same criteria weight is applied. This is because REV is developed to evaluate the appropriateness of rankings but not the appropriateness of criteria weight. The formula of REV used in this study is as follows:

$$REV = (w_{ESV} \times CESV) + (w_{SR} \times CSR) + \left(w_P \times \frac{1}{CP}\right) + (w_{NPR} \times CNPR) \quad \text{Equation 3.15}$$

where w_{ESV} is the weightage of ESV, w_{SR} is the weightage of SR, w_P is the weightage of SR, w_{NPR} is the weightage of NPR, $CESV$ is the criteria value of ESV, CSR is the criteria value of ESV, CP is the criteria value of P and $CNPR$ is the criteria value of NPR. In this study, the formula for price criteria in REV is $\frac{1}{CP}$ indicating that it is a non-beneficial criterion. It is important to consider non-beneficial criterion when making decision. Considering non-beneficial criteria ensures that negative drawbacks can be minimized in return to maximize the positive outcome.

3.6 Experiment environment

The experiment was conducted on a Windows 11 system equipped with an AMD Ryzen 7 processor. The Integrated Development Environment used was PyCharm 2020 together with Python 3.9 as the programming language. Besides, data collection is carried out using Selenium WebDriver 4.6.0, paired with Google Chrome version 108 to facilitate the browser automation. A pre-defined Python script was pre-defined for the data collection process via browser automation. Key libraries such as scikit-learn (sklearn) and pandas were utilize for data processing throughout the experiment.

3.7 Summary

In this chapter, the methodology, experiment design and experiment environment are studied and discussed in-depth. The methodology consists of 3 main phases such as criteria selection, weight computation and hybrid-based ranking. Criteria selection is an important phase that identified the criteria for product selling recommendation in the E-commerce marketplace. The selected aspects of the product selling recommendation were performance, cost and quality. Meanwhile criteria that matched the selected aspects were ESV, SR, P and NPR. For the weight computation of each criterion, AHP and BWM are studied for the integration purpose in the next phase. During the hybrid-based ranking phase, TOPSIS and WASPAS were integrated with weight of each criterion for hybrid-based ranking (integrated weighted-ranking), The hybrid approach was used for the product selling recommendation ranking. After that, REV is used to examine the reliability of the hybrid-ranking methodology. Hence, sellers can choose their preferred product based on the ranking via hybrid-based ranking. The higher the product ranking indicated the better alternative.

CHAPTER 4

EXPERIMENTAL RESULTS

4.1 Introduction

This chapter explores various aspects that include the preliminary experiment, computation of weights, hybrid-based ranking, discussion of findings, and evaluation of results based on the hybrid ranking model. The preliminary experiment is centered on testing and validating the experimental variables. The application of weight computation and hybrid-based ranking discusses the procedures in Chapter 3 for computation. Discussion and findings on the selection of weightage estimation model and hybrid approach ranking model are elaborated in depth. Last but not least, results and evaluation on the application of hybrid-based ranking model in the E-commerce marketplace is discussed.

4.2 Preliminary experiment

Moving window and criteria such as SR and NPR are discussed to explain their necessity and validity in this study.

4.2.1 Moving window

Moving window is a technique that takes a subset of data in a fixed amount, adding a new value to the subset and removing an old value from the subset simultaneously while shifting across time. The interval of a moving window plays an upmost important role. This is because moving windows of short intervals are too sensitive to the trending status of a product. Such a situation will give wrong information to the seller. On the other hand, moving windows with too long intervals may overlook the trending status of a product. Therefore, in order to identify the suitable interval of the moving window, average lifespan of products in E-commerce is studied. In this study, a list of 600 products related to Mobile and Accessories category is used for the investigation of product average lifespan. The formula to calculate ALP at time, t in percentage format is as follows:

$$ALP = \frac{TLET\ at\ t}{Total\ number\ of\ product \times t} \times 100\% \qquad \text{Equation 4.1}$$

Where t is time and TLET is summation of LET of all products at time, t. Table 4.1 shows the tabulated sample data for demonstration of ALP computation.

Table 4.1: Sample data for LET of Product A, B and C

	LET (Last Engagement Timestamp)		
Product / Day	**A**	**B**	**C**
1	1	1	1
2	2	2	2
3	3	3	3
4	4	4	3
5	5	4	3

From Table 4.1, we can know that there are 3 products (Product A, Product B and Product C) used as the samples for demonstration. In this sample, Day is used at the unit of time, t and LET indicates the most recent time a product is sold. In Table 4.1, Product C was purchased on Day 1, 2 and 3 but there were no sales on Day 4 and 5. Consequently, the LET for Day 4 and 5 is 3 because the most recent sales took place on Day 3. Likewise, for Product B the last sale occurred on Day 4, resulting in a LET of 4 for Day 5. Notably, Product A was sold every day from Day 1 to Day 5. Table 4.2 shows the computed ALP using the sample in Table 4.1.

Table 4.2: Sample data for ALP computation

		TLET	TEET	ALP
Day	1	3	3	100.00
	2	6	6	100.00
	3	9	9	100.00
	4	11	12	91.67
	5	12	15	80.00

To compute TLET, the row of LET of all products are sum up. For example, TLET is 11 on Day 4. It is the accumulation of LET for Product A, Product B and Product C (4+4+3). Meanwhile TEET is 12 as TEET is total number of products multiply by the given time (3 products × Day 4). After TLET and TEET is obtained, ALP can be compute using the value of TLET and TEET (see Equation 4.1). From Table 4.2, it shows that the ALP of products in context is declining across time. In order to study the ALP of products in the E-commerce marketplace, scraped data discussed in section 4.2 is used. Figure 4.1 shows the ALP of 600 products related to Mobile and Accessories category in the E-commerce marketplace for a period of 300 days.

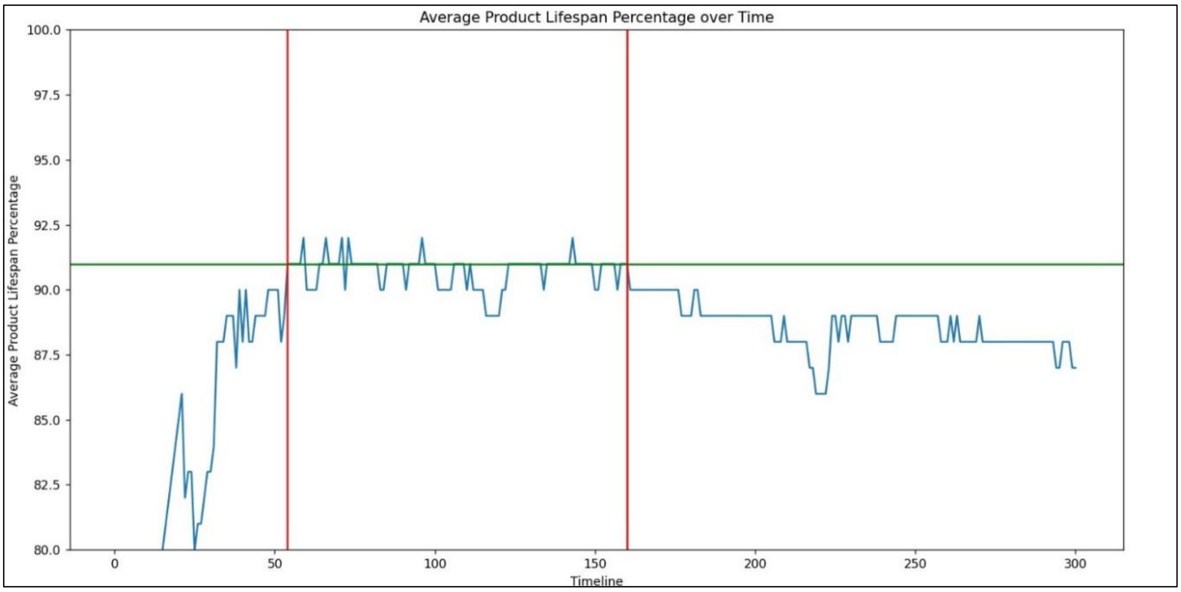

Figure 4.1: Average product lifespan percentage over time.

From Figure 4.1, the average lifespan of E-commerce products reached the highest stable state starting at Day 54 (left vertical line) until Day 160 (right vertical line). It starts to decline after Day 160 (right vertical line). The shape of the ALP over time obtained is similar to the shape of product life cycle, where it increases to the peak, remains at the highest stable state and then declines (see Figure 4.2).

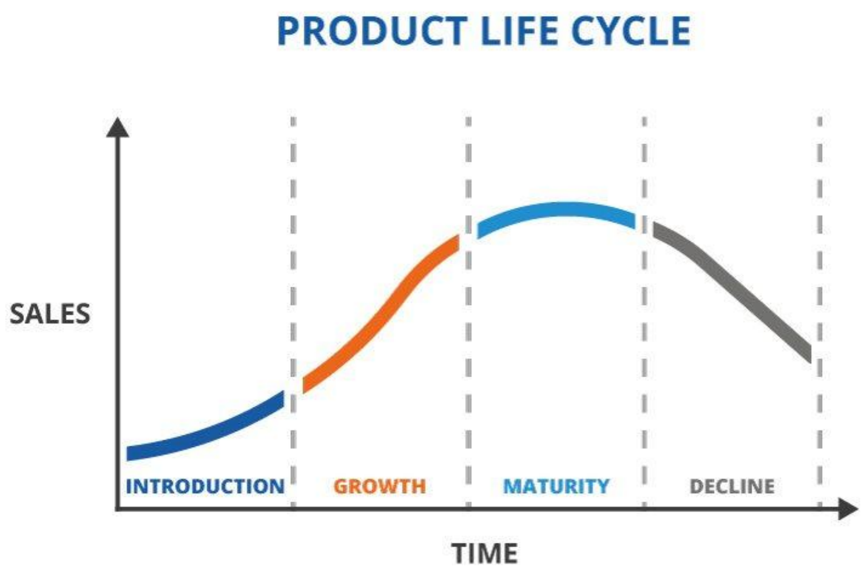

Figure 4.2: Product life cycle (What Is A Product Life Cycle?, n.d.)

Therefore, a moving window of 50 days (nearest tenth to 54 days) followed by an extra 10 days for validation purposes will be used throughout the experiment. Hence, a total of 60 days is required.

4.2.2 Sales rate

SR is computed using the actual sold quantity and the estimated sold quantity. Actual sold quantity is the accumulated daily sales of a product, whereas estimated sold quantity is derived from sold quantity using the moving window technique. The first estimated sold quantity only exists on Day 51 because it is computed from the data of the past 50 days (i.e., moving window size of 50). In this study, Product ID-8 is arbitrarily selected and used to demonstrate the calculation of sales rate. The sold quantity and daily sales of Product ID-8 is shown in Table A.1 in Appendix A. Table 4.3 shows the estimated sold quantity and actual sold quantity of Product ID-8 for Day 51 until 60.

Table 4.3: Forecasted and actual sold quantity

Day	**Sold quantity**	
	Estimated	**Actual**
51	97982	98100
52	98186	98100
53	98134	98300
54	98388	98400
55	98488	98600
56	98690	98600
57	98688	98700
58	98788	98900
59	98990	99000
60	99092	99200

After that, the value of both estimated sold quantity and actual sold quantity are smoothed into a straight line to show the stiffness of the line. Smoothing is a process that estimates a trend using observed data. In this study, the least square polynomial fit with 1st degree is used for the smoothing process in order to produce the straight line. The purpose of using smoothing is for the comparison between the rate of change of estimated sold quantity and actual sold quantity trend. Figure 4.3 shows the smoothed estimated sold quantity and smoothed actual sold quantity using the data from Table 4.3.

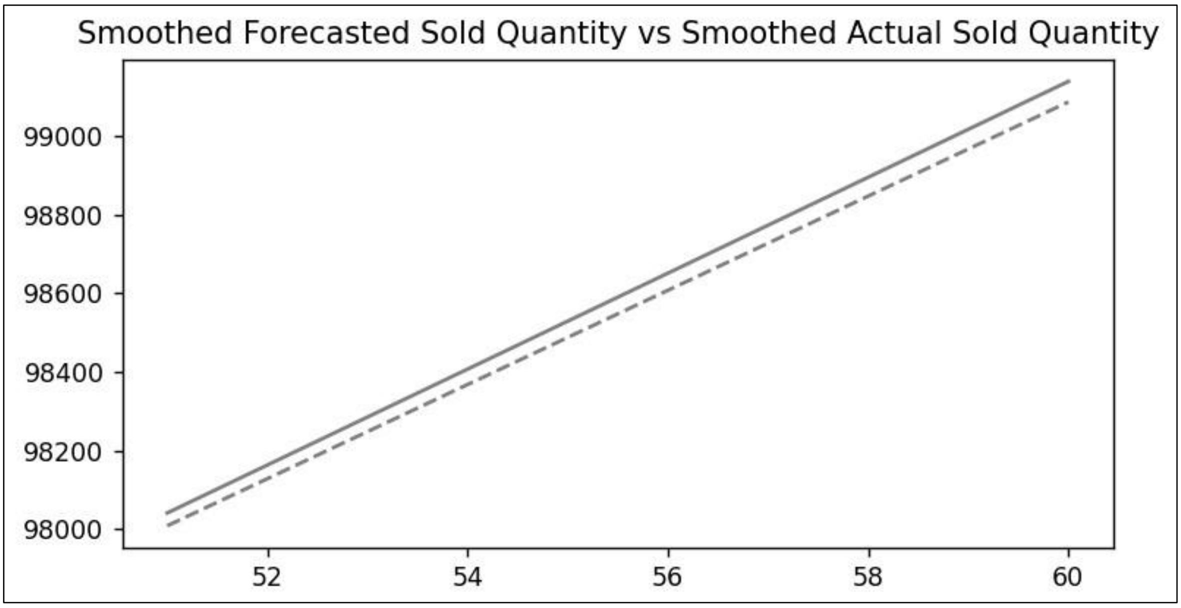

Figure 4.3: Smoothed estimated sold quantity versus smoothed actual sold quantity

Finally, SR is computed by dividing the rate of change of smoothed actual sold quantity trendline to the rate of change of smoothed estimated sold quantity trendline using the Equation 3.3 from section 3.2.2. The first and last value for a trendline in the moving window is taken into consideration for the computation of SR. To compute SR, the first and last values for smoothed actual sold quantity trendline and smoothed estimated sold quantity trendline is used. The calculation below shows an example (the values for this sample calculation are smoothed value from the data in Figure 4.3).

$$Sales\ Rate = \frac{\Delta Actual}{\Delta Estimated}$$

$$= \frac{\left(\frac{99138 - 98041}{10}\right)}{\left(\frac{99085 - 98009}{10}\right)}$$

$$= 1.0195$$

Since SR obtained is 1.0195 (more than 0), it is a potential product in terms of SR.

4.2.3 Net promoter rating

NPR is introduced in this study because the rating of a list of products does not directly reflect the potential of product selling to the seller. Table 4.4 shows the comparison of product rating and NPR of products matched ‘gaming’ keyword under ‘Audio’ category from Dataset A.

Table 4.4: Comparison of product rating and NPR

Product	Rating	NPR
7	4.9	0.3549
27	4.8	0.3738
28	4.9	0.5418
44	4.8	0.3849
48	4.8	0.4406
49	5.0	0.5920
56	4.8	0.4759
68	4.8	0.3806
71	4.8	0.3628
77	4.9	0.4797
81	4.9	0.5046
83	4.8	0.4832
89	4.8	0.4753

91	4.9	0.4946
93	4.8	0.2423
94	4.9	0.5159

Clearly from Table 4.4, NPR shows the significant variation which indicates the addition characteristics. Whereas the product rating is only able to show the basic information. For example, both product 7 and product 28 in Table 4.4 share the same rating of 4.9. However, when NPR is used to evaluate the products, the results indicate a significant difference. It is evident that product 28 has a higher NPR than product 7.

4.3 Application of weight computation

Weight computation is used to determine the relative importance of each criterion as these criteria have different relative importance among other criteria in a decision problem. In this study, AHP and BWM are carried out using the 4 selected criteria. Table 4.5 shows the criteria and their notations respectively.

Table 4.5: Product selling recommendation criteria and notations

Criteria	Notations
Estimated sales volume	CESV
Sales rate	CSR
Price	CP
Net promoter rating	CNPR

4.3.1 AHP

Step 1: Refer Figure 3.2 for the hierarchy model of addressed problem.

Step 2: The relative importance of different criteria is determined with respect to the goal and forms a pairwise comparison matrix using the preference scale as shown in Table 3.1. The preference scale is used to rank the criteria head-to-head by comparing their preference against other criteria in pairs. To compare the criteria head-to-head, the rule of comparing row criteria to column criteria is applied. The pairwise comparison matrix formed usually is a diagonal matrix because the criterion is equally important when compared to itself. Table 4.6 shows the pairwise comparison matrix formed based on empirical observation.

Table 4.6: Pairwise comparison matrix

Criteria	CESV	CSR	CP	CNPR
CESV	1	2	3	5
CSR	$\frac{1}{2}$	1	3	3
CP	$\frac{1}{3}$	$\frac{1}{3}$	1	1
CNPR	$\frac{1}{5}$	$\frac{1}{3}$	1	1

Step 3: Normalise the pairwise comparison matrix by dividing each value to the sum in each respective column (see Table 4.7).

Table 4.7: Normalised pairwise comparison matrix

Criteria	CESV	CSR	CP	CNPR
CESV	0.49180	0.54545	0.37500	0.50000
CSR	0.24590	0.27273	0.37500	0.30000
CP	0.16393	0.09091	0.12500	0.10000

CNPR	0.09836	0.09091	0.12500	0.10000

Step 4: Calculate the average of each row in Table 4.7 to obtain the criteria weight. Table 4.8 shows the weight obtained through AHP.

Table 4.8: Weight obtained through AHP

Criteria	Weight
CESV	0.4781
CSR	0.2984
CP	0.1200
CNPR	0.1036

Step 5: To evaluate the consistency of pairwise comparison, a weighted pairwise comparison matrix is formed by multiplying the pairwise comparison matrix (Table 4.6) to the respective weightage (Table 4.8). Table 4.9 shows the outcome of this multiplication.

Table 4.9: Weighted pairwise comparison matrix

Criteria	CESV	CSR	CP	CNPR
CESV	0.47806	0.59681	0.35988	0.51784
CSR	0.23903	0.29841	0.35988	0.31070
CP	0.15935	0.09947	0.11996	0.10357
CNPR	0.09561	0.09947	0.11996	0.10357

After that, obtain lambda (λ) by dividing the sum of each row from Table 4.9 to each respective weight from Table 4.8. Table 4.10 shows the lambda values obtained from each criterion.

Table 4.10: Lambda obtained

Criteria	**Lambda, λ**
CESV	4.08406
CSR	4.04832
CP	4.01958
CNPR	4.04064

Finally, calculate the CR (Consistency Ratio) by dividing CI (Consistency Index) to the RI (Random Index). Firstly, we calculated the value of CI. The formula to calculate CI is as follows:

$$CI = \frac{\lambda_{max} - n}{n - 1} \quad \text{Equation 4.2}$$

where λ_{max} is the maximum lambda from Table 4.10 and n is the number of criteria. The outcome of CI in this example is 0.02813.

Secondly, we obtained the value of RI. The value of RI depends on the number of criteria used. The value of RI in this study is 0.90 because 4 criteria are used (Awasthi & Chauhan, 2011). Table 4.11 shows the Random Consistency Index Values according to the number of criteria used.

Table 4.11: Random Consistency Index Values (Abdulvahitoglu & Kilic, 2022)

n	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
RI	0	0	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49

Once CI and RI are determined, we compute the value of CR. The calculation below shows an example to calculate CR.

$$CR = \frac{CI}{RI}$$

$$= \frac{0.02802}{0.90}$$

$$= 0.03113$$

From the calculation, CR is 0.03125 which is less than 0.1 and this shows that the pairwise comparison formed is consistent (Zulkifly & Said, 2022). Therefore, this validates the pairwise comparison matrix in Table 4.6 is consistent and the criteria weight obtained through AHP (see Table 4.8) can be apply to this study. Otherwise, pairwise comparison is required to be revised until a consistent pairwise comparison matrix is formed.

4.3.2 BWM

Step 1: Refer Figure 3.2 for the hierarchy model of addressed problem.

Step 2: The most important and the least important criteria were determined before constructing the pairwise comparison matrix. Most important criterion is the best criterion while least important criterion is the worst criterion. Table 4.12 shows the best and the worst criteria selected based on empirical observation in the pairwise comparison matrix formed.

Table 4.12: Best and worst criteria

Relative importance	**Criteria**
Best	CESV (Estimated sales volume)
Worst	CNPR (Net promoter rating)

Step 3: Determine the relative importance of criterion among other criteria. To ensure that BWM and AHP are having the similar relative importance throughout the experiment, pairwise comparison matrix from Table 4.6 is applied and formatted into BWM form. The row formed during AHP is formatted into BWM form by taking the row of best criterion and comparing it other criteria. Table 4.13 shows the relative importance of the best criterion over other criteria.

Table 4.13: Relative importance of best criterion over other criteria

Criteria	**CESV**	**CSR**	**CP**	**CNPR**
CESV	1	2	3	5

Step 4: Determine the relative importance of other criteria over the least important criterion. Pairwise comparison matrix formed as shown in Table 4.6 is applied and formatted into BWM form to ensure that the AHP and BWM are having similar relative importance throughout the experiment. The column formed during AHP is formatted into BWM form by taking the row of other criteria and comparing it to worst criterion. Table 4.14 shows the relative importance of other criteria over the worst criterion.

Table 4.14: Relative importance of other criteria over the worst criterion

Criteria	**CNPR**

CESV	5
CSR	3
CP	1
CNPR	1

Step 5: In order to compute the criteria weight using BWM, BWM solver is used for the computation part. BWM solver is an MS-Excel solver made to compute criteria weight using BWM approach. Table 4.15 shows the weight obtained through BWM using a BWM solver.

Table 4.15: Weight obtained through BWM

Criteria	Weight
CESV	0.4706
CSR	0.2941
CP	0.1176
CNPR	0.1176

Step 6: BWM solver also is used to determine the consistency of pairwise comparison formed. For four criteria, the associated threshold provided by BWM solver is 0.1994. If the Input-based Consistency Ratio obtained is larger than the associated threshold, it indicates that the pairwise comparison formed is inconsistent. Therefore, a new pairwise comparison need to be revised. The Input-based Consistency Ratio is an indicator provided by BWM solver which is used to determine the consistency of the pairwise comparison formed. In this study, the Input-based Consistency Ratio (0.10) of the pairwise comparison matrix is less

than the associated threshold. Hence, the consistency level of pairwise comparison using BWM for weight computation is acceptable in this study.

4.4 Application of hybrid-based ranking

Criteria weight obtained using AHP and BWM are integrated on the ranking method such as TOPSIS and WASPAS to carry out hybrid-based ranking computation. For example, criteria weight computed from AHP will be integrated to TOPSIS and WASPAS ranking model to form AHP-TOPSIS and AHP-WASPAS. This also applies to the integration of BWM to TOPSIS and WASPAS. Therefore, application of hybrid-based ranking such as AHP-TOPSIS, AHP-WASPAS, BWM-TOPSIS and BWM-WASPAS are carried out in this study.

A list of products from Dataset A that have ‘gaming’ keyword under the Audio category is used as an example for the step-by-step implementation of hybrid-based ranking in this section. These products and their corresponding criteria obtained are shown in Table 4.16.

Table 4.16: List of ‘gaming’ audio products and their criteria

Product ID	CESV	CSR	CP	CNPR
7	2639	0.9426	2.50	0.3549
27	2136	1.0173	9.50	0.3738
28	2355	1.0705	23.70	0.5418
44	2278	1.0357	9.80	0.3849
48	1217	1.1072	56.00	0.4406
49	520	1.0417	139.00	0.5920
56	0	0	15.00	0.4759

68	1014	1.1274	6.89	0.3806
71	1332	1.0253	4.59	0.3628
77	717	0.8971	3.50	0.4797
81	518	1.0369	229.00	0.5046
83	881	0.8016	14.00	0.4832
89	1854	10302	17.45	0.4753
91	1079	1.0791	18.99	0.4946
93	0	0	2.99	0.2423
94	1157	0.9649	5.90	0.5159

4.4.1 AHP-TOPSIS

AHP-TOPSIS is the hybrid-ranking model that comes from the integration of AHP as the weight model and TOPSIS as the ranking model. To carry out the AHP-TOPSIS computation, procedures as discussed in Section 4.3.1 (AHP) and Section 3.4.1 (TOPSIS) are conducted.

Step 1: Compute weighted normalised decision matrix (see Table 4.17).

Table 4.17: Weighted normalised decision matrix using AHP-TOPSIS

Product ID	CESV	CSR	CP	CNPR
7	0.21537	0.07398	0.00108	0.02033
27	0.17432	0.07985	0.00411	0.02141
28	0.19219	0.08402	0.01025	0.03104
44	0.18591	0.08129	0.00424	0.02205
48	0.09932	0.08690	0.02423	0.02524

49	0.04244	0.08176	0.06014	0.03391
56	0.00000	0.00000	0.00649	0.02726
68	0.08275	0.08849	0.00298	0.02180
71	0.10871	0.08047	0.00199	0.02078
77	0.05851	0.07041	0.00151	0.02748
81	0.04227	0.08138	0.09909	0.02891
83	0.07190	0.06292	0.00606	0.02768
89	0.15131	0.08086	0.000755	0.02768
91	0.08806	0.08470	0.00822	0.02833
93	0.00000	0.00000	0.00129	0.01388
94	0.09442	0.07573	0.00255	0.02955

Step 2: Compute the ideal best and ideal worst. Table 4.18 shows the ideal best and ideal worst computed.

Table 4.18: Ideal best and ideal worst using AHP-TOPSIS

Criteria	**CESV**	**CSR**	**CP**	**CNPR**
Ideal best	0.21537	0.08849	0.00108	0.03391
Ideal worst	0.00000	0.00000	0.09909	0.01388

Step 3: With the ideal best and ideal worst from Table 4.18, compute Euclidean distance (Equation 3.9) for ideal best and Euclidean distance for ideal worst (Equation 3.10).

Step 4: Calculate the performance score by adding both Euclidean distance from ideal best and Euclidean distance from ideal worst.

Step 5: Rank the alternatives (product) based on the performance score obtained. The higher the performance score, the higher the ranking as it indicates better alternative (see Table 4.19).

Table 4.19: Euclidean distance from ideal best and ideal worst, performance score and ranking computed using AHP-TOPSIS

Product ID	S_i^+	S_i^-	P_i	Rank
7	0.01987	0.24800	0.92582	1
27	0.04388	0.21410	0.82992	4
28	0.02549	0.22844	0.89963	2
44	0.03272	0.22413	0.87261	3
48	0.11866	0.15215	0.56182	7
49	0.18286	0.10200	0.35806	13
56	0.23300	0.09356	0.28650	16
68	0.13318	0.15485	0.53761	10
71	0.10777	0.16664	0.60726	6
77	0.15802	0.13449	0.45977	12
81	0.19910	0.09293	0.31822	14
83	0.14595	0.13406	0.47877	11
89	0.06518	0.19491	0.74938	5
91	0.12769	0.15295	0.54501	9
93	0.23370	0.09779	0.29501	15
94	0.12170	0.15561	0.56114	8

4.4.2 BWM-TOPSIS

BWM-TOPSIS is the hybrid-ranking model that comes from the integration of BWM as the weight model and TOPSIS as the ranking model. To carry out BWM-TOPSIS computation, procedures as discussed in Section 4.3.2 (BWM) and Section 3.4.1 (TOPSIS) are conducted.

Step 1: Compute weighted normalised decision matrix (see Table 4.20).

Table 4.20: Weighted normalised decision matrix using BWM-TOPSIS

Product ID	CESV	CSR	CP	CNPR
7	0.21200	0.07292	0.00106	0.02309
27	0.17159	0.07870	0.00403	0.02432
28	0.18919	0.08281	0.01006	0.03526
44	0.18300	0.08012	0.00416	0.02505
48	0.09777	0.08565	0.02376	0.02867
49	0.04177	0.08059	0.05898	0.03852
56	0.00000	0.00000	0.00637	0.03097
68	0.08146	0.08722	0.00292	0.02477
71	0.10701	0.07932	0.00195	0.02361
77	0.05760	0.06940	0.00149	0.03122
81	0.04161	0.08021	0.09718	0.03284
83	0.07077	0.06201	0.00594	0.03144
89	0.14894	0.07970	0.00740	0.03093
91	0.08668	0.08348	0.00806	0.03219
93	0.00000	0.00000	0.00127	0.01577
94	0.09295	0.07464	0.00250	0.03357

Step 2: Compute the ideal best and ideal worst. Table 4.21 shows the ideal best and ideal worst computed.

Table 4.21: Ideal best and ideal worst using BWM-TOPSIS

Criteria	CESV	CSR	CP	CNPR
Ideal best	0.21200	0.08722	0.00106	0.03852
Ideal worst	0.00000	0.00000	0.09718	0.01577

Step 3: With the ideal best and ideal worst from Table 4.21, compute Euclidean distance (Equation 3.9) for ideal best and Euclidean distance for ideal worst (Equation 3.10).

Step 4: Calculate the performance score by adding both Euclidean distance from ideal best and Euclidean distance from ideal worst.

Step 5: Rank the alternatives (product) based on the performance score obtained. The higher the performance score, the higher the ranking as it indicates better alternative (see Table 4.21).

Table 4.22: Euclidean distance from ideal best, Euclidean distance from ideal worst, performance score and ranking using BWM-TOPSIS

Product ID	S_i^+	S_i^-	P_i	Rank
7	0.02103	0.24404	0.92065	1
27	0.04377	0.21068	0.82798	4
28	0.02513	0.22499	0.89953	2
44	0.03290	0.22056	0.87019	3

48	0.11690	0.14894	0.56175	7
49	0.17994	0.10107	0.35968	13
56	0.22943	0.09207	0.28639	16
68	0.13128	0.15234	0.53712	10
71	0.10635	0.16392	0.60652	6
77	0.15560	0.13240	0.45972	12
81	0.19584	0.09196	0.31954	14
83	0.14372	0.13200	0.47875	11
89	0.06428	0.19189	0.74909	5
91	0.12573	0.15064	0.54507	9
93	0.23037	0.09591	0.29395	15
94	0.11983	0.15327	0.56122	8

4.4.3 AHP-WASPAS

AHP-WASPAS is the hybrid-ranking model that comes from the integration of AHP as the weight model and WASPAS as the ranking model. To carry out AHP-WASPAS computation, procedures as discussed in Section 4.3.1 (AHP) and Section 3.4.2 (WASPAS) are conducted.

Step 1: Compute the normalised decision matrix. To ease the calculation in Step 2 and Step 3, the AHP criteria weight is used to compute the weighted normalised decision matrix and tabulated in Table 4.23.

Table 4.23: Weighted normalised decision matrix using AHP criteria weight

Product ID	CESV	CSR	CP	CNPR

7	0.47806	0.24949	0.11996	0.06209
27	0.38694	0.26927	0.45585	0.06539
28	0.42662	0.28335	1.13723	0.09479
44	0.41267	0.27414	0.47025	0.06734
48	0.22046	0.29306	2.68712	0.07708
49	0.09420	0.27572	6.66982	0.10357
56	0.00000	0.00000	0.71977	0.08326
68	0.18369	0.29841	0.33061	0.06658
71	0.24130	0.27138	0.22025	0.06347
77	0.12989	0.23745	0.16795	0.08392
81	0.09384	0.27445	10.98842	0.08828
83	0.15960	0.21217	0.67178	0.08453
89	0.33586	0.27268	0.83733	0.08315
91	0.19546	0.28562	0.91122	0.08653
93	0.00000	0.00000	0.14347	0.04239
94	0.20959	0.25540	0.28311	0.09025

Step 2: Calculate the WSM performance score (Equation 3.12) using the weighted normalised decision matrix computed in Step 1.

Step 3: Calculate the WPM performance score (Equation 3.13) using the weighted normalised decision matrix computed in Step 1.

Step 4: Compute WASPAS using the WSM and WPM performance score (Equation 3.14) computed in Step 2 and Step 3.

Step 5: Rank the alternatives (product) based on the performance score obtained. The higher the performance score, the higher the ranking as it indicates better alternative (see Table 4.22).

Table 4.24: WSM, WPM, WASPAS and ranking obtained using AHP-WASPAS

Product ID	WSM	WPM	WASPAS	Rank
7	0.90961	0.00089	0.455525	1
27	1.17746	0.00311	0.59028	4
28	1.94198	0.01303	0.97750	2
44	1.22439	0.00358	0.61398	3
48	3.27773	0.01338	1.64556	10
49	7.14332	0.01794	3.58063	13
56	0.80302	0.00000	0.40151	16
68	0.87929	0.00121	0.44025	8
71	0.79640	0.00092	0.39866	6
77	0.61920	0.00043	0.30982	11
81	11.44498	0.02498	5.73498	14
83	1.12808	0.00192	0.56500	12
89	1.52902	0.00638	0.76770	5
91	1.47884	0.00440	0.74162	9
93	0.18586	0.00000	0.09293	15
94	0.83835	0.00137	0.41986	7

4.4.4 BWM-WASPAS

BWM-WASPAS is the hybrid-ranking model that comes from the integration of BWM as the weight model and WASPAS as the ranking model. To carry out BWM-WASPAS computation, procedures as discussed in Section 4.3.2 (BWM) and Section 3.4.2 (WASPAS) are conducted.

Step 1: Compute the normalised decision matrix. To ease the calculation in Step 2 and Step 3, the BWM criteria weight is used to compute the weighted normalised decision matrix and tabulated in Table 4.25.

Table 4.25: Weighted normalised decision matrix using BWM criteria weight

Product ID	**CESV**	**CSR**	**CP**	**CNPR**
7	0.47059	0.24591	0.11765	0.06209
27	0.38089	0.26539	0.44706	0.06539
28	0.41995	0.27927	1.11529	0.09479
44	0.40621	0.27019	0.46118	0.06734
48	0.21702	0.28885	2.63529	0.07708
49	0.09273	0.27176	6.54118	0.10357
56	0.00000	0.00000	0.70588	0.08326
68	0.18082	0.29412	0.32424	0.06658
71	0.23752	0.26748	0.21600	0.06347
77	0.12786	0.23404	0.16471	0.08392
81	0.09237	0.27051	10.77647	0.08828
83	0.15710	0.20912	0.65882	0.08453
89	0.33061	0.26876	0.82118	0.08315
91	0.19241	0.28152	0.89365	0.08653

93	0.00000	0.0000	0.14071	0.04239
94	0.20632	0.25172	0.27765	0.09025

After that, use the weighted normalised decision matrix in the previous step to calculate the performance score of WSM and WPM.

Step 2: Calculate the WSM performance score (Equation 3.12) using the weighted normalised decision matrix computed in Step 1.

Step 3: Calculate the WPM performance score (Equation 3.13) using the weighted normalised decision matrix computed in Step 1.

Step 4: Compute WASPAS using the WSM and WPM performance score (Equation 3.14) computed in Step 2 and Step 3.

Step 5: Rank the alternatives (product) based on the performance score obtained. The higher the performance score, the higher the ranking as it indicates better alternative (see Table 4.26).

Table 4.26: WSM, WPM, WASPAS and ranking obtained using BWM-WASPAS

Product ID	**WSM**	**WPM**	**WASPAS**	**Rank**
7	0.90467	0.00096	0.45282	1
27	1.16763	0.00336	0.58549	4
28	1.92218	0.01408	0.96813	2
44	1.21408	0.00387	0.60897	3
48	3.22872	0.01446	1.62159	10
49	7.02331	0.01939	3.52135	13

56	0.80046	0.00000	0.40023	16
68	0.87481	0.00130	0.43806	8
71	0.79310	0.00099	0.39705	6
77	0.62193	0.00047	0.31120	11
81	11.23963	0.02700	5.63331	14
83	1.12107	0.00208	0.56158	12
89	1.51500	0.00689	0.76095	5
91	1.46586	0.00476	0.73531	9
93	0.18886	0.00000	0.09443	15
94	0.83821	0.00148	0.41985	7

4.5 Discussion and findings

In order to investigate the ranking pattern of product selling recommendation using hybrid-based ranking models as discussed in Section 4.4, another list of products with ‘earphone’ keyword under the Audio category is taken as an example for the discussion. The criteria (i.e., ESV, SR, P and NPR) and rankings (i.e., AHP-TOPSIS, BWM-TOPSIS, AHP-WASPAS and BWM-TOPSIS) of these products at different timelines are shown in Table A.2 and Table A.3.

4.5.1 Selection of weight computation model

Since there is no reference for comparison, a heuristic method is used to study the pattern of weighting results in order to identify the logical criteria weight. The result of criteria weight computation may affect the results of rankings as the hybrid-based ranking is highly depends on the weight computation. Therefore, evaluation on the criteria weight need to be carried out. To identify a logical criteria weight, comparison of criteria weight must be made under the same ranking model as a control. For example, comparing AHP-TOPSIS to BWM-TOPSIS that are having the same ranking model (i.e., TOPSIS) but different weightage (i.e., AHP and BWM). In this study, we will be comparing AHP-TOPSIS to BWM-TOPSIS and AHP-WASPAS to BWM-WASPAS.

To compare the criteria weight using AHP-TOPSIS to BWM-TOPSIS (in terms of TOPSIS), Product ID 1 and Product ID 2 from Dataset A are studied. The computed rankings of products that matched 'earphone' keyword under Audio category are shown in Table A.2 in Appendix A. From Table A.2, both Product ID 1 and Product ID 2 have the same ranking (1^{st}) ranked by AHP-TOPSIS and BWM-TOPSIS. Table 4.27 shows the criteria of Product ID 1 and Product ID 2 extracted from Table A.2 for ease of explanation.

Table 4.27: Criteria of Product ID 1 and Product ID 2

Product ID	CESV	CSR	CP	CNPR
1	12095	0.9997	1.50	0.2646
2	11864	0.9970	13.98	0.3588

By comparison, Product ID 1 is cheaper than Product ID 2 (refer to CP column from Table 4.26) while the other criteria such as CESV and CSR are similar. Although the Product ID 2 has a higher CNPR than Product ID 1, but NPR is the least concerned factor when it comes to AHP weighting. On the other hand, criteria weight for both P and NPR in BWM are having equal weightage (as discussed in Section 4.3.2). So, it cannot determine an appropriate product ranking when CESV and CSR are similar. Besides, difference of CP among these 2 products is huge. So, it is clear that P can make more impact when compared to NPR. From this comparison, AHP that prioritize Product ID 1 with lesser price is more logical in this case and it is in line with the consumers' lower cost preference. Hence, AHP weighting is preferred in this scenario.

To compare the criteria weight using AHP-WASPAS to BWM-WASPAS (in terms of WASPAS), Product ID 50 and Product ID 31 from Dataset B are studied. The computed rankings of products that matched 'earphone' keyword under Audio category are shown in Table A.3 in Appendix A. From Table A.3, both products have the same ranking (12^{th}) ranked by AHP-WASPAS and BWM-WASPAS. Dataset B is used because there is no ranking difference when comparing the product ranking ranked by AHP-WASPAS and BWM-WASPAS using Dataset A. Table 4.28 shows the criteria of Product ID 50 and Product ID 31.

Table 4.28: Criteria of Product ID 50 and Product ID 31

Product ID	CESV	CSR	CP	CNPR
50	1570	0.8264	4.50	0.4214
31	2330	0.8035	44.90	0.5058

By comparison, we can know that Product ID 31 has more CESV and CNPR than Product ID 50. The criteria weight of CESV is more when compared to the other factors. So, it can make the most impact. Hence, BWM weighting is preferred in this scenario.

From the observation, we can know that AHP weighting is price sensitive while BWM is quality oriented. If we want to target customer that prefers low-cost product, we will need to apply AHP weighting. If we want to target customer that is concerns on quality, then we need to apply BWM weighting. In this study, our target is customer that preferred low-cost product. Therefore, AHP weighting is applicable because it is a logical approach in terms of weightage that can meet the expected weighting in terms of TOPSIS and WASPAS.

4.5.2 Selection of hybrid-based ranking model

After identifying the weighting method, the hybrid-based ranking models (AHP-TOPSIS and AHP-WASPAS) are compared. It is noteworthy that the hybrid-based ranking models have set to use AHP as determined in Section 4.5.1 and the evaluation is between TOPSIS and WASPAS. In this study, REV is used to estimate the weighted value of a product in order to examine the accuracy of ranking result. Table 4.29 and Table 4.30 show the top 10 products from Dataset A ranked by AHP-TOPSIS and AHP-WASPAS. It is clear that the results of AHP-TOPSIS and AHP-WASPAS ranking model are likely the same. When both ranking models yield similar results, it suggests that the results are consistent although different methods are used. It is a positive sign that both methods are providing reliable results.

Table 4.29: Top 10 products ranked by AHP-TOPSIS ranking model

AHP-TOPSIS Ranking	Product ID
1	1
2	2
3	13
4	5
5	8
6	21
7	67
8	17

9	26
10	18

Table 4.30: Top 10 products ranked by AHP-WASPAS ranking model

AHP-WASPAS Ranking	Product ID
1	1
2	2
3	13
4	21
5	17
6	5
7	8
8	26
9	67
10	18

Based on Table 4.29 and Table 4.30, the 4th ranking product will be selected as an example for the discussion. This is because the products ranked by AHP-TOPSIS and AHP-WASPAS are different. REV is computed to determine the appropriate ranking. Table 4.31 shows the computed REV values for Product ID 5 and 21.

Table 4.31: Criteria of Product ID 5 and Product ID 21

Product ID	CESV	CSR	CP	CNPR	REV
5	5453	0.9915	11.90	0.3994	2607.427

21	4704	0.9801	1.50	0.3218	2249.388

Based on Table 4.31, it is clear that Product ID 5 has higher priority than Product ID 21 due to the REV value of Product ID 5 is higher. Therefore, Product ID 5 should have higher ranking than Product ID 21 and this is in line with the ranking by AHP-TOPSIS. To further validate the application of hybrid-based ranking, Dataset B is used.

Table 4.32 and Table 4.33 show the top 10 products from Dataset B ranked by AHP-TOPSIS and AHP-WASPAS.

Table 4.32: Top 10 products ranked by AHP-TOPSIS ranking model

AHP-TOPSIS Ranking	**Product ID**
1	2
2	1
3	5
4	8
5	26
6	67
7	17
8	54
9	13
10	40

Table 4.33: Top 10 products ranked by AHP-WASPAS ranking model

AHP-WASPAS Ranking	Product ID
1	2
2	1
3	5
4	8
5	26
6	67
7	17
8	54
9	40
10	13

Based on Table 4.32 and Table 4.33, Product ID 13 and Product ID 40 have the same ranking (9^{th}) ranked by AHP-TOPSIS and AHP-WASPAS. So, these 2 products will be used for comparison. Table 4.34 shows the criteria and evaluation value of Product ID 13 and Product ID 40.

Table 4.34: Criteria of Product ID 13 and Product ID 40

Product ID	CESV	CSR	CP	CNPR	REV
13	2299	0.7185	4.80	0.3928	1099.432
40	1647	1.0981	8.88	0.4302	787.817

Based on Table 4.34, Product ID 13 has higher REV compared to Product ID 40 and this ranking is in line with AHP-TOPSIS which ranked Product ID 13 higher than Product ID 40.

Both results at different timelines (Dataset A and Dataset B) show that the AHP-TOPSIS can rank a product better than AHP-WASPAS. Therefore, the appropriate ranking from the method can suggest better ranking alternative for the seller.

4.6 Results and evaluation

From Section 4.6, AHP-TOPSIS has proven its superiority. This section will conduct further experiment to evaluate the overall performance of the method. In addition to the Audio category, other categories like Cable & Chargers, Cases & Covers and Powerbanks & Batteries are used for the evaluation. Besides, different datasets of the mentioned categories are used to imitate the data at different timelines in E-commerce marketplace. This is to ensure that the selected hybrid-based ranking model is functioning consistently. Since there is no reference for evaluation, the REV method is used to evaluate the performance of different hybrid-based ranking model. Table 4.35 shows the 6 different subsets extracted from Table A.4 to Table A.9 in Appendix A is used for evaluation. Subset I, III and V are products from Dataset A meanwhile Subset II, IV and VI are products from Dataset B.

Table 4.35: Criteria of different product at different subset

Subset	Product ID	CESV	CSR	CP	CNPR	REV
I	109	4503	0.8831	2.89	0.2957	2153.220
	188	3125	0.9471	5.53	0.3132	1494.399
II	118	5526	0.8249	6.99	0.3049	2642.276
	116	4649	0.8942	0.05	0.2545	2225.380
III	201	5250	0.9906	8.00	0.1769	2510.354
	213	3445	1.0766	0.50	0.2428	1647.641
IV	219	1210	0.8072	6.59	0.4148	578.803
	227	1010	0.7775	0.99	0.2637	483.262
V	328	1394	0.9298	55.9	0.4729	666.8
	388	400	2.0000	42.9	0.4929	191.891
VI	317	1420	0.8357	23.9	0.5094	679.209
	301	1284	1.1673	73.9	0.5641	614.289

Subset I and Subset II are products that matched ‘charger’ keyword under Cables & Chargers category (see Table A.4 and Table A.5). For Subset I, Product ID 109 and Product ID 188 have the same ranking (i.e., the 4th) ranked by AHP-TOPSIS and AHP-WASPAS, respectively. For Subset II, Product ID 118 and Product ID 116 have the same ranking (i.e., the 2nd) ranked by AHP-TOPSIS and AHP-WASPAS, respectively.

Subset III and Subset IV are products that matched ‘casing’ keyword under Cases & Covers category (see Table A.6 and Table A.7). For Subset III, Product ID 201 and Product ID 213 have the same ranking (i.e., the 1st) ranked by AHP-TOPSIS and AHP-WASPAS, respectively. For Subset IV, Product ID 219 and Product ID 227 have the same ranking (i.e., the 5th) ranked by AHP-TOPSIS and AHP-WASPAS, respectively.

Subset V and Subset IV are products that matched 'pineng' keyword under Powerbanks & Batteries category (see Table A.8 and Table A.9). For Subset V, Product ID 328 and Product ID 388 have the same ranking (i.e., the 4th) ranked by AHP-TOPSIS and AHP-WASPAS, respectively. For Subset IV, Product ID 317 and Product ID 301 have the same ranking (i.e., the 3rd) ranked by AHP-TOPSIS and AHP-WASPAS, respectively.

Products ranked by AHP-TOPSIS have higher REV compared to the products ranked by AHP-WASPAS in spite of different subset is used (see Table 4.34). For example, Product ID 109 ranked by AHP-TOPSIS in Subset I has higher REV than Product ID 188 ranked by AHP-WASPAS. Subset II also shows that product ranked by AHP-TOPSIS has higher REV value. From the result of 6 different subsets, we can know that AHP-TOPSIS perform consistently even though the dataset used are different for the same category.

From all experiments, it is clear that the AHP-TOPSIS chose products with higher REV at different categories and timelines. Thus, this proves that AHP-TOPSIS is suitable and can be applied in the E-commerce marketplace for product selling recommendations.

4.7 Summary

Process of implementation and evaluation of the methodology is clearly described in Chapter 4. Implementations of hybrid-based ranking model is carried out based on the methodology in Chapter 3. Preliminary experiments are also carried out to ensure the variables such as moving window, sales rate and net promoter rating used in this study are necessary and valid. Evaluations across different product categories and timelines are made to further ensure that the methodology can be applied in the E-commerce marketplace in order to meet the objectives stated in Chapter 1.

CHAPTER 5

CONCLUSION AND FUTURE WORKS

5.1 Introduction

Project achievement, project limitation and future works on this study are included in this chapter.

5.2 Project achievement

First objective of this study is to develop MCDM method that provides product selling recommendation. Hybrid-based MCDM method is used in this study. Hybrid-based MCDM method is the combination of two different MCDM method. First part of the hybrid-based MCDM is to find the criteria of product feature. Second part of the hybrid-based MCDM is to find potential product by ranking the products based on the criteria weight generated in the first part. Hence, potential product can be determined by using the hybrid-based MCDM method based on the product feature. AHP-TOPSIS, BWM-TOPSIS, AHP-WASPAS and BWM-WASPAS are the hybrid-based MCDM methods developed in this study.

Second objective of this study is to identify product features to form criteria for product selling recommendation. Product feature such as ESV, SR, P and NPR are determined as the criteria for product selling recommendation. These criteria will be used for the MCDM method.

Third objective of this study is to evaluate the performance of the MCDM method for product selling recommendation. MCDM methods developed in this study are compared among each other by evaluating the ranking to ensure that the result for product selling recommendation is accurate and consistent. Sample data that mimics different timeline and product categories are used as a metric for evaluation. From the result of evaluation, AHP-TOPSIS can be applied in the E-commerce marketplace for product selling recommendations.

Table 5.1 shows the summary of project objectives and achievements.

Table 5.1: Summary of project objectives and achievements

No.	Objective	Achievement
1	To develop multi-criteria decision-making (MCDM) method that provides product selling recommendation.	Hybrid-based MCDMs (AHP-TOPSIS, AHP-WASPAS, BWM-TOPSIS and BWM-WASPAS) developed in this study can provide product selling recommendation.
2	To identify product features to from criteria for product selling recommendation.	Product feature such as ESV, SR, P and NPR are identified as the criteria for product selling recommendation.
3	To evaluate the performance of the multi-criteria decision-making (MCDM) method for product selling recommendation.	MCDM (AHP-TOPSIS) can be applied for product selling recommendation after evaluated using sample data that mimics different timeline and product categories.

5.3 Project limitation

A total of 600 products from Shopee Malaysia were scraped daily. The automation tool scraped the information of each product one by one. Therefore, it is a very long and slow process. It will be more relevant if real time data can be used for experiment study. Besides, evaluation of hybrid-based ranking method is difficult due to the lack of comparable sample. There is no other study conducting similar comparison study. Furthermore, the relationship between sales performance, price and quality are complicated and difficult to come out with a solid inference although these three variables are related. Even slight changes may affect lots of differences and result in different outcome.

Another limitation is that MCDM relies heavily on the availability and quality of data. If the data is incomplete, inaccurate or biased, it can lead to incorrect rankings. In real life, it is challenging to retrieve accurate and comprehensive data for all criteria. Besides, MCDM methods sometimes may oversimplify complex real-world scenarios by reducing them into a set of predefined criteria. This may lead to wrong decision-making process due to oversimplification technical error.

5.4 Future works

Larger dataset will be included to explore the big data approach. More product features can be included to improve the MCDM approach. This will improve the precision of the MCDM ranking method. Besides, increase the scraping variety of product categories within an E-commerce platform during scraping process can also be considered. This will increase the learning attributes and benefits to the MCDM approach. MCDM is particularly effective for comparing products with diverse features and weights because it offers a structured, systematic framework for evaluating multiple options based on various criteria. To incorporate this into the current work, the weights of the different features should be adjusted according to the defined goals, ensuring that they align with the MCDM process and ultimately help achieve the specified objectives. Further study on categorization of potential product into specific selling category to help seller to select a group of products instead of a single product.

Application of AI (Artificial Intelligence) is considerable. AI can perform a more detailed analysis than MCDM which only show the ranking score. This is because AI can consider a wider data of availability to be interpret when larger dataset is included. AI can analyse large datasets to identify hidden patterns and trends, which we may miss. This can provide more informative insights on the relationship between each criterion.

On the other hand, big data approach can be applied when larger dataset that has variety of product features and categories within an E-commerce platform. Big data consists of large amount of data mainly in terms of variety and huge volume. Big data can help seller to make informed decision based on the historical data insights in the E-commerce marketplace. With big data, seller can better understand the relative importance of criteria and the changes of criteria in the market across time. Therefore, sellers are able to monitor the market based on the big data insights and to improve their business.

By integrating both AI and big data, sellers can have more detailed information from big data and more detailed analysis from AI. The AI will help to analyze the huge amount of information from the big data. Thus, this can increase the accuracy of decision making and enhance the ability to overcome complex and multi-dimensional data. The integration of AI and big data can also provide hidden insights that which we may missed when using traditional analysis method.

5.5 Conclusion

The method has achieved its main goal although there are limitations. Complex decisive problem in the E-commerce marketplace can be solved by using the product selling recommendation. The method is suitable to be used as a recommendation tool for sellers to consider when choosing a product to sell in the E-commerce marketplace. Thus, the method not only can save sellers' time in finding products with selling opportunities, but it can also increase their chances of making sales and reducing business risks.

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APPENDICES

Appendix A: Experiment data

Table A.1: Sold quantity and daily sales of Product ID-8

Day	Sold quantity	Daily sales
1	93800	0
2	93900	100
3	93900	0
4	94000	100
5	94100	100
6	94200	100
7	94300	100
8	94400	100
9	94400	0
10	94500	100
11	94500	0
12	94600	100
13	94700	100
14	94700	0
15	94800	100
16	94800	0
17	94900	100
18	94900	0
19	95000	100
20	95100	100
21	95100	0
22	95200	100
23	95300	100
24	95400	100
25	95400	0
26	95500	100
27	95500	0
28	95500	0
29	95600	100
30	95800	200
31	95900	100
32	96100	200
33	96200	100
34	96300	100

35	96500	200
36	96600	100
37	96700	100
38	96800	100
39	96900	100
40	97000	100
41	97100	100
42	97200	100
43	97300	100
44	97400	100
45	97500	100
46	97600	100
47	97700	100
48	97800	100
49	97800	0
50	97900	100
51	98100	200
52	98100	0
53	98300	200
54	98400	100
55	98600	200
56	98600	0
57	98700	100
58	98900	200
59	99000	100
60	99200	200

Table A.2: Products with ‘earphone’ keyword under Audio from Dataset A

Product ID	CESV	CSR	CP	CNPR	TOPSIS		WASPAS	
					AHP	BWM	AHP	BWM
1	12095	0.9997	1.50	0.2646	1	2	1	1
2	11864	0.9970	13.98	0.3588	2	1	2	2
4	3036	0.9796	10.80	0.3981	12	12	13	13
5	5453	0.9915	11.90	0.3994	4	4	6	6
7	2639	0.9426	2.50	0.3549	13	13	12	12
8	4785	1.0182	12.49	0.4086	5	5	7	7
12	0	0.0000	2.20	0.2626	51	51	54	54
13	6412	1.0688	7.79	0.3957	3	3	3	3
14	1506	1.0045	119.00	0.5099	56	56	39	38
15	1828	1.0758	12.99	0.4480	19	19	19	19
17	4355	1.0370	3.99	0.3998	8	8	5	5

18	3767	0.9661	7.90	0.4317	10	10	10	10
21	4704	0.9801	1.50	0.3218	6	6	4	4
26	3960	0.9902	3.86	0.2743	9	9	8	8
28	2355	1.0705	23.70	0.5418	17	17	15	15
29	0	0.0000	12.00	0.3808	54	54	57	56
30	2921	1.1687	5.00	0.3007	11	11	11	11
31	2668	1.0675	44.90	0.5173	16	16	16	16
33	1173	0.9780	39.00	0.5182	45	45	42	42
36	0	0.0000	3.00	0.4536	49	49	52	52
39	1594	0.9381	18.59	0.4013	27	27	35	37
40	1391	0.9941	9.99	0.4278	26	26	30	29
43	1730	0.9108	3.80	0.3186	21	21	23	23
44	2278	1.0357	9.80	0.3849	15	15	17	17
46	1872	0.9361	44.90	0.4904	33	33	32	31
48	1217	1.1072	56.00	0.4406	47	47	38	39
50	1966	1.0349	4.50	0.4230	18	18	14	14
51	0	0.0000	12.00	0.1347	55	55	58	58
54	1332	0.9516	14.99	0.4683	32	32	37	36
57	1629	1.0861	26.00	0.5105	25	23	25	25
58	1181	0.9843	229.00	0.4495	59	59	48	48
59	2097	1.1651	79.00	0.4882	35	35	21	20
62	629	1.0495	9.99	0.4149	42	42	45	45
66	0	0.0000	46.80	0.0770	57	57	59	59
67	4550	0.9893	13.55	0.3733	7	7	9	9
68	1014	1.1274	6.89	0.3806	29	30	31	32
69	833	1.0417	129.00	0.5322	58	58	47	46
70	530	1.0611	3.99	0.2474	39	41	46	47
71	1332	1.0253	4.59	0.3628	23	24	26	26
72	1653	1.2723	49.50	0.3924	30	29	24	24
75	988	0.8982	5.88	0.4391	38	38	41	41
76	932	1.1662	4.49	0.3580	28	28	27	28
77	717	0.8971	3.50	0.4797	40	39	40	40
79	1163	1.2931	9.50	0.4508	22	22	20	21
82	856	1.0714	5.88	0.4799	34	34	33	33
83	881	0.8016	14.00	0.4832	44	44	49	49
84	465	0.5814	11.50	0.3892	48	48	51	51
85	0	0.0000	2.00	0.2950	50	50	53	53
86	2517	1.0068	12.00	0.3683	14	14	18	18
87	1217	1.0147	28.90	0.4086	41	40	43	43
88	1493	0.9335	7.90	0.4060	24	25	29	30
89	1854	1.0302	17.45	0.4753	20	20	22	22
91	1079	1.0791	18.99	0.4946	36	36	34	34
92	794	0.9936	12.50	0.4172	43	43	44	44
93	0	0.0000	2.99	0.2423	52	52	55	55
94	1157	0.9649	5.90	0.5159	31	31	28	27

95	575	0.9592	13.90	0.4025	46	46	50	50
98	660	1.3208	22.00	0.4935	37	37	36	35
100	0	0.0000	5.90	0.3038	53	53	56	57

Table A.3: Products with 'earphone' keyword under Audio from Dataset B

Product ID	CESV	CSR	CP	CNPR	TOPSIS		WASPAS	
					AHP	BWM	AHP	BWM
1	10267	0.8556	1.00	0.2559	2	2	2	2
2	12531	1.1935	14.10	0.3588	1	1	1	1
4	1527	0.8488	9.90	0.3922	16	16	22	22
5	6092	0.7429	12.50	0.4001	3	3	3	3
7	991	0.9013	2.50	0.3503	25	25	19	20
8	4705	1.0012	12.50	0.4061	4	4	4	4
12	0	0.0000	10.00	0.2624	43	44	57	57
13	2299	0.7185	4.80	0.3928	9	9	10	10
14	1411	0.7843	149.00	0.5104	52	52	29	29
15	1013	0.7797	16.99	0.4426	30	30	30	30
17	2579	0.9211	6.99	0.3937	7	7	7	7
18	1352	0.9017	7.90	0.4231	18	19	18	18
21	0	0.0000	1.50	0.3157	35	35	37	37
26	4516	0.9410	3.90	0.2682	5	5	5	5
28	1626	0.8562	23.49	0.5427	19	18	16	16
29	0	0.0000	12.00	0.3808	45	45	51	51
30	425	0.7097	3.99	0.2966	33	33	34	34
31	2330	0.8035	44.90	0.5058	11	11	14	12
33	1495	0.9346	29.00	0.5133	21	21	17	17
36	0	0.0000	10.00	0.4385	42	42	45	46
39	1785	0.8502	19.80	0.3847	13	13	21	21
40	1647	1.0981	8.88	0.4302	10	10	9	9
43	1248	0.8320	3.90	0.3057	24	24	25	25
44	1233	0.8225	9.90	0.3742	26	26	28	28
46	0	0.0000	44.90	0.4883	54	54	44	44
48	0	0.0000	38.00	0.4449	53	53	48	48
50	1570	0.8264	4.50	0.4214	14	14	12	13
51	0	0.0000	12.00	0.1347	48	48	58	58
54	2376	0.9904	14.99	0.4586	8	8	8	8
57	781	1.1166	29.90	0.5019	28	28	26	26
58	775	0.8621	249.00	0.4432	58	58	32	33
59	0	0.0000	79.00	0.4887	57	57	46	45
62	955	1.1939	9.99	0.4087	15	15	15	15
66	0	0.0000	46.80	0.0770	55	56	59	59

67	3226	0.9219	19.98	0.4373	6	6	6	6
68	861	1.0766	6.90	0.3790	22	22	23	23
69	0	0.0000	139.00	0.5327	59	59	41	41
70	0	0.0000	3.99	0.2354	40	40	56	56
71	1026	0.8557	4.59	0.3580	27	27	27	27
72	0	0.0000	49.50	0.3894	56	55	55	55
75	1409	0.9394	14.50	0.4359	17	17	20	19
76	0	0.0000	4.50	0.3557	38	39	47	47
77	957	1.0638	5.00	0.4758	20	20	13	14
79	680	1.3619	8.60	0.4621	12	12	11	11
82	0	0.0000	5.88	0.4780	37	37	40	39
83	530	0.7583	14.00	0.4804	32	32	33	32
84	0	0.0000	11.50	0.3868	44	43	50	50
85	0	0.0000	2.00	0.2782	36	36	39	40
86	0	0.0000	12.00	0.3667	46	46	53	53
87	0	0.0000	28.90	0.4067	51	51	52	52
88	997	0.7126	8.90	0.3905	29	29	31	31
89	0	0.0000	17.45	0.4741	49	49	43	43
91	337	0.5625	19.39	0.4886	34	34	36	36
92	950	1.0557	12.50	0.4134	23	23	24	24
93	85	0.8578	2.99	0.2363	31	31	35	35
94	0	0.0000	6.90	0.5169	39	38	38	38
95	0	0.0000	13.90	0.3981	47	47	49	49
98	0	0.0000	25.00	0.4986	50	50	42	42
100	0	0.0000	5.90	0.3102	41	41	54	54

Table A.4: Products with 'charger' keyword under Cables & Chargers from Dataset A

Product ID	CESV	CSR	CP	CNPR	AHP-TOPSIS ranking	AHP-WASPAS ranking
107	7144.186	0.992248	0.34	0.097309	2	2
108	10844.2	0.994881	0.1	0.085839	1	1
109	4503.843	0.883106	2.89	0.295674	4	5
113	4156.171	0.944584	6.49	0.351727	5	6
116	5027.778	0.985839	1.8	0.256853	3	3
118	3125.359	0.947078	5.53	0.31322	8	9
121	1398.305	0.998789	0.42	0.094009	15	16
123	3140.752	1.046917	4.5	0.283024	7	7
124	3053.331	0.984946	26.99	0.539888	9	8
137	0	0	10.98	0.148126	33	34
138	0	0	6.9	0.426785	31	31
140	1963.534	0.935016	2.86	0.297427	10	13
142	696.7742	1.16129	0.39	0.134254	17	19

144	1621.426	1.158161	3.6	0.292367	11	11
153	1168.521	0.973768	39.9	0.504221	29	20
154	1911.848	1.006236	18	0.43605	14	14
157	645.6241	1.07604	4.86	0.33362	21	23
161	985.342	0.895765	0.45	0.170606	19	21
164	729.1667	1.041667	3.18	0.244098	20	25
166	1141.167	1.267963	0.89	0.189466	13	12
169	0	0	37.9	0.351244	34	33
171	282.3529	0.941176	3.9	0.394112	28	28
175	1055.156	1.318945	0.21	0.133223	12	10
176	681.2652	0.851582	3.2	0.375257	24	27
177	893.3406	0.893341	0.89	0.177206	23	26
178	1461.482	1.124217	15	0.398607	16	15
179	1585.439	0.932611	13.12	0.436074	18	17
183	802.168	1.00271	13.7	0.422188	27	22
186	1290.441	0.992647	34.9	0.561858	26	18
187	352.9412	0.882353	22.9	0.433075	30	30
188	3665.659	1.024213	0.34	0.079556	6	4
190	830.2583	0.922509	0.9	0.204314	22	24
192	0	0	8.54	0.351614	32	32
193	530.7498	0.884583	1.99	0.197496	25	29

Table A.5: Products with ‘charger’ keyword under Cables & Chargers from Dataset B

Product ID	CESV	CSR	CP	CNPR	AHP-TOPSIS ranking	AHP-WASPAS ranking
107	3433.58	1.040479	0.29	0.096686	6	5
108	6745.121	0.887516	0.1	0.084209	1	1
109	2588.576	0.835294	2.9	0.292938	8	8
113	5159.448	0.706774	6.49	0.345526	4	6
116	4649.841	0.8942	0.05	0.254544	5	2
118	5526.75	0.824888	6.99	0.304861	2	4
121	671.5917	0.83949	0.35	0.093875	21	25
123	1794.872	0.641026	4.8	0.281085	11	16
124	3191.377	0.742181	26.99	0.52359	7	7
137	0	0	0.99	0.148744	29	34
138	805.3691	0.894855	6.9	0.421636	17	19
140	1903.461	1.001821	2.61	0.292265	9	9
142	827.3165	0.752106	0.26	0.13288	19	21
144	1869.586	0.890279	4	0.287372	10	10
153	1056.751	1.174168	79	0.502986	26	11
154	0	0	18	0.43475	32	28

157	1461.538	0.769231	5.5	0.310227	12	15
161	678.5137	0.848142	0.45	0.163022	20	22
164	461.0951	0.768492	3.18	0.2289	24	26
166	1028.807	1.028807	0.89	0.188724	13	12
169	1245.02	0.830013	37.9	0.332616	25	20
171	0	0	3.9	0.392669	30	30
175	923.6234	0.71048	0.21	0.159634	18	18
176	845.3085	1.056636	3.6	0.368863	14	14
177	0	0	0.99	0.176262	28	33
178	1293.141	0.808213	15.99	0.400838	15	17
179	0	0	13.12	0.43776	31	27
183	575.5396	0.959233	13.9	0.40824	23	23
186	1489.362	0.827423	34.9	0.554226	22	13
187	0	0	22.9	0.432792	33	29
188	5450.756	0.825872	0.3	0.078145	3	3
190	0	0	0.9	0.205229	27	32
192	0	0	23.9	0.349275	34	31
193	681.8182	0.974026	3.99	0.200439	16	24

Table A.6: Products with ‘casing’ keyword under Cases & Covers from Dataset A

Product ID	CESV	CSR	CP	CNPR	AHP-TOPSIS ranking	AHP-WASPAS ranking
201	5250.427	0.990647	8	0.17686	1	2
210	2234.043	1.06383	7.85	0.381458	4	6
213	3445.168	1.076615	0.5	0.242794	2	1
219	1519.111	1.012741	6.59	0.407792	7	9
224	1267.081	1.055901	7.85	0.415755	11	13
226	2285.402	1.038819	7.25	0.361526	3	5
227	1739.13	1.15942	0.98	0.251829	6	3
228	875.9124	0.973236	5.99	0.3636	20	23
234	1503.899	0.835499	8.99	0.415168	8	14
242	944.5844	1.049538	7.25	0.457838	17	20
247	734.6767	1.049538	1.5	0.390178	19	17
248	1266.332	1.055276	3.8	0.480156	9	8
253	0	0	10.9	0.379286	28	28
259	803.0593	1.147228	4.87	0.447178	18	19
262	2155.537	1.267963	8.89	0.39432	5	4
263	863.3094	0.959233	6.9	0.422758	23	22
267	478.4689	0.956938	4.9	0.497354	25	25
271	0	0	6.88	0.370592	27	27
272	1059.545	0.963222	6.98	0.451792	16	18

274	1115.242	0.929368	3.98	0.417536	14	16
281	1130.653	1.256281	6.88	0.375617	12	11
284	1330.848	0.968594	5.8	0.467374	10	10
291	747.6636	1.068091	5.5	0.48205	22	21
293	574.1627	0.956938	5	0.4311	24	24
294	892.6417	1.115802	3.8	0.45	15	15
295	1009.091	1.121212	3.8	0.460681	13	12
297	612.5	0.875	11.9	0.090582	26	26
300	1124.122	1.873536	59.55	0.528116	21	7

Table A.7: Products with ‘casing’ keyword under Cases & Covers from Dataset B

Product ID	CESV	CSR	CP	CNPR	AHP-TOPSIS ranking	AHP-WASPAS ranking
201	3187.251	0.796813	8	0.179996	2	2
210	0	0	7.85	0.385443	25	25
213	3292.429	0.914564	0.5	0.238817	1	1
219	1210.733	0.807155	6.59	0.414838	5	6
224	0	0	7.85	0.430422	24	23
226	1605.744	0.76464	7.59	0.372952	3	3
227	1010.69	0.777454	0.99	0.263691	6	5
228	0	0	5.99	0.356955	21	27
234	1384.929	0.814664	8.99	0.417671	4	4
242	0	0	7.25	0.457838	22	20
247	0	0	1.5	0.390331	17	17
248	942.1001	0.785083	4.3	0.469194	7	10
253	0	0	10.9	0.37931	27	28
259	0	0	4.87	0.441147	19	19
262	0	0	8.5	0.41	26	24
263	281.9549	0.56391	6.9	0.414405	16	16
267	719.1781	1.027397	3.96	0.485276	11	8
271	0	0	6.88	0.373966	23	26
272	0	0	6.2	0.444648	20	21
274	734.6767	1.049538	3.98	0.402202	10	9
281	839.3285	0.839329	6.99	0.371165	12	12
284	776.0141	0.705467	5.8	0.4622	13	14
291	861.244	0.956938	5.5	0.466041	8	7
293	630.6306	0.900901	5.99	0.430816	14	13
294	0	0	4.3	0.416604	18	22
295	971.0234	0.647349	4.3	0.456238	9	11
297	502.3923	0.837321	11.9	0.086643	15	15
300	0	0	59.55	0.5229	28	18

Table A.8: Products with 'pineng' keyword under Powerbanks & Batteries from Dataset A

Product ID	CESV	CSR	CP	CNPR	AHP-TOPSIS ranking	AHP-WASPAS ranking
301	619.9678	0.885668	69.9	0.573005	13	10
302	350.2919	0.87573	29.9	0.524552	19	17
303	150	1.5	55	0.424711	6	14
305	44.77586	0.844828	40	0.558801	20	21
306	57.53226	1.403226	53	0.5103	9	19
307	479.6163	0.959233	44.9	0.570618	14	11
308	440.044	0.880088	55.9	0.561913	18	15
309	0	0	42	0.474081	30	28
310	386.0294	1.286765	40.9	0.572969	8	6
311	0	0	36.9	0.512519	29	26
312	352.9693	0.956556	44.9	0.498312	16	16
313	6239.138	1.02281	28	0.461557	1	1
317	2909.091	1.038961	32	0.510173	2	2
319	2382.671	1.083032	29.9	0.502467	3	3
321	624.4805	1.039069	27.8	0.424016	10	7
328	1394.7	0.9298	55.9	0.472865	4	5
348	0	0	30.9	0.515641	25	25
356	564.7059	0.941176	62.9	0.529314	12	12
358	0	0	17.5	0.368004	23	30
360	519.5345	1.039069	26.9	0.51	11	9
363	576.4706	0.823529	45	0.49863	15	13
370	0	0	36	0.503501	28	27
371	0	0	20.5	0.307844	24	32
374	0	0	29.5	0.361836	27	31
376	224.0896	0.746965	28.9	0.474365	21	20
379	0	0	1	0.21669	22	22
381	0	0	75	0.538404	32	24
384	0	0	28.9	0.449977	26	29
386	0	0	75.9	0.563252	31	23
388	400	2	42.9	0.492895	5	4
398	397.7273	1.325758	32.8	0.424315	7	8
400	288	0.96	38.9	0.532513	17	18

Table A.9: Products with ‘pineng’ keyword under Powerbanks & Batteries from Dataset B

Product ID	CESV	CSR	CP	CNPR	AHP-TOPSIS ranking	AHP-WASPAS ranking
301	1284.047	1.167315	73.9	0.564076	4	3
302	0	0	37.9	0.523483	22	18
303	0	0	62.8	0.427642	30	29
305	19	1.357143	40	0.558772	8	12
306	33.24771	1.385321	56	0.50904	7	11
307	575.5396	0.959233	41	0.566382	6	6
308	530.9735	1.327434	62.9	0.562671	5	5
309	0	0	45	0.49265	26	25
310	0	0	45.9	0.57936	24	15
311	0	0	39.9	0.509188	23	21
312	0	0	48.9	0.482015	28	26
313	3153.969	0.788492	28	0.459642	1	1
317	1420.613	0.835655	23.9	0.509407	3	4
319	2334.077	0.864473	30	0.501352	2	2
321	0	0	89	0.424451	32	30
328	560.4203	0.700525	55.9	0.472184	11	8
348	0	0	35.9	0.508277	21	20
356	0	0	88.5	0.545172	31	16
358	0	0	17.5	0.368004	15	31
360	0	0	28.9	0.5085	17	19
363	0	0	48.8	0.495318	27	24
370	0	0	35	0.503289	20	22
371	0	0	20.5	0.307844	16	32
374	6.857143	1.142857	37	0.364744	13	13
376	0	0	32	0.49625	18	23
379	0	0	1	0.216622	14	14
381	435.7298	0.87146	73	0.540675	12	7
384	0	0	58	0.451052	29	27
386	132.0755	1.320755	92.9	0.561284	9	10
388	228.5714	1.142857	44.9	0.480746	10	9
398	0	0	41.9	0.427402	25	28
400	0	0	34.9	0.529631	19	17