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Advanced processor selection guidance system for optimal computing performance using AHP-profile matching

Slamet Winardi [a*], Agustinus Bimo Gumelar[b], Che Zalina Zulkifli[c], Ageng Salmanarrizqie[d], Philipus Suryo S[e]

[a,b,d,e]Department of Engineering, Faculty of Informatics, Widya Mandala Catholic University, Surabaya, Indonesia
[c]Department of Engineering, Faculty of Computing and Meta-Technology, Sultan Idris Education University, Perak, Malaysia
E-mail: slamet.winardi@ukwms.ac.id*, bimo@ukwms.ac.id, chezalina@meta.upsi.edu.my, kerjageng@gmail.com , philipus@ukwms.ac.id

Abstract

The increasing complexity of modern processors and rapid advances in computing technology pose significant challenges for users seeking to select the optimal processor to satisfy their specific requirements. The " Processor Selection with AHP-Profile Matching: Implementation and Performance Analysis" addresses this problem by providing a structured, evidence-based approach to processor selection. This system integrates the Analytic Hierarchy Process (AHP) and profile matching algorithms to evaluate and rank processors based on parameters such as brand, price, socket type, thermal design power (TDP), core count, thread count, clock speed (GHz), DDR compatibility, and PCIe version. User inputs were collected and analyzed using the AHP to determine the relative importance of each criterion. Profile matching aligns user requirements with optimal processor configurations in a database. Results are presented through a comparative analysis that highlights each processor's strengths and limitations. Compatibility checks ensure seamless integration with existing hardware. The results indicate an accuracy of 81% with AHP alone and 91% with the combined AHP-Profile Matching approach. The proposed system significantly improves decision-making efficiency by providing a robust, user-centric processor selection approach and optimizing computational performance.

Key words: AHP, Decision Support System, Guidance System, Hardware Selection, Profile Matching.

INTRODUCTION

Modern technological advancements have profoundly impacted the development of computers, making them indispensable tools for boosting productivity across various fields, such as public services, industry, offices, education, commerce, and entertainment [1], [2]. As a result, numerous desktops or personal computer (PC) users prefer to have their machines assembled to achieve optimal performance tailored to their specific needs and preferences. The assembly process involves integrating various components to ensure that the system operates as desired [3]. However, the rapidly increasing complexity of contemporary processors and the rapid progress in computing technology present significant challenges for users seeking to select processors that satisfy their specific requirements. With numerous options differing in performance, efficiency, and cost, selecting the most appropriate processor has become increasingly difficult [4]. Traditional processor selection methods often overlook the nuanced requirements of different users, which highlights the need for a more systematic and personalized approach.

To address these challenges, the "Processor Selection with AHP-Profile Matching: Implementation" was developed. This system integrates the well-established Analytic Hierarchy Process (AHP) with Profile Matching to evaluate and rank processors based on parameters such as brand, price, socket type, thermal design power (TDP), core and thread count, clock speed (in GHz), DDR compatibility, and PCIe version. In today's rapidly evolving hardware landscape, selecting the optimal component has become increasingly complex. Although AHP is widely recognized for its reliability in decision-making, when used alone it is limited in its ability to provide comprehensive rankings. Our novel approach leverages AHP to determine the relative weights of various evaluation criteria, while Profile Matching is employed to rank the processors by measuring how closely each one aligns with the user's desired profile.

This integrated approach overcomes the shortcomings of using AHP in isolation, offering a more robust framework for addressing the intricacies of hardware selection. The system begins by collecting detailed user inputs, which are then analyzed using AHP to assign importance to each criterion. Profile Matching subsequently aligns these weighted criteria with the corresponding processor configurations in a comprehensive database, and thorough compatibility checks ensure seamless integration with existing hardware components. The outcome is presented through a comparative analysis that highlights both the strengths and limitations of each option, thereby ensuring consistency across the title, abstract, and main content while focusing squarely on optimal hardware selection.

Previous research has explored various methodologies for technology selection decision-making. One study focused on developing a Decision Support System (DSS) for laptop selection using AHP and Profile Matching and demonstrated how these methods can aid in selecting technology that meets user-specific requirements [5]. In addition, previous studies on computer component recommendation systems used AHP and Profile Matching to streamline the selection process, emphasizing the importance of aligning components with user preferences [3]. Despite these advancements, no study has yet implemented a DSS for processors that use the profile matching and AHP methods. Parameters such as socket, core, thread, TDP, GHz, DDR, and PCIe version, which are categorized under specifications, price, and brand, are used to determine and find processors that align with user preferences and budgets. This study, however, focuses specifically on creating an advanced guidance system for optimal processor selection in computing by combining AHP and Profile Matching to address the unique challenges of processor evaluation and ranking, thereby offering a more tailored and effective solution.

The purpose of this study was to develop a processor selection guidance system to optimize computing performance. This system integrates the Analytic Hierarchy Process (AHP) and profile matching algorithms to evaluate and rank processors based on critical parameters, such as brand, price, socket type, thermal design power (TDP), core count, thread count, Clock rate measured in Gigahertz (GHz), Double Data Rate (DDR) compatibility, and Peripheral Component Interconnect Express (PCIe) version. By leveraging these methodologies, the proposed system aims to provide a robust, evidence-based framework for processor selection that enhances user satisfaction and decision-making efficiency, thereby ultimately optimizing computational performance and user experience.

MATERIAL AND METHODS

The research methodology explains where and how the dataset was obtained, the flow of calculations performed to obtain the results, and the application of the AHP weighting method and profile matching ranking methods. The proposed model also includes the evaluation model using the confusion matrix, providing a comprehensive framework for the study.

Dataset

The processor dataset was sourced from Zenodo and comprises 300 entries focusing on sockets AM4, AM5, LGA 1200, and LGA 1700. The data was gathered from three key platforms: Enterkomputer, Rakitan.com, and

Tokopedia. Specifications were cross-checked with official Intel and AMD resources to ensure accuracy. This dataset provides reliable pricing insights for market analysis in Indonesia [6].

This dataset provides valuable market-based pricing, covering a wide range of processors by price and brand. It is useful for market research, price comparisons, and analyzing socket-specific trends in Indonesia. Details are shown in Table 1.

Table 1. The processor category

No	Categories	Description
1	Specification	This category shows essential technical details like clock speed, core count, cache size, and supported features, all key for evaluating a processor's performance and [7].
2	Price	The price category goes beyond simply looking at cost. It takes into account market competitiveness, value for money, available promotions, and how well performance aligns with affordability [8].
3	Brand	The brand category identifies the manufacturer (for example, Intel or AMD) and also evaluates the company's legacy, reputation for reliability, history of innovation, and quality of customer support [9], [10].

In addition, the Specifications subcategory includes parameters that can be seen in the Table 2 [11].

Table 2. Subcategory specification

No	Parameter	Description
1	Socket	The connector on the motherboard for the CPU. Each processor family requires a specific socket type, such as LGA 1200 or AM4.
2	TDP	The maximum heat a CPU is designed to dissipate, measured in watts. This helps in determining the cooling requirements and power consumption.
3	Core	A processing unit within the CPU. Modern processors usually have multiple cores (for example, dual-core or quad-core) to support multitasking.
4	Thread	A thread is the basic unit of instructions the CPU processes. Multi-threading allows a core to handle several threads at the same time.
5	GHz	A measurement of the processor's clock speed. A higher GHz value indicates faster data processing.
6	DDR	Indicates the type of memory interface used in RAM. Each generation (e.g., DDR3 or DDR4) offers improvements in speed and efficiency.
7	PCIe Version	Specifies the generation of the PCI Express interface on the motherboard. Newer versions, such as PCIe 3.0 or PCIe 4.0, provide higher data transfer rates.

These details are elaborated in Table 3, which features columns for Parameters, Specifications, Price, and Brand, elucidating all categories and subcategories considered in this study

Table 3. Research datasets

Parameter	Specification	Price Range	Brand
Socket	LGA 1700 AM5 LGA 1200 AM4	< Rp. 12.000.00 0,00 <	Intel AMD
Core	24 Core ≤ 16 Core ≤ 8 Core ≤ 4 Core 2 Core	Rp.10.000 .000,00 <Rp.8.000 .000,00 <	

Parameter	Specification	Price Range	Brand
Thread	≤ 32 ≤ 16 8 4 2	Rp.6.000.000,00 < Rp.4.000.00,00 < Rp.2.000.000,00 < Rp.1.000.000,00	
DDR	DDR5 DDR4		
PCIe Ver	PCIe 5.0 PCIe 4.0 PCIe 3.0		
TDP	170 ≤ 150 ≤ 100 ≤ 50		
GHz	< 5 GHz ≤ 4 GHz ≤ 3 GHz 2 Ghz		

Table 3 gives the details and explains these seven parameters, associated each with its specific specifications, price range, and brand options. This provides a comprehensive overview necessary for informed decision-making in processor selection, highlighting seven parameters and the available options for each.

Research Stage

The research stages begin with the critical task of selecting processor parameters from the seven available options. The initial phase is fundamental as it lays the groundwork for subsequent analysis. Each parameter—Socket, TDP, Core, Thread, GHz, DDR, and PCIe Version—plays a pivotal role in the overall performance and compatibility of the processor, thus necessitating careful consideration.

Following parameter selection, the next step involves determining the priority of categories and subcategories. To accomplish this, the study employs the Analytic Hierarchy Process (AHP) for parameter weighting. The AHP is a structured technique that is particularly useful in making complex decisions. This involves breaking down the decision-making process into a multi-level hierarchical structure of objectives, criteria, sub-criteria, and alternatives. Initially, a structured hierarchy is created from the chosen computer parameters, which are then meticulously categorized and subcategorized.

Then a pairwise comparison matrix is developed for each priority. This matrix allows for a systematic comparison of the elements within each level of the hierarchy, enabling the calculation of priority values and the eigenvector value from the matrix results. The consistency of each pairwise comparison matrix was verified to maintain hierarchical integrity. This verification process is crucial because it ensures the reliability and validity of the comparisons made within the matrix.

Upon completing the weighting process, the study progresses to the ranking phase, which employs the Profile Matching method. The proposed method is instrumental in aligning parameters with desired profiles, thereby facilitating more accurate ranking. The Profile Matching process involves gap mapping, which aligns with the Profile Matching calculations. During this stage, the values of the main and secondary factors are identified and organized based on the established priorities. The total value is calculated by combining the various weighted criteria, thereby determining the ranking of each alternative. This comprehensive ranking provides a clear perspective on the relative performance of each processor based on the selected parameters.

In this study, we propose a systematic framework that uniquely combines the strengths of AHP and Profile Matching. The process is structured into two primary phases:
AHP Weighting Phase:

1. Data Collection: Hardware data including specifications, price, and brand are gathered from reliable sources.
2. Criterion Hierarchy Formation: A hierarchical structure is developed with the overall goal at the top, followed by the criteria and sub criteria.
3. Pairwise Comparisons and Weight Determination: The AHP method is applied to construct pairwise comparison matrices, ensuring consistency in the subjective judgments of decision makers. The outcome of this phase is a weight vector for all evaluation parameters.

Profile Matching Ranking Phase:

1. Profile Development: A standard profile is defined based on user requirements covering essential hardware attributes.
2. Gap Analysis: For each alternative, the gap between the actual hardware specifications and the standard profile is calculated.

3. Mapping & Ranking: Using a predefined weighting scheme for the gap values, the alternatives are scored and then ranked based on their total gap mapping. The alternative with the smallest gap—that is, the one closest to the desired profile—is ranked highest.

The overall system workflow is illustrated in Fig. 1, which depicts the computational flow from data collection through AHP weighting and Profile Matching ranking. This schematic clarifies the simulation process used to derive our results.

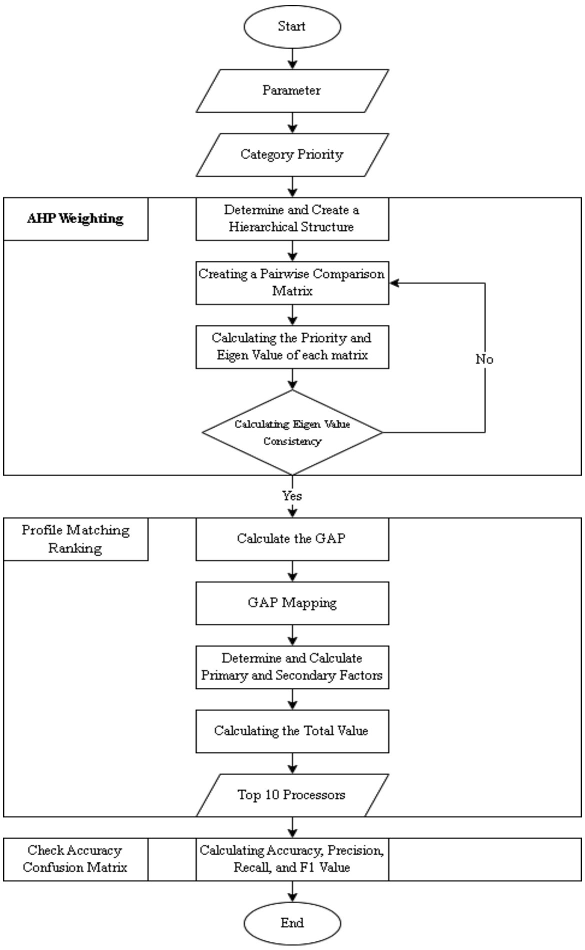

Fig. 1. Calculation method

This two-step approach integrates the classical rigor of AHP for weighting with the adaptability of Profile Matching for ranking, thereby generating a novel decision support system for hardware selection.

Moreover, the detailed computational flow of these methodologies is visually represented in Figure 1, which enhances the clarity of the study's intricate processes. Through this meticulous approach, the evaluation and selection of processors are both systematic and thorough. Ultimately, the combination of AHP for weighting and Profile Matching for ranking provides a robust framework for decision-making, facilitating the identification of the most suitable processors that meet the specific needs and preferences outlined in the research objectives.

Decision Support System

Decision Support Systems (DSS) are specialized tools in information systems that enhance and support managerial decision-making by combining data analysis, model selection, and human intuition [12]. Unlike automated systems that handle routine and well-structured decisions, DSS is designed for semi-structured or unstructured scenarios, offering flexibility to decision-makers [13]. For instance, in addressing the complexity of modern processor selection, the integration of methods like AHP and Profile Matching within a DSS provides a structured, evidence-based framework to evaluate and rank options based on various parameters. This approach improves decision-making efficiency by aligning user requirements with optimal solutions, ensuring both accuracy and compatibility.

Analytic Hierarchy Process (AHP) Method

The Analytic Hierarchy Process (AHP) is a problem-solving method that uses multiple criteria and parameters [14], [15], [16]. The hierarchical analysis process is also a decision support method that analyzes the quantity and quality data. The AHP method compares and prioritizes alternatives based on different criteria using a pairwise comparison matrix [17], [18]. The following weighting steps are performed using AHP:

Step 1: Building a Structured Hierarchy; Structured Hierarchy is a natural human thinking system used to indirectly separate and combine groups based on their levels. The hierarchy starts with the overall goal at the top, followed by criteria, and then sub-criteria at subsequent levels.

Step 2: Creating a Pairwise Comparison Matrix; The pairwise comparison matrix is constructed based on the level of importance of each element relative to others. The elements were compared in pairs to judge their relative importance or preference using the scale shown in Table 4 [17], [18].

Table 1. Comparison scale

Value	Description
1	Category or Alternative A is as Important as Category or Alternative B
3	A is slightly more important than B.
5	A is definitely more important than B.
7	A is clearly more important than B.
9	A is absolutely more important than B.
2, 4, 6, and 8	Value between two adjacent assessments (Used when in doubt between two adjacent values)

Step 3: Calculate normalized eigenvector; eigenvector is calculated by normalizing the pairwise comparison matrix. This involves summing the values in each column of the matrix, dividing each element by its column sum, and then averaging the rows to obtain the priority vector. The eigenvector represents the relative weights of the criteria and parameters. The eigenvector is calculated using equation (1) [17], [18].

$$CI = \frac{\lambda \mathrm{MAX-N}}{n-1} \tag{1}$$

Here, the CI variable is the consistency index value, and n is the number of criteria or parameters.

Step 4: Consistency Check; Consistency of the pairwise comparisons is checked using (2) [17], [18].

$$CR = \frac{\mathrm{CI}}{IR} \tag{2}$$

Where CR (Consistency Ratio) is computed by dividing CI by RI (Ratio Index). The ratio index value itself varies according to the matrix size shown in Table 5 [17], [18], which shows the Matrix size along with the Ratio Index (IR) value obtained at that size. A CR value of 0.1 or less indicates acceptable consistency.

Table 2. Ration index [17], [18]

Matrix Size	RI Value
1 and 2	0,00
3	0,58
4	0,90
5	1,12
6	1,24
7	1,32
8	1.41

Profile Matching

Profile matching is a Gap analysis approach [19]. This mode of analysis is typically used as an objective employee evaluation measurement method by comparing an employee's profile with the profile of a position [20]. The following are the ranking steps of the profile matching method:

Step 1: Gap Calculation Process; Gap is the distance or differentiator between the standard and alternative profiles, as described in (3) [20].

$$Gap = Standard\ Profile - Alternative\ Profile \tag{3}$$

Here, the standard profile is the value that must be fulfilled by the Alternative Profile, and the Alternative Profile is the value possessed by the alternative.

Step 2: Gap Mapping; Gap Mapping or Gap Weighting is carried out with reference to Table 6, which describes each weight obtained when the difference in the Gap value obtained has been found and a description that explains each difference and weight obtained [20].

Table 3. Weighting of Gap Value

Difference	Weight	Description
5	0,5	Item matches over 5 values
4	1,5	Item matches over 4 values
3	2,5	Item matches over 3 values
2	3,5	Item matches over 2 values
1	4,5	Item matches over 1 value
0	5	There is no difference (Competency Match)
-1	4	Item Match less 1 value
-2	3	Item Match less 2 values
-3	2	Item Match less 3 values
-4	1	Item Match less 4 values
-5	0	Item Match less 5 values

Step 3: Calculation and Grouping of Main and Secondary Factors; The Main Factor uses (4) [20].

$$NCI = \frac{\sum NM}{\sum IM} \quad (4)$$

Here, the NMI variable is the result of the average value of the Main Factor from the division of the NM variable, which is the total value of the main factor, and the IM variable, which is the number of Main Factor items. Also, the calculation and grouping of secondary factors were performed using (5) [20].

$$NSI = \frac{\sum NS}{\sum IS} \quad (5)$$

Here, the NSI variable is the result of the average value of the Secondary Factor from the division of the NS variable, which is the total number of secondary factor values, and the IS variable, which is the number of Secondary Factor items.

Step 4: Total Score Calculation; The total value of each aspect was calculated using (6) [20].

$$NI = (0.6\ x\ NCI) + (0.4\ x\ NSI) \quad (6)$$

Here, NI is the total value of each parameter and category obtained from 60% NMI plus added 40% NSI.

Confusion Matrix

Confusion Matrix is an evaluation method used in statistical modeling, classification, and machine learning to assess model performance on test data with known labels [15], [21]. This matrix gives an idea of how well the model predicts the target class [22].

Step 1: Calculate Actual and Predicted Values Count the True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN) as shown in Table 7 [23].

Table 4. Confusion matrix [23]

		Predicted Value	
		True	*False*
Actual Value	*True*	TP	FN
	False	FP	TN

Here, TP indicates cases where the positive outcome is correctly predicted, TN shows cases where the negative outcome is correctly predicted, FP marks cases where a negative instance is mistakenly predicted as positive, and FN denotes cases where a positive instance is wrongly predicted as negative.

Step 2: Calculate Accuracy: Measure the overall correctness of the model's predictions using (7) [23].

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \quad (7)$$

Step 3: Calculate Recall: Determine the ratio of TP to the sum of TP and FN, indicating how well the model identifies positive cases using (8) [23].

$$Recall = \frac{TP}{TP+FN} \quad (8)$$

Step 4: Calculate Precision: Determine the ratio of TP to the sum of TP and FP, reflecting the accuracy of positive predictions using (9) [23].

$$Precision = \frac{TP}{TP+FP} \quad (9)$$

Step 5: Calculate F1 Score: Combine precision and recall into a single performance metric using (10) [23].

$$F1\ Value = \frac{2\ x\ Recall\ x\ Precision}{Recall+Precision} \quad (10)$$

RESULT AND DISCUSSION

The results of this research are presented as a logical narrative with a clear progression of ideas. Factual information and calculated data are provided using tables and numbers, while ensuring that the same information is not redundantly repeated in images, tables, and text. Subtitles are used throughout to clarify and further explain specific sections.

The numerical outputs in this study are derived from simulated calculations using the AHP model for weighting criteria and Profile Matching for ranking alternatives. These simulations are conducted using data from reliable sources, revealing the potential performance of the proposed model in the context of hardware selection.

For instance, consider a case study involving a user who is seeking a motherboard under Rp.6,000,000 from the Intel brand and with specific requirements such as a socket LGA 1200, TDP of 150, 8 cores, 8 threads, a clock speed of 4 GHz, DDR4 compatibility, and PCIe 4.0 support. The simulation results for this case clearly illustrate how the model evaluates and ranks the available options, demonstrating the practical applicability of our approach.

AHP weighting

The calculation simulation begins by organizing processor data into a hierarchical structure based on specifications, price, and brand. As shown in Fig. 2, the selection process starts with the goal of identifying the best processor, followed by categorization, and then specification breakdown into seven key parameters.

Once the hierarchy is established, the next step is weighting, which involves constructing a pairwise comparison matrix. Step 1 calculates the priority of each criterion based on pairwise comparisons, where higher row values indicate greater importance. The results are then normalized, as shown in Table 8, to determine category priorities.

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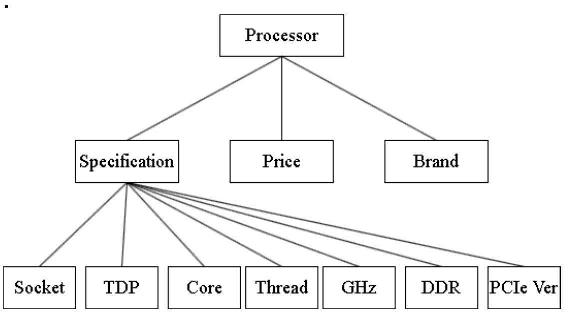

Fig. 2. Hierarchical structure of the processor

Table 5. Result of pairwise comparison matrix (category prioritization)

Category	Price	Spec	Brand	Total Value
Price	1	3	5	9
Spec	0.33	1	3	4.33
Brand	0.2	0.33	1	1.53

After prioritizing the categories through the pairwise comparison in Table 8, the next step is to identify the priority weight for each specification in the category. Table 9 displays the pairwise comparison matrix used to prioritize the sub-categories of specifications, such as socket, core, thread, TDP, clock speed (GHz), DDR compatibility, and PCIe version.

Step 2: Determine the priority of alternatives for the PCIe Version sub-category by analyzing the pairwise comparison matrix shown in Table 10.

Table 6. Result of pairwise comparison Matrix (PCIe version priority)

PCIe Ver	5.0	4.0	3.0	Total Value
5.0	1	3	5	9
4.0	0.33	1	3	4.33
3.0	0.2	0.33	1	1.53

Step 3: Divide each cell by the sum of its row to get the normalized pairwise priority. Table 11 shows the results from this first stage.

Table 7. First stage normalization process of eigenvector

Category	Price	Specification	Brand
Price	0.111	0	0.556
Specification	0.08	0.231	0.692
Brand	0.130	0.22	0.652

Next, we add up the values from the same column to obtain the total normalized value, such as by adding up the values in the Price column in Table 12, which shows the second stage of the Eigen Vector normalization process.

Table 8. Second stage normalization process of eigenvector

Category	Price	Specification	Brand
Price	0.111	0	0.556
Specification	0.08	0.231	0.692
Brand	0.130	0.22	0.652
Total	0.318	0.781	1.900

Next, divide the total value by the size of the matrix to get the priority value. In Table 13, the total price is divided by three since there are three parameters. This step is the third stage of the eigenvector normalization process.

Table 9. Third Stage Normalization Process of Eigenvector

Category	Price	Specification	Brand
Total	0.318	0.781	1.900
Priority	0.106	0.260	0.633

Step 4: Multiply the priority value from Table 13 by the total value from Table 8, then sum all the eigenvector values to get the final normalization result shown in Table 14.

Table 10. Priority and Eigenvalue Categories

Category	Price	Specification	Brand	Total
Priority	0.106	0.260	0.633	1
Eigenvalue	0.955	1.129	0.971	3.055

Table 15 shows the entire normalization stage of the eigenvalue vector for the Specification Category. Table 16 shows the entire stage of vector eigenvalue normalization for the specification subcategory. Tables 15 and 16 show illustrations of the overall vector eigenvalue normalization process, which is divided into several stages, from Table 11 for the first stage to Table 14 for the final stage.

Table 11. Result of priority and eigenvalue of pcie version

PCIe Ver	5.0	4.0	3.0	Total
5.0	0.11	0.33	0.56	1
4.0	0.08	0.23	0.69	1
3.0	0.13	0.22	0.65	1
Total	0.32	0.78	1.90	3
Priority	0.11	0.26	0.63	1
Eigenvalue	0.96	1.13	0.97	3.06

Step 5: Determine the consistency of weighting. The consistency ratio is calculated. This ensures the matrix's correctness from the stage of determining the priority value in Table 8 to the normalization process of the eigenvalue vector in Table 16, as shown in Table 17.

Table 12. Consistency result

Priority	Formula	Result
Category	CI RI CR Consistency	0.028 0.58 0.048 Consistency
Specification	CI RI CR Consistency	- 1.12 1.32 - 0.85 Consistency
PCIe Version	CI RI CR Consistency	0.028 0.58 0.048 Consistency

Profile Matching Rankings

The next stage is to perform ranking using the Profile Matching method by determining the Processor Requirement Value based on the results shown in Table 18, which shows the requirement value for each Category and Sub-Category.

Step 1: Calculate the gap and gap mapping using the reference weights listed in Table 6. Determining and grouping the main and secondary factors with the results in Table 19 showing which categories and subcategories were grouped.

Step 2: Each processor's Total Score is determined by combining the percentages from the Main and Secondary Factors that affect performance. A lower score indicates a better match with the requirement profile. Based on the parameters in Table 20, the top ten processors with the most suitable specifications and competitive prices are ranked according to user preferences. This final stage of the Profile Matching method ensures that the best options are identified and prioritized.

Table 13. Processor requirement value

Category	Sub	Aspect	Requirement Value
Price		Price	3.5
Brand		Brand	5
Specification	P1	Socket	3
	P2	Core	3
	P3	Thread	3
	P4	DDR	4
	P5	PCIe Ver.	4
	P6	TDP	5
	P5	GHz	4

Table 14. Grouping of main and secondary Factors

Category	Sub	Aspect	CF	SF
Price		Price	CF	
Brand		Brand	CF	
Specification	P1	Socket	CF	
	P2	Core	CF	
	P3	Thread	CF	
	P4	DDR		SF
	P5	PCIe Ver.		SF
	P6	TDP		SF
	P7	GHz		SF

The following is a comparison of the best or lowest prices for each processor item on the three websites Fig. 3.

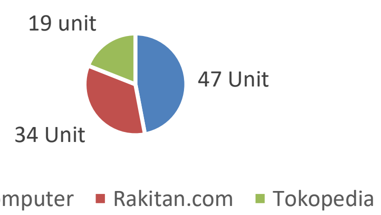

Fig. 1. Processor Price Comparison

Table 15**.** Result of pairwise comparison matrix (specification prioritization)

Spec.	P1	P2	P3	P4	P5	P6	P7	TV*
P1	1	3	3	5	7	9	9	37
P2	0.33	1	1	3	5	7	7	24.33
P3	0.33	1	1	3	5	7	9	26.33
P4	0.20	0.33	0.33	1	3	5	7	16.87
P5	0.14	0.20	0.20	0.33	1	3	5	9.88
P6	0.11	0.14	0.14	0.20	0.33	1	1	2.93
P&	0.11	0.14	0.11	0.14	0.20	1	1	2.71

*TV = Total Value

Table 16**.** Result of priority and eigen*v*ector of the specification

Specification	P1	P2	P3	P4	P5	P6	P7	Total
P1	0.03	0.08	0.08	0.14	0.19	0.24	0.24	1
P2	0.01	0.04	0.04	0.12	0.21	0.29	0.29	1
P3	0.01	0.04	0.04	0.11	0.19	0.27	0.34	1
P4	0.01	0.02	0.02	0.06	0.18	0.30	0.42	1
P5	0.01	0.02	0.02	0.03	0.10	0.30	0.51	1
P6	0.04	0.05	0.05	0.07	0.11	0.34	0.34	1
P7	0.04	0.05	0.04	0.05	0.07	0.37	0.37	1
Total	0.16	0.30	0.29	0.59	1.05	2.11	2.50	7
Priority	0.02	0.04	0.04	0.08	0.15	0.30	0.36	1
Eigenvalue	0.001	0.002	0.002	0.005	0.015	0.103	0.132	0.259

Table 17. Result of ranking processors

Name Unit	Price	Socket	DDR	Core	Thread	PCIe Ver	GHz	TDP	Total Score
Intel Core i7-10700KF	5,190,000	LGA 1200	DDR4	8	16	3.0	3.8	125	0.02
Intel Core i7-10700K	5,290,000	LGA 1200	DDR4	8	16	4.0	3.8	126	0.02
Intel Core i9-11900F	6,890,000	LGA 1200	DDR4	8	16	4.0	2.5	65	-0.02
Intel Core i9-11900	7,090,000	LGA 1200	DDR4	8	16	4.0	2.5	65	-0.02
Intel Core i5-11600KF	3,770,000	LGA 1200	DDR4	6	12	4.0	3.9	125	0.06
Intel Core i3-12100F	1,345,000	LGA 1700	DDR5	4	8	5.0	3.3	58	0.1
Intel Core i3-12100	1,775,000	LGA 1700	DDR5	3	8	5.0	3.3	65	0.1
Intel Core i3-13100F	1,782,000	LGA 1700	DDR5	4	8	5.0	3.4	58	0.1
Intel Core i9-10900F	6,500,000	LGA 1200	DDR4	10	20	3.0	2.8	65	0.12
Intel Core i9-10900	6,920,000	LGA 1200	DDR4	10	20	3.0	2.8	65	0.12

Evaluation Confusion Matrix

The evaluation model used in this study was a user to calculate the accuracy value of the ranking obtained using the Confusion Matrix method in Table 21, which shows the number of True Positive and False Negative data that appear in the ranking.

Table 18. Confusion Matrix of Ranking Results

		Prediction Value	
		True	False
Actual Value	True	129	6
	False	11	34

Next, we calculate the accuracy using (7) with a result of 0.9056 or 91%.

$$\text{Accuracy} = \frac{129+34}{129+11+34+6} = \frac{163}{180} = 0.905556 = 91\%$$

Next, we calculate recall using (8) with the result of 0.9556 or 96%.

$$Recall = \frac{129}{129+6} = \frac{129}{135} = 0.95556 = 96\%$$

Then calculate the Precision using (9) with a result of 0.92142 or 92%.

$$\text{Precision} = \frac{129}{129+11} = \frac{129}{140} = 0.92142 = 92\%$$

Finally, calculate the value of F1 using (10) with the result of 0.9381 or 94%

$$F1 = \frac{2\ x\ 0.95556\ x\ 0.92142}{0.95556 + 0.92142} = \frac{1.76095}{1.87698} = = 0.93818 = 94\%$$

Fig. 4 presents a comparison of the confusion matrix results between two methods: AHP-profile matching and AHP. This comparison includes key performance metrics such as accuracy, recall, precision, and F Score, to provide a comprehensive evaluation of each method's effectiveness.

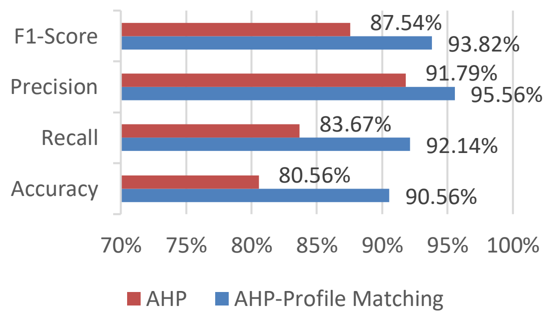

Fig. 2. Comparison of confusion matrix results between AHP and AHP-Profile matching methods

Discussion

Previous research has extensively explored various methodologies for technology selection decision-making, including applications in employee recruitment and laptop selection. Several studies have successfully applied the Analytical Hierarchy Process (AHP) and Profile Matching methods to evaluate multiple criteria and streamline the selection process. However, there remains a gap in the literature regarding a simulation-based decision support framework specifically designed for processor selection using these methods.

This study addresses that gap by developing an advanced guidance system for processor selection that integrates AHP and Profile Matching. In our approach, AHP is used to determine the relative weights of critical parameters such as socket type, core count, thread count, thermal design power (TDP), clock speed (GHz), DDR compatibility, and PCIe version. Profile Matching is then applied to evaluate how closely each processor meets the user-defined requirements. The decision outcomes are derived solely from simulated calculations based on these models.

Our simulation results demonstrate that applying AHP alone yields an accuracy of approximately 81 percent, while the combined AHP–Profile Matching approach improves accuracy to around 91 percent. These findings highlight the potential of our simulation model to enhance decision-making efficiency in processor selection by effectively capturing both quantitative and qualitative aspects of hardware evaluation.

The calculated outcomes presented herein show that the integrated AHP–Profile Matching approach offers a robust, user-centric framework to meet the challenges of modern processor evaluation. This simulation-based decision framework not only confirms the validity of the proposed method but also lays the groundwork for future research aimed at refining the calculations, expanding the dataset, and ultimately translating the approach into a complete and operational decision support system.

CONCLUSION

This study set out to develop an advanced processor selection guidance system that integrates the traditional AHP method with Profile Matching to enhance decision-making. The objective was to create a model capable of accurately weighing evaluation parameters including brand, price, socket type, TDP, core count, thread count, clock speed measured in gigahertz, DDR compatibility, and PCIe version, and then ranking hardware alternatives based on how well they match user-defined profiles.

Our formulation utilizes pairwise comparisons through AHP to determine the criterion weights and follows with a gap analysis using Profile Matching to score and rank the alternatives. Rigorous testing on a dataset obtained from real-world sources showed that the combined approach raises selection accuracy from 81 percent, when using AHP alone, to 91 percent when both methods are integrated. These outcomes validate the methodology and confirm that the proposed system effectively bridges the gap between theoretical objectives and practical performance.

The study successfully aligns the entire process from the initial objectives through the methodological formulation, testing, analysis of the results, and formation of the conclusions. Future work will concentrate on expanding the dataset, fine-tuning the model, and conducting further validations in order to enhance the robustness and scalability of the proposed framework.

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