Global Research Network Publishing
e-ISSN: 3047-2466
TECHNOVATE: Journal of Information Technology and Strategic Innovation Management
Vol 3, No 1, January 2026, pp.17-24

A Profile Matching-Based Decision Support Framework for Selecting Generative AI Tools in Higher Education

Indra Pratistha[1], Aditha Diva Anggaswara[2*], Gusti Bagus Arya Saputra[3], I Gede Anugrah Adi Krisna[4] , I Gede Iwan Sudipa[5]

[1,2*,3,4,5]*Institut Bisnis dan Teknologi Indonesia, Denpasar, Indonesia*
[1]indra.pratistha@instiki.ac.id ; [2*]anugrahkrisna@gmail.com ; [3]anggaswara@gmail.com ; [4]arya.suputra@gmail.com

ARTICLE INFO

Article History:
Received 12 November
Revised 19 December 2025
Accepted 29 January 2026

Keywords:
AI Application, Students, Profile Matching Method

ABSTRACT

This study aims to develop a decision-making model for determining the best AI application, specifically for students, in selecting the best alternative based on various criteria. This study used the Profile Matching Method to rank alternatives. Data was collected from students through an online survey, with criteria including ease of use (C1), task completion support (C2), creativity and idea support (C3), output quality and accuracy (C4), flexibility of use (C5), and access cost (C6). A decision-making analysis was conducted to determine the application that best suited students' preferences and identified the factors that most influenced their choice. The results showed the ChatGPT application alternative (A1) as the best student choice.

1. Introduction

The integration of Artificial Intelligence technologies, particularly in the form of Generative AI, into the higher education ecosystem has disrupted the way students work by offering significant efficiencies in academic task automation and complex data analysis(Dwivedi et al., 2021; Judijanto et al., 2025; Kasneci et al., 2023) . However, the rapid proliferation of AI tools today creates a "paradox of choice" phenomenon for academic users. Students often do not have sufficient technical competence to evaluate the appropriateness of the specifications of the various platforms available(Crompton & Burke, 2023) . As a result, app selection decisions are often based on popularity bias alone, without considering whether the specific features of the app align with the rigorous standards of their academic assignments(Tlili et al., 2023) . This functional mismatch risks degrading academic integrity and hampering learning efficiency .(Fawaid et al., 2025; Zou & Huang, 2023)

To mitigate the risk of inefficiency due to such subjective tool selection, technological intervention is required in the form of a Decision Support System that is capable of objectifying the selection process. In contrast to the manual intuitive approach, DSS offers an algorithmic framework to align user expectations with software technical capabilities in a scalable manner. The main challenge in this domain is how to quantitatively measure the degree of matching between dynamic academic needs and static AI application specifications. Therefore, an evaluation method that is not only capable of ranking, but also effective in mapping the feature competency gap between requirements and availability is needed (Ahmad & Santoso, 2023).

This research adopts the Profile Matching method as the core approach due to its unique characteristics that focus on gap analysis. Unlike other SPK methods, Profile Matching works by defining an "Ideal Profile" (standard academic requirements) and comparing it with the candidate's actual profile (AI application features)(Maulidah et al., 2024) . The method systematically calculates gap weighting, where a smaller gap value indicates a higher level of compatibility. The fundamental advantage of this method lies in the mechanism of partitioning criteria into Core Factor and Secondary Factor, which allows for a more granular and comprehensive evaluation of priorities than simple weighting methods .(Sudipa et al., 2024)

This research aims to develop a Profile Matching-based decision support system framework for selecting the best Generative AI applications in higher education. Through gap mapping and weighting aspects of cost, accuracy, and feature capability (Kharisma & Sudipa, 2023)(Pratistha et al., 2025) , the model is designed to provide precise and bias-free recommendations. The main contribution of this research is to provide an objective validation instrument for students, minimize technology adoption errors, and ensure that the selected AI tool truly serves as a catalyst for optimal academic productivity.

2. Literature Review

Recent research confirms that the adoption of Generative AI in higher education offers significant efficiencies, but triggers new complexities in tool selection due to the overwhelming variety of platforms in the market(Dwivedi et al., 2021; Kasneci et al., 2023; Tlili et al., 2023) . The literature indicates that students often experience cognitive overload and fall prey to popularity bias due to the lack of objective technical evaluation instruments(Crompton & Burke, 2023; Liu et al., 2023; Zou & Huang, 2023) . Although various Multi-Criteria Decision Making (MCDM) methods(Thanh, 2022) such as AHP and SAW have been applied for educational technology selection, such approaches generally focus on relative preference weights and often ignore the specific degree of fit against standardized competency standards .(Kraugusteeliana & Violin, 2024; Sudipa et al., 2025)

On the other hand, the Profile Matching method has been proven to excel in mapping the gap between target and candidate profiles, especially in the human resource management domain. The advantage of this method lies in the Core Factor and Secondary Factor weighting mechanism that allows for more granular feature prioritization(Akmaludin et al., 2022) . However, the application of this method to evaluate the capabilities of AI tools based on the taxonomy of academic needs is still very limited. The majority of existing research still focuses on Learning Management Systems (LMS) or hardware selection(Muni et al., 2024; Putri et al., 2024) . Therefore, this research fills the gap in the literature by adapting the Profile Matching algorithm to build an A-application selection framework, offering recommendation accuracy based on essential feature compatibility rather than user perception.

3. Research Methods

Profile Matching Method

The Profile Matching method is a decision-making mechanism that assumes the existence of an ideal level of competency variables that must be met by each alternative, rather than simply a minimum level that must be met or passed(Akmaludin et al., 2022) . In the context of this research, the method was chosen because of its very specific ability to compare the feature profiles or technical competencies of AI applications (actual values) with the standard needs or ideal expectations of students in supporting academic tasks (target values). This process is very effective in identifying the gap or difference between the actual feature availability and the user requirement profile, so that the resulting decision is more personalized and accurate. Furthermore, the advantage of Profile Matching lies in its ability to conduct a fair evaluation by considering both positive and negative aspects of deviations from the ideal profile(Hugo et al., 2026) . This approach does not only look for the highest value, but looks for alternatives that are closest to the predefined profile(Sudipa & Sudiani, 2019) . In its application to technology selection, this method allows the categorization of criteria into crucial main factors (Core Factor) and supporting factors (Secondary Factor), thus providing flexibility in weighting based on the urgency of AI application functionality for students.

Systematically, the calculation process in Profile Matching involves the following mathematical steps:

a) Determining the Ideal Profile
The ideal profile is a description of the conditions or values that are considered the most suitable and expected for each criterion used in the study.
b) Calculation of GAP Value
The GAP value is the difference between the value owned by the alternative and the ideal value on each criterion.
c) Conversion of GAP Value to Weight
The GAP value obtained is then converted into value weights according to the GAP conversion table. This conversion aims to adjust the level of difference in value to the level of importance in the assessment process.
d) Core Factor (CF) Calculation
Core Factor is the main criterion that has a major influence on the final result.
e) Calculation of Secondary Factor (SF)
Secondary Factor is a supporting criterion that still influences the assessment, but not as much as the Core Factor.
f) Calculation of Final Value
The final value of each alternative is obtained from combining the Core Factor and Secondary Factor values with certain weights.
g) Alternative Ranking
The last stage is to rank all alternatives based on the final value obtained.

Data source

In the initial stage, it starts with analyzing the problem, namely determining the best AI application, especially among students. The data collection process is carried out by distributing online questionnaires to a sampling of 34 student respondents regarding the selection of the best AI. In the literature study, look for literature related to problems and solutions with decision modeling by applying the Profile Matching method. Furthermore, the calculation process uses the Profile Matching method to determine the feasibility of AI. The final stage of this research is to conclude the results based on the highest value obtained from the application of Profile Matching.

4. Results and Discussions

Alternative Data

Alternative data in this study consists of 5 alternatives obtained from the determination made by researchers. Alternative data consists of A1, namely ChatGPT, A2, namely Gemini.AI, A3, namely DeepSeek.AI, A4, namely Claude.AI, and A5, namely Blackbox.AI.

Criteria and Subcriteria Data

In the process of determining criteria, it is necessary to include an explanation in each table so that the results of the analysis can be understood properly, especially in understanding the best alternative to be selected.

Table 1. Criteria Data

Criteria	Description	Type
C1	Ease of Use	Core Factor
C2	Task Completion Support	Core Factor
C3	Creativity and Idea Support	Secondary Factor
C4	Output Quality and Accuracy	Core Factor
C5	Flexibility of Use	Secondary Factor

C6	Access Cost	Secondary Factor

Criteria Explanation

1) C1 = Ease of Use, which assesses the extent to which AI applications are easy for students to understand and use without requiring complicated learning. This criterion includes interface appearance and comfort of use.
2) C2 = Task Completion Support, which assesses the AI application's ability to help students complete academic tasks such as writing, programming, and data analysis.
3) C3 = Creativity and Idea Support, which assesses the ability of AI applications to help generate ideas, creative concepts, and inspiration for design assignments, presentations, and other academic projects.
4) C4 = Output Quality and Accuracy, which assesses the level of accuracy, relevance, and clarity of answers or results produced by AI applications according to the academic needs of students.
5) C5 = Flexibility of Use, which assesses the ability of AI applications to be used in various contexts and types of academic tasks from various majors.
6) C6 = Access Cost, which assesses the affordability of using AI applications, both free and paid versions, for students.

Each criterion has sub-criteria with a scale value for each sub-criterion, the value scale used is value 1 = Strongly Disagree, value 2 = Disagree, value 3 = Undecided. Value 4 = Agree, and value 5 = Strongly Agree

Table 2. Explanation of Sub Criteria

No	Criteria	Description of Sub Criteria
1	(C1) Ease of Use	AI is easy for students to learn
		AI display and menu are easy to understand
		AI is comfortable to use in working on college assignments
2	(C2) Task Completion Support	AI helps to complete technical lecture tasks
		AI provides solutions that are relevant to the needs of the assignment
		AI speeds up the assignment process
3	(C3) Creativity and Idea Support	AI helps generate initial ideas
		AI helps develop concepts or ideas
		AI supports the creative thinking process
4	(C4) Output Quality and Accuracy	AI answers or outputs have a good level of accuracy
		AI output is reliable for academic needs
5	(C5) Flexibility of Use	AI can be used for various types of coursework
6	(C6) Cost of Access	AI can be accessed for free or at an affordable cost
		AI's free features are sufficient for student needs
		The costs incurred are proportional to the benefits obtained

Profile Matching Calculation

The following is the calculation process using one of the decision support system methods, namely the Profile Matching method:

Table 3. Alternative Values on Each Criterion

Alternative	Criteria					
	C1	C2	C3	C4	C5	C6
A1	4,66	4,84	3,86	3,79	4,78	3,85

A2	4,04	4,84	4,32	3,21	4,63	3,31
A3	4,7	3,35	3,99	3,46	3,88	3,97
A4	4,1	4,22	4,36	3,91	4,18	3,41
A5	4,21	4,72	3,91	3,31	3,22	3,94

a) Determination of the Ideal Profile

The ideal profile in this study is determined based on the expected performance value on each criterion, namely Ease of Use (C1) = 5, Task Completion Support (C2) = 5, Creativity and Idea Support (C3) = 4, Output Quality and Accuracy (C4) = 5, Flexibility of Use (C5) = 4, and Access Cost (C6) = 4. These values represent the ideal condition of the AI application that best suits the academic needs of students.

b) Calculation of GAP Value

Calculation of the GAP value is done by calculating the difference between the alternative value and the ideal profile value for each criterion, where the difference is used to determine the level of conformity of each alternative to the predetermined ideal profile (Decimals are rounded to the nearest GAP).

Table1 . GAP Calculation

Alternative	**Criteria**					
	C1	C2	C3	C4	C5	C6
A1	4,66	4,84	3,86	3,79	4,78	3,85
A2	4,04	4,84	4,32	3,21	4,63	3,31
A3	4,7	3,35	3,99	3,46	3,88	3,97
A4	4,1	4,22	4,36	3,91	4,18	3,41
A5	4,21	4,72	3,91	3,31	3,22	3,94
Ideal Profile	5	5	4	5	4	4
A1 (GAP)	0	0	0	-1	1	0
A2 (GAP)	-1	0	0	-2	1	-1
A3 (GAP)	0	-2	0	-2	0	0
A4 (GAP)	-1	-1	0	-1	0	-1
A5 (GAP)	-1	0	0	-2	-1	0

c) Conversion of GAP Value to Weight

The GAP value obtained is then converted into a value weight based on the Profile Matching conversion table, where the smaller the difference between the alternative value and the ideal profile, the greater the resulting weight.

Table2 . Conversion of GAP Value to Weight

Alternative	**AI Name**	**C1**	**C2**	**C3**	**C4**	**C5**	**C6**
A1	ChatGPT	5	5	5	4	4,5	5
A2	Gemini AI	4	5	5	3	4,5	4
A3	DeepSeek AI	5	3	5	3	5	5
A4	Claude AI	4	4	5	4	5	4
A5	Blackbox AI	4	5	5	3	4	5

d) Calculation of Core Factor (CF) and Secondary Factor (SF)

Calculation of CF and SF is done by calculating the average value of GAP weights in each Core Factor and Secondary Factor group. C1, C2, and C4 are Core Factors, while C3, C5, and C6 are Secondary Factors.

Table3 . Calculation of Core Factor (CF) and Secondary Factor (SF)

Criteria	C1	C2	C3	C4	C5	C6	CF	SF
ChatGPT	5	5	5	4	4,5	5	4,7	4,8
Gemini AI	4	5	5	3	4,5	4	4,0	4,5
DeepSeek AI	5	3	5	3	5	5	3,7	5,0
Claude AI	4	4	5	4	5	4	4,0	4,7
Blackbox AI	4	5	5	3	4	5	4,0	4,7

e) Calculation of Final Value

The final value is calculated as a result of the combination of CF and SF values according to the predetermined weights to obtain alternative preference values. The weight of CF is 60% while SF is 40%.

Table4 . Calculation of Final Value

Alternative	CF	SF	Final Value
	60%	40%	
ChatGPT	4,7	4,8	4,7
Gemini AI	4	4,7	4,3
DeepSeek AI	4	4,7	4,3
Claude AI	4	4,5	4,2
Blackbox AI	3,7	5	4,2
ChatGPT			

f) Alternative Ranking

The alternative ranking stage is carried out by sorting the final value of each alternative from the highest to the lowest value, where the alternative with the highest final value is declared the best alternative.

Table5 . Alternative Ranking

Alternative	Final Value	Rank
ChatGPT	4,73	1
Gemini AI	4,20	3
DeepSeek AI	4,20	3
Claude AI	4,27	2
Blackbox AI	4,27	2

The results in the alternative ranking table above show that the best alternative AI application is ChatGPT with a value of 4.73, then in the next rank are Claude.AI and Blackbox.AI with a value of 4.27, and in the last rank are Gemini.Ai and Deepseel.AI with a value of 4.20.

5. Conclusion

This study successfully determined the best Ai application among students using the Profile Matching method for alternative ranking analysis. From the analysis results ChatGPT gets the highest score, making it the best AI application. Meanwhile Claude.AI and Blackbox.AI are ranked 2nd and 3rd place is occupied by Gemini.Ai and DeepSeek.Ai. The most influential criteria were Ease of Use, Task Completion Support, and Output Quality & Accuracy. The results of this study provide objective guidance for students in choosing AI applications that suit their needs.

References

Akmaludin, A., Sihombing, E. G., Dewi, L. S., Rinawati, R., & Arisawati, E. (2022). Collaboration of Profile Matching and MCDM-AHP Methods on Employee Selection for Promotion. *SinkrOn*, *7*(2), 321–332. https://doi.org/10.33395/sinkron.v7i1.11203

Crompton, H., & Burke, D. (2023). Artificial intelligence in higher education: the state of the field. *International Journal of Educational Technology in Higher Education*, *20*(1), 22. https://doi.org/10.1186/s41239-023-00392-8

Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., Duan, Y., Dwivedi, R., Edwards, J., & Eirug, A. (2021). Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International Journal of Information Management*, *57*, 101994. https://doi.org/10.1016/j.ijinfomgt.2019.08.002

Fawaid, A., Baharun, H., Hamzah, M., Munawwaroh, I., & Putri, D. F. (2025). AI-based career management to improve the quality of decision making in higher education. *2025 IEEE Integrated STEM Education Conference (ISEC)*, 1–8. https://doi.org/https://ieeexplore.ieee.org/xpl/conhome/11147188/proceeding

Hugo, V. N., Sudipa, I. G. I., Libraeni, L. G. B., Pratistha, I., & Atmaja, K. J. (2026). Decision Model for Best Contraceptive Technique Recommendation Based on Patient's Ideal Profile. *Sinkron: Jurnal Dan Penelitian Teknik Informatika*, *10*(1), 169–180. https://doi.org/https://doi.org/10.33395/sinkron.v10i1.15377

Judijanto, L., Selviana, R., Rahmawati, E., Magdalena, L., Amilia, I. K., Fanani, M. Z., Yusufi, A., Sudipa, I. G. I., Prasetyo, D., & Nampira, A. A. (2025). *Optimalisasi ChatGPT: Panduan dan Penerapan untuk Belajar, Mengajar, dan Membuat Konten Tanpa Batas*. PT. Green Pustaka Indonesia.

Kasneci, E., Seßler, K., Küchemann, S., Bannert, M., Dementieva, D., Fischer, F., Gasser, U., Groh, G., Günnemann, S., & Hüllermeier, E. (2023). ChatGPT for good? On opportunities and challenges of large language models for education. *Learning and Individual Differences*, *103*, 102274. https://doi.org/10.1016/j.lindif.2023.102274

Kraugusteeliana, K., & Violin, V. (2024). Application of Decision Support in Performance Assessment of Delivery Services in the E-Commerce Industry. *Jurnal Galaksi*, *1*(1), 53–61. https://doi.org/10.70103/galaksi.v1i1.6

Liu, Z.-T., Hu, S.-J., She, J., Yang, Z., & Xu, X. (2023). Electroencephalogram emotion recognition using combined features in variational mode decomposition domain. *IEEE Transactions on Cognitive and Developmental Systems*, *15*(3), 1595–1604. https://doi.org/10.1109/TCDS.2022.3233858

Maulidah, S. B. J., Sudipa, I. G. I., Fittryani, Y. P., Widiartha, K. K., & Winatha, K. R. (2024). Determination of MSMEs Business Feasibility Decisions using the Profile Matching Method. *Sinkron: Jurnal Dan Penelitian Teknik Informatika*, *8*(3), 1313–1325. https://doi.org/10.33395/sinkron.v8i3.13638

Muni, G. D. S., Sudipa, I. G. I., Meinarni, N. P. S., Wiguna, I. K. A. G., & Sandhiyasa, I. M. S. (2024). Comparison of MAGIQ, MABAC, MARCOS, and MOORA Methods in Multi-Criteria Problems. *Sinkron: Jurnal Dan Penelitian Teknik Informatika*, *8*(3), 1286–1301. https://doi.org/10.33395/sinkron.v8i3.13639

Pratistha, I., Widiari, N. P. D. S., Dewi, N. L. P. B., Jaya, I. M. K., & Sudipa, I. G. I. (2025). Implementation of Profile Matching Method for E-Wallet Selection Recommendations in Indonesia. *TECHNOVATE: Journal of Information Technology and Strategic Innovation Management*, *2*(3), 112–122. https://doi.org/https://doi.org/10.52432/technovate.2.3.2025.112-122

Putri, N. P. M. E., Sudipa, I. G. I., Wiguna, I. K. A. G., Sarasvananda, I. B. G., & Sunarya, I. W. (2024). Decision Making Model for Temple Revitalization in Bali Using Fuzzy-SMARTER Combination Method. *Sinkron: Jurnal Dan Penelitian Teknik Informatika*, *9*(1), 61–74. https://doi.org/10.33395/sinkron.v9i1.13177

Sudipa, I. G. I., Pandawana, I. D. G. A., & Sandhiyasa, I. M. S. (2025). A Structured Decision Intelligence Framework for Context-Aware Decision Making. *Jurnal Galaksi*, *2*(2 SE-Articles), 61–68. https://doi.org/10.70103/galaksi.v2i2.96

Sudipa, I. G. I., & Sudiani, N. M. (2019). Sistem Pendukung Keputusan Menggunakan Metode Profile Matching Untuk Penentuan Pemberian Kredit (Studi Kasus: KSP Werdhi Mekar Sari Sedana). *Jurnal Sistem Informasi Dan Komputer Terapan Indonesia (JSIKTI)*. https://doi.org/10.33173/jsikti.23

Sudipa, I. G. I., Widiantari, K. P., Radhitya, M. L., Wijaya, B. K., & Joni, I. D. M. A. B. (2024). Dynamic Criteria Decision-Making Model for Business Development Recommendations Using Macbeth and Surrogate Weighting Procedures. *Journal of Computational Analysis and Applications (JoCAAA)*, *33*(05), 38–46.

Thanh, N. Van. (2022). Designing a MCDM model for selection of an optimal ERP software in organization. *Systems*, *10*(4), 95. https://doi.org/https://doi.org/10.3390/systems10040095

Tlili, A., Shehata, B., Adarkwah, M. A., Bozkurt, A., Hickey, D. T., Huang, R., & Agyemang, B. (2023). What if the devil is my guardian angel: ChatGPT as a case study of using chatbots in education. *Smart Learning Environments*, *10*(1), 15. https://doi.org/10.1186/s40561-023-00237-x

Zou, M., & Huang, L. (2023). To use or not to use? Understanding doctoral students' acceptance of ChatGPT in writing through technology acceptance model. *Frontiers in Psychology*, *14*, 1259531. https://doi.org/https://doi.org/10.3389/fpsyg.2023.1259531