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# EVALUATING THE SIGNIFICANCE OF ARTIFICIAL INTELLIGENCE (AI) IN ACADEMIC PLATFORMS BY USING PIPRECIA-S METHOD

**Abstract**

*The purpose of this paper is to determine the importance of artificial intelligence (AI) on academic platforms by utilizing a multi-criteria determination method. The aim is to enhance our understanding of how incorporating AI can enhance the efficacy and effectiveness of the study process. The study employs the Simplified PIPRECIA (Pivot Pairwise Relative Criteria Importance Assessment) method to assess the significance of various factors and characteristics when choosing an academic platform. Five decision-makers conducted a comprehensive literature review to evaluate a list of elements and characteristics of three platforms. The paper begins with an overview of the theoretical foundation and methodology, then presents the research findings and discusses their implications. The results corroborate the relevance of multi-criteria decision-making methods (MCDM) in this context, providing authoritative insights and demonstrating their advantages. The conclusion emphasizes the potential application of these results to make informed choices about academic platform selection, ultimately contributing to improved learning outcomes and research efficiency.*

***Key words:*** *PIPRECIA-S, MCDM, Artificial intelligence (AI), academic platforms.*

***JEL classification: C44, M12***

# ЕВАЛУАЦИЈА ВЕШТАЧКЕ ИНТЕЛИГЕНЦИЈЕ (АИ) НА АКАДЕМСКИМ ПЛАТФОРМАМА ПРИМЕНОМ PIPRECIA-S МЕТОДЕ

**Апстакт**

Сврха овог рада је да се утврди значај вештачке интелигенције (АИ) на академским платформама коришћењем методе вишекритеријумског одређивања. Циљ је да побољшамо наше разумевање како укључивање вештачке интелигенције може побољшати ефикасност и ефективност процеса студирања. Студија користи Симплифиед ПИПРЕЦИА (Пивот Паирвисе Релативе Цритериа Им-

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портанце Ассессмент) метод за процену значаја различитих фактора и карактеристика при избору академске платформе. Пет доносиоца одлука је спровело свеобухватан преглед литературе да би проценило листу елемената и карактеристика три платформе. Рад почиње прегледом теоријске основе и методологије, затим представља налазе истраживања и разматра њихове импликације. Резултати потврђују релевантност метода вишекритеријумског одлучивања (МЦДМ) у овом контексту, пружајући ауторитативне увиде и демонстрирајући њихове предности. Закључак наглашава потенцијалну примену ових резултата за доношење информисаних избора о избору академске платформе, што на крају доприноси побољшању исхода учења и ефикасности истраживања.

Кључне речи: ПИПРЕЦИА С, МЦДМ, Вештачка интелигенција, академске платформе.

## Introduction

Artificial intelligence (AI) has significantly changed academic and research platforms, fundamentally changing several aspects of education and administrative activities (Ahmad et al., 2022). Artificial intelligence (AI) advancements have significantly transformed information development, causing a shift in traditional research methods and opening opportunities for exploration across various disciplines (Lainjo, 2024). As the academic community places more emphasis on achieving efficient outcomes using AI, there are growing concerns about how this may affect knowledge sharing and research progress (Markowitz, 2024). Tang (2023) emphasizes the importance of transparency in academic writing, especially when using generative AI, to uphold scholarly integrity.

The effect of AI expands beyond academics and reaches other businesses, where it improves safety and security in social media and brings about a revolution in online education (Chaiyarak et al., 2022; Hakimi, 2024). In scientific research, AI and machine learning models expedite material development and enable autonomous scientific exploration via self-driving laboratories (Park et al., 2023; Seifrid et al., 2022). Digital platforms utilize artificial intelligence (AI) to improve efficiency and elevate consumer interaction (Brecht et al., 2021).

ResearchGate, Google Scholar, and Semantic Scholar demonstrate the transformative impact of AI-powered platforms on the sharing and accessibility of information in the research community. These platforms provide a diverse range of services, including articles, research papers, and scientific publications, to promote scientific advancement (Fan, 2020). Nevertheless, there are still obstacles to overcome to maximize the effectiveness of AI, improve sophisticated methodologies, and guarantee the transparency of models in academic settings (Ahn & Al, 2024).

To summarize, the rapid progress of AI, driven by extensive data training and hardware advancements, is continuously pushing the development of complex algorithms that impact several areas of human understanding (Taha et al., 2022). The incorporation of artificial intelligence (AI) into academic platforms not only improves research capacities but also presents issues that necessitate ongoing improvement and adjustment in AI applications (Gupta, 2024).

ResearchGate, Google Scholar, and Semantic Scholar are significant digital platforms that serve as important online academic networks. These platforms are vital in promoting collaboration among researchers, facilitating the sharing of data, organizing research projects, and improving scholarly communication (Brack et al., 2020). These platforms, which have a large number of members, offer opportunities for academics to exchange articles and data material and interact with a wide audience (Flanagin et al., 2023). Google Scholar is a popular academic search engine that catalogs a vast number of scholarly publications from different fields of study. It provides a user-friendly interface and a large collection of academic materials (Greenberg, 2020). Semantic Scholar is a research tool that uses artificial intelligence, namely natural language processing and machine learning, to improve the search and retrieval features of scholarly papers (Chu et al., 2022).

The incorporation of artificial intelligence (AI) into systems such as Google Scholar and Semantic Scholar has fundamentally transformed the manner in which academics get and engage with scholarly literature (Hsu, 2023). These platforms, through the use of AI and machine learning, have the capability to offer scholars scientific literature that is both more pertinent and easily accessible. This, in turn, assists in the process of scientific discovery and the diffusion of knowledge (Shehata & Fatouh, 2021). Semantic Scholar is notable for its AI-powered structure, which allows for sophisticated understanding of research papers and grants access to a vast collection of scholarly publications, such as conference proceedings and journals (Maatouk, 2022). The platform's dedication to guaranteeing prompt and effective services for the research community highlights the significance of AI in enhancing scholarly search experiences (Lainjo & Tsmouche, 2023).

Although AI shows potential for improving research procedures and academic communication, there remain obstacles concerning trust and comprehension among users (Cao et al., 2021). Researchers' understanding of the regulations and techniques related to AI systems may be lacking, which raises worries about the dependability and ethical consequences of AI-based platforms (Kostagiolas et al., 2020). To promote higher adoption and utilization of AI technologies among researchers, it is essential to tackle trust issues and increase awareness of the potential and limitations of AI in academic contexts (Thomas et al., 2023).

Academic publishing is developing AI applications to enhance process efficiency and increase productivity (Ezenwoke & Emebo, 2020). Authors and publishers are using AI models to assist in tasks like content production, peer review, and data analysis, aiming to reduce human involvement and enhance productivity (Janssen et al., 2020). AI can help academics streamline their publication workflow by automating specific tasks. This includes reducing redundancy, enhancing data accessibility, and optimizing the distribution of scholarly work (Al-Kadhimi et al., 2023). However, the incorporation of AI in academic writing raises significant ethical, prejudice, and transparency concerns that require meticulous resolution (Heidari et al., 2021).

AI's influence on scholarly literature is significant, as AI technologies are shaping the methods of conducting, publishing, and accessing research (D'Souza et al., 2021). The academic ecosystem is adapting to include advanced AI solutions, such as AI-driven search engines and AI-authored material, which present novel opportunities for the exploration and sharing of knowledge (Can et al., 2021). To effectively utilize AI technology in their scholarly pursuits, researchers and academics must remain updated on the newest advancements in AI tools and platforms (Wright, 2024).

ResearchGate, Google Scholar, and Semantic Scholar are essential resources for researchers and academics. They provide opportunities for cooperation, data sharing, and scholarly communication (Bah & Artaria, 2020). The incorporation of artificial intelligence (AI) into platforms such as Google Scholar and Semantic Scholar has fundamentally transformed the process of searching for and retrieving scholarly material. Researchers have access to a diverse array of academic resources because numerous sources have been integrated (Marar, 2024). To enhance their capacity to explore and assess these resources, academics can employ systematic methods for making decisions, such as the PIPRECIA method established by Stanujkic et al. According to Mladenović et al. (2022), implementing AI in academic settings requires addressing trust concerns and boosting comprehension of its potential.

MCDM has been used to solve a various of problems in different areas (Tomašević et al., 2020; Stanujkić et al., 2021; Karabasevic et al., 2019; Stanujkic et al., 2017). Hadad (2023) has illustrated that this approach is applicable in a variety of contexts, such as learning assessments. The Simplified PIPRECIA Method assists decision-makers in comprehending the influence of many factors, which ultimately results in the facilitation of decisions that are more properly informed. Aytekin (2022) demonstrated the applicability of the fuzzy PIPRECIA approach in the selection of vehicle monitoring systems, highlighting its efficacy in decision-making. In addition, the advancement of AFL through platforms such as Educandy, as emphasized by Maryanti et al. (2022), showcases the capacity of technology-enhanced learning approaches to promote educational achievements and student involvement.

Zhang (2022) investigates the correlation between deep learning ideas in education and systematic assessment and decision-making procedures, such as those supported by PIPRECIA. These techniques prioritize the use of effective learning mechanisms, which in turn leads to improved educational outcomes. According to Petrović et al. (2019), multi-criteria decision-making approaches (MCDM) like PIPRECIA and ARAS assist decision-makers in impartially assessing options using several criteria. Jocic et al. (2020) evaluated the efficacy of PIPRECIA and ARAS in selecting e-learning courses while guaranteeing alignment with established criteria and learning objectives. This study emphasizes the effective use of PIPRECIA in educational decision-making processes. Zhang (2022) explores the utilization of Piaget's ideas in scientific education, highlighting the significance of constructivist methods that are in line with systematic evaluation and decision-making principles. This method emphasizes the importance of active learning and direct experience in obtaining information.

Hadad et al. (2023) applied the simplified PIPRECIA method to assess and prioritize students according to their learning evaluations. This study provided evidence of the effectiveness of PIPRECIA in objectively and comprehensively evaluating learning outcomes and student performance.

Jirasatjanukul (2023) conducted research on novel educational approaches, including cloud-based constructivism and networked learning. The study proposed that the use of structured decision-making methodologies, such as PIPRECIA, might improve the implementation and evaluation of these models. Verna (2020) highlighted the significance of adaptation in both learning and teaching approaches. The study underscored the importance of employing comprehensive teaching approaches, supported by systematic decision-making procedures like PIPRECIA. This approach is essential for maximizing educational results and meeting the different learning demands of students. Schoors et al. (2021) conducted a systematic review of digitally customized learning, emphasizing the importance of identifying the distinctive characteristics of students. PIPRECIA uses criteria-based evaluation to tailor learning experiences to individual needs. Ranjbaran (2022) investigated the shift from traditional classroom lectures to blended learning environments that use digital technologies. The study highlighted the need for employing innovative teaching methods and suggested that PIPRECIA might aid in the selection of appropriate educational instructional strategies, ensuring a comprehensive and effective approach. Samani et al. (2022) investigated the use of emotional learning analytics to improve student engagement. Their study showed the efficacy of data-driven approaches such as PIPRECIA in enhancing learning experiences by using emotional responses, hence promoting more student engagement and satisfaction. Nahum (2022) prioritized the development of 21st-century abilities in education, highlighting the importance of employing diverse teaching methods. This notion is in line with PIPRECIA S systematic evaluation and decision-making procedures, which help educators create approaches that foster important abilities in pupils. In conclusion, using PIPRECIA and related decision-making methods in schools is a structured way to evaluate and improve many aspects of teaching and learning. These solutions offer instructors the information to make educated judgments, resulting in improved educational results and a more streamlined learning environment.

Various business and research domains, including PIvot Pairvise Relative Criteria Importance Assessment (PIPRECIA), have employed MCDM approaches. These methodologies provide an impartial and systematic assessment of choices, considering several factors (Petrović et al., 2019; Ćirić et al., 2020). The MCDM writers have employed these methodologies to address several challenges in the field of tourism (Lin 2020; Yang et al., 2020). Numerous domains, including hospitality, tourism (Stanujkić et al., 2021), information technology, user satisfaction evaluation (Stanujkić et al., 2019), quality assessment of e-learning materials (Jaukovic Jocic et al., 2020), personnel selection (Popović et al., 2021; Ulutaş et al., 2020), employee motivation (Đukić, T., 2022), the aviation industry (Bakir et al., 2020), and transport company selection problem-solving (Ulutaş et al., 2021), have applied the PIPRECIA method. The goal of this study is to establish the primary elements and standards used in the process of selecting human resources using the PIPRECIA method.

## Method

Stanujkic et al. facilitate the definition of importance in group decision-making using the PIPRECIA method. Kersuliene et al. initially devised the SWARA method, which was perceived as deficient in its ability to pre-sort criteria according to their anticipated significance.

PIRECIA method can be illustrated by the following series of steps:

***Step* 1**. Selection of the evaluation criteria where presorting is not mandatory.

***Step* 2**. Determination of the relative importance that begins from the second criterion as follows:

$$s_j : s_j = \begin{Bmatrix} >1 & when & C_j \succ C_{j-1} \\ 1 & when & C_j = C_{j-1} \\ <1 & when & C_j \prec C_{j-1} \end{Bmatrix}. \quad (1)$$

***Step* 3**. Definition of the coefficient in the following way: $k_j$

$$k_j = \begin{cases} 1 & j = 1 \\ 2 - s_j & j > 1 \end{cases} \quad (2)$$

***Step* 4**. Detection of the recalculated value as follows: $q_j$

$$q_j = \begin{cases} 1 & j = 1 \\ \dfrac{q_{j-1}}{k_j} & j > 1 \end{cases} . \quad (3)$$

***Step* 5**. Determination of the relative weights of the estimated criteria by using the following Eq.:

$$w_j = \frac{q_j}{\sum_{k=1}^{n} q_k} , \quad (4)$$

where *wj* represents the relative weight of the criterion *j*.

***Step 6.*** In the case of a larger number of decision-makers, the mean value is taken out of the account using the formula:

$$wj = \frac{\Sigma wj}{n} \quad (5)$$

When $w_j$ * is the average value of $w_j$ of decision-makers, n is the number of decision-makers.

Simplified PIPRECIA (PIPRECIA-S) method

In the PIPRECIA method, the value of *sj* is assigned based on a comparison of the significance of the evaluated criterion with the significance of the previous (j-1) criterion. While using the PIPRECIA method so far, some respondents stated that it would be easier for them to always make comparisons with the first criterion instead of the previous one. To enable this, one adaptation of the PIPRECIA method, named the Simplified PIPRECIA method, is proposed in this article. The change in the way of criteria comparisons was reflected in Eq. (1) and Eq. (3) so that the calculation procedure of the Simplified PIPRECIA method can be presented as follows:

Step 1. Determine the set of evaluation criteria.

Step 2. Set the relative significance $s_j$ of each criterion, except the first, as follows:

$$= \begin{cases} > 1 & if\ C_j > C_1 \\ 1 & if\ C_j = C_1 \\ < 1 & if\ C_j < C_1, \end{cases} \quad (6) \text{ where } j \neq 1.$$

Similar to the PIPRECIA method, the value of $s_1$ is set to 1, while values of $s_j$ belong to the interval (1, 1.9] when $C_j > C_1$,, that is to the interval [0.1, 1) when $C_j < C_1$.

Step 3. Calculate the value of coefficient $k_j$ as follows:

$$k_j = \begin{cases} 1 & if\ j = 1 \\ 2 - s_j & if\ j > 1 \end{cases} . \quad (7)$$

Step 4. Calculate the recalculated weight $q_i$ as follows:

$$q_j = \begin{cases} 1 & if\ j = 1 \\ \frac{1}{k_j} & if\ j > 1 \end{cases} . \quad (8)$$

Step 5. Determine the relative weights of the evaluation criteria as follows:

## Research results and discussion

The purpose of this paper, as previously mentioned, is to identify the significance of elements and characteristics that suggest the significance of platforms for academic learning that incorporate artificial intelligence. This will be achieved through a group of decision-makers who, through scientific research, assess the previously mentioned platforms and the implementation of the method that will prioritize the most critical factors. Table 1 illustrates a variety of characteristics and attributes that are significant to academic learning platforms.

*Table 1. Overview of various elements and characteristics of ResearchGate, Google Scholar, and Semantic Scholar*

| Elements | | Characteristics | |
|---|---|---|---|
| *Rg* 1 | ResearchGate | $Rg_{11}$ | Interactive dashboards |
| | | $Rg_{12}$ | Intuitive profile creation |
| | | $Rg_{13}$ | Follower system, messaging |
| | | $Rg_{14}$ | Project and research group creation |
| | | $Rg_{15}$ | RG score, publication impact |
| | | $Rg_{16}$ | Free paper uploads, full-text access |
| | | $Rg_{17}$ | Engagement analytics, paper impact tracking |
| *Gs* 2 | Google Scholar | $Gs_{21}$ | Basic user interface |
| | | $Gs_{22}$ | Simple search functionality |
| | | $Gs_{23}$ | Citation alerts |
| | | $Gs_{24}$ | Public profile view |
| | | $Gs_{25}$ | Citation count, h-index |
| | | $Gs_{26}$ | Access to open-access papers |
| | | $Gs_{27}$ | Basic metrics, reference management tools |
| *Ss* 3 | Semantic Scholar | $Ss_{31}$ | User-friendly interface |
| | | $Ss_{32}$ | Semantic search features |
| | | $Ss_{33}$ | Connect with authors |
| | | $Ss_{34}$ | Recommendations for collaboration |
| | | $Ss_{35}$ | Citation contexts, influence metrics |
| | | $Ss_{36}$ | Full-text search, millions of papers |
| | | $Ss_{37}$ | AI-driven paper suggestions, citation graph analysis |

*Source: Author's research*

To ensure the most dependable results, the decision-making process includes five decision-makers from various educational backgrounds: the first is a professor, then two doctoral students, the fourth is a primary researcher, and the fifth is a master's student. The significance of fundamental cognitive abilities will be determined by the formulas (1) – (6). Table 2 presents the obtained results.

*Table 2. The relative importance of elements group*

| | $D_{prof}$ | $D_{phd}$ | $D_{phd}$ | $D_{rc}$ | $D_{msc}$ | $Wj^*$ |
|---|---|---|---|---|---|---|
| $Rg_{1}$ | 0.38 | 0.37 | 0.34 | 0.39 | 0.35 | 0.36 |
| $Gs_{2}$ | 0.35 | 0.30 | 0.29 | 0.35 | 0.37 | 0.33 |
| $Ss_{3}$ | 0.27 | 0.34 | 0.35 | 0.26 | 0.27 | 0.30 |

*Source: Author's research*

Formula (5) was applied to calculate the mean value of the received weights to reduce the subjectivity of decision-makers and identify the most pertinent results. $Gs_{2}$ - Google Scholar is the most significant, while $Ss_{3}$ - Semantic Scholar is the least significant, according to the results obtained.

According to Table 1, it is apparent that each aspect has multiple elements. As a result, the next step of the study will be to determine the relative significance of these factors, as indicated in Tables 3–6.

*Table 3. Weights of the platform ResearchGate*

| | $D_{prof}$ | $D_{phd}$ | $D_{phd}$ | $D_{rc}$ | $D_{msc}$ | $Wj^*$ |
|---|---|---|---|---|---|---|
| $R_{g1}1$ | 0.08 | 0.12 | 0.13 | 0.13 | 0.08 | 0.11 |
| $Rg_{12}$ | 0.12 | 0.12 | 0.13 | 0.13 | 0.12 | 0.12 |
| $Rg_{13}$ | 0.12 | 0.12 | 0.11 | 0.10 | 0.12 | 0.11 |
| $Rg_{14}$ | 0.14 | 0.14 | 0.13 | 0.12 | 0.14 | 0.13 |
| $Rg_{15}$ | 0.15 | 0.14 | 0.14 | 0.12 | 0.15 | 0.14 |
| $Rg_{16}$ | 0.17 | 0.17 | 0.16 | 0.15 | 0.17 | 0.16 |
| $Rg_{17}$ | 0.22 | 0.21 | 0.18 | 0.24 | 0.22 | 0.21 |

*Source: Author's research*

From the results obtained, the most significant characteristic of the Research Gate platform is $Rg_{17}$ - engagement analytics, which tracks the impact of papers. This feature is particularly important for individuals who participate in scientific research. The least significant characteristic, $Rg_{11}$ - Interactive dashboards and $Rg_{13}$ - Follower system, messaging.

*Table 4. Weights of the platform Google Scholar*

| | $D_{prof}$ | $D_{phd}$ | $D_{phd}$ | $D_{rc}$ | $D_{msc}$ | $Wj^*$ |
|---|---|---|---|---|---|---|
| $Gs_{21}$ | 0.15 | 0.16 | 0.14 | 0.14 | 0.16 | 0.15 |
| $Gs_{22}$ | 0.15 | 0.12 | 0.14 | 0.13 | 0.13 | 0.13 |

| | | | | | | |
|---|---|---|---|---|---|---|
| $Gs_{23}$ | 0.15 | 0.12 | 0.12 | 0.13 | 0.10 | 0.12 |
| $Gs_{24}$ | 0.15 | 0.13 | 0.14 | 0.13 | 0.13 | 0.14 |
| $Gs_{25}$ | 0.12 | 0.13 | 0.14 | 0.14 | 0.13 | 0.13 |
| $Gs_{26}$ | 0.12 | 0.15 | 0.15 | 0.16 | 0.15 | 0.15 |
| $Gs_{27}$ | 0.14 | 0.19 | 0.19 | 0.18 | 0.19 | 0.18 |

*Source: Author's research*

The results indicate that the most significant characteristic of the Google Scholar platform is $Gs_{27}$ - Basic metrics and reference management tools. The least significant characteristic is $Gs_{23}$ - Citation Alerts.

*Table 5. Weights of the platform Semantic Scholar*

| | $D_{prof}$ | $D_{phd}$ | $D_{phd}$ | $D_{rc}$ | $D_{msc}$ | *Wj** |
|---|---|---|---|---|---|---|
| $Ss_{31}$ | 0.16 | 0.14 | 0.15 | 0.13 | 0.17 | 0.15 |
| $Ss_{32}$ | 0.16 | 0.15 | 0.12 | 0.13 | 0.13 | 0.14 |
| $Ss_{33}$ | 0.14 | 0.15 | 0.18 | 0.11 | 0.09 | 0.13 |
| $Ss_{34}$ | 0.17 | 0.18 | 0.18 | 0.13 | 0.12 | 0.15 |
| $Ss_{35}$ | 0.12 | 0.13 | 0.15 | 0.14 | 0.12 | 0.13 |
| $S_{s3}6$ | 0.10 | 0.10 | 0.11 | 0.16 | 0.14 | 0.12 |
| $Ss_{3}7$ | 0.14 | 0.15 | 0.12 | 0.18 | 0.23 | 0.16 |

*Source: Author's research*

The results indicate the most significant characteristic of the Semantic Scholar platform is $Ss_{37}$ which includes AI-driven paper suggestions and citation graph analysis. This feature is especially significant for people who take part in scientific research since it allows them to contribute. The feature that is the least important is $Ss_{36}$ which allows for full-text searches on millions of documents.

## Conclusion

The results of this research demonstrate the significance of using multiple decision criteria (MCDM) approaches to assess artificial intelligence on academic platforms. The simplified PIPRECIA approach was utilized to acquire relevant findings that validate the importance of important characteristics and factors in the selection of ResearchGate, Google Scholar, and Semantic Scholar platforms. ResearchGate stands out for its engagement analytics and paper impact tracking, which are crucial for scholars seeking to track and improve their academic influence. The primary determinant of the ResearchGate platform's effectiveness is Rg17, a collection of engagement analytics that tracks the influence of publications. This knowledge is critical for scientists conducting research. The interactive interfaces and the messaging system for followers, Rg11 and Rg13, have minimal impact. Google Scholar's user-friendly interface and efficient search capabilities were the main factors that led to its recognition as the most prominent platform, as indicated by the significance assigned to different elements and criteria. The weights assigned to key characteristics determined Google Scholar as the most significant platform, with a weight of 0.33. The most crucial elements of the Google Scholar platform are the simplicity of its design and the effectiveness of its search functionality. The factor weights ranged from 0.12 to 0.19, with core metrics and reference management tools being the most influential ones. Semantic Scholar was assigned a weight of 0.30, which was the lowest of all the weights. Despite this, the Semantic Scholar Platform showed noticeable changes in the weight of its parts. The most important ones were Ss37 - AI-powered paper suggestions and citation graph analysis. Despite ranking as the least significant in the overall classification, Semantic Scholar shows promise by utilizing artificial intelligence to provide article suggestions and analyze citation graphs.

In summary, the methodology used demonstrated its usefulness and feasibility in this field's decision-making process. Future studies should concentrate on evaluating and rating certain influential elements. The study illustrates that the utilization of artificial intelligence on academic platforms significantly improves the effectiveness and pertinence of searching for scientific papers.

This research shows that the use of structured approaches, like PIPRECIA, can greatly improve and facilitate the decision-making process in academic research. In future research, it would be beneficial to broaden the evaluation to include additional academic platforms and tools. Furthermore, a more comprehensive analysis of individual factors and their associations with research success should be conducted.

The assessment criteria should be consistently checked and modified to guarantee their pertinence in a scientific research setting that is progressively evolving. Here is the suggested course of action for future work. By adopting this approach, the platforms will be capable of providing their customers with even better services, making it easier to find, analyze, and make use of scientific information efficiently.

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