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(JISTM)**www.gaexcellence.com/jistm**EVALUATING DRIVERS OF AI WRITING TOOL
ADOPTION AMONG UNDERGRADUATES AT UITM
NEGERI SEMBILAN: AN EWM-DEMATEL APPROACH**

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Abstract:

Academic writing and completing assignments can be challenging for undergraduate students, particularly when they are required to use disciplinary vocabulary, organize their ideas coherently, and apply analytical reasoning beyond basic coursework. With the growing availability of artificial intelligence (AI) writing assistance tools, students can now obtain writing-related support whenever they need it. However, the factors that influence students' use of these tools and the relationships among these factors are still not well understood. Therefore, this study examined the factors that drive undergraduates to use AI writing assistance tools. The study focused on students from the Faculty of Computer and Mathematical Sciences (FSKM) at Universiti Teknologi MARA (UiTM) Seremban Campus, Malaysia. An integrated Entropy Weight Method (EWM) and Decision-Making Trial and Evaluation Laboratory (DEMATEL) approach was used to examine the eight identified adoption drivers. EWM was used to determine the objective weights of the criteria based on the variation in students' responses, while DEMATEL was used to examine the causal relationships among the drivers. Data was collected through a structured

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questionnaire from 27 undergraduate students who reported using AI writing tools on a daily basis and were therefore selected as the experts for this study. The results showed that Security and Privacy was the highest-ranked driver (Rank 1) and was classified as a Cause driver. This was followed by Learning Support and Motivation (Rank 2) and Cost and Value (Rank 3), which were also classified as Cause drivers. In contrast, Ease of Use (Rank 6) and Accessibility (Rank 8) were classified as Effect drivers. This suggests that students' expectations regarding usability and accessibility may be influenced by more fundamental concerns related to trust, educational support, and perceived value. Overall, the findings indicate that institutions should pay attention not only to the usability of AI writing tools but also to the underlying factors that shape students' willingness to use them. The findings may help e-learning designers and higher education administrators identify areas that require greater attention when developing policies and support for the responsible use of AI writing assistance tools.

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DEMATEL, EWM, AI in Higher Education, Technology Adoption, Undergraduate



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Introduction

Academic writing and completing assignments can be challenging for undergraduate students, particularly for those who use English as a second language. Students may struggle with grammar and language use, limited vocabulary, organizing their ideas clearly, and managing time when completing writing tasks. These difficulties may continue even after students have completed formal writing courses (Al Marwani, 2020; Jimenez et al., 2024). The challenge becomes greater when students are expected to paraphrase and summarize information, as well as critically evaluate and integrate ideas from multiple sources across different types of assignments (Al Marwani, 2020).

With the difficulties students face in academic writing, AI writing assistance tools have become an increasingly familiar part of the writing process. Tools such as ChatGPT, Google Gemini, Grammarly, and QuillBot are now used for a range of writing-related tasks, from generating initial ideas and developing drafts to checking grammar and improving written feedback (Aljuaid, 2024; Nguyen et al., 2024). Evidence from Malaysian universities also points to the potential of these tools in supporting students' writing. For example, ChatGPT has been reported to help students improve their vocabulary and grammar while providing personalised feedback that can assist them in developing and organising their ideas (Shah et al., 2025; Yazid et al., 2026). These developments suggest that AI writing tools are becoming more than occasional sources of assistance; for some students, they have become part of how academic

writing is approached and completed. This growing use, however, also brings attention to an important issue: what makes students willing to adopt these tools and continue using them for their academic work? Identifying the factors behind these decisions is therefore important, particularly for higher education institutions that are developing guidance and support for the use of AI in academic settings

Despite the growing use of AI writing assistance tools, it is still unclear which factors are most important in influencing students' decisions to adopt and continue using these tools for their academic work. Previous studies have examined the adoption of AI-based information systems in educational settings and have identified various factors that influence students' adoption decisions. However, many of these studies have focused mainly on identifying or describing these factors, with less attention given to comparing their relative importance or examining how they influence one another (Wiangkham & Vongvit, 2024; Sasikumar & Sunil, 2023). This creates an important gap in understanding AI adoption, as knowing which factors matter is only part of the issue. It is also necessary to understand which factors have greater influence and how they are connected within the adoption process.

The Technology Acceptance Model (TAM) is one of the commonly used models for explaining why users accept and use technology. The model mainly focuses on perceived usefulness and perceived ease of use as key factors influencing technology acceptance. While TAM has been widely applied to different types of software and digital technologies, its traditional focus may not fully reflect the considerations involved in using generative AI tools. Unlike conventional software, generative AI tools interact with user-generated prompts and may involve the processing of personal information and other forms of content through online platforms. As a result, students may also consider issues such as privacy, security, ethical concerns, and the value they gain from using these tools. Recent studies support the view that ease of use alone may not explain students' adoption of AI tools. Pitts and Motamedi (2026) found that perceived ease of use did not have a statistically significant direct effect on students' intention to use AI chatbots when other factors were considered. Similarly, Mustofa et al. (2025) reported that ethical concerns were more strongly associated with students' adoption attitudes than ease of use. These findings suggest that AI adoption involves a wider range of considerations beyond the traditional TAM factors.

To examine these adoption drivers in a systematic way, this study combines two multi-criteria decision-making (MCDM) methods, namely the Entropy Weight Method (EWM) and the Decision-Making Trial and Evaluation Laboratory (DEMATEL). EWM is used to assign objective weights to the eight criteria based on the variation in the collected responses (Zhu et al., 2020), while DEMATEL is used to examine the relationships and causal structure among the criteria (Si et al., 2018). Using the two methods together provides a more complete view of the adoption problem by showing both the relative weights of the criteria and the relationships between them. Therefore, this study evaluates the drivers of AI writing assistance adoption among undergraduate students at Universiti Teknologi MARA Cawangan Negeri Sembilan (UiTCNS), Seremban Campus, Malaysia, using an integrated EWM-DEMATEL approach. Specifically, the study aims to (1) determine the objective weights of the eight identified adoption drivers and (2) examine the causal relationships among these drivers to identify the factors that influence the adoption system. The findings are expected to provide a clearer understanding of the factors underlying students' adoption of AI writing assistance tools and offer useful insights for higher education institutions when developing policies and support for their use.

Literature Review

Theoretical Context: AI vs. Traditional Software Adoption

Using an AI writing tool is not quite the same as using conventional academic software. With most conventional software, students select a function, enter the required information, and obtain an output based on how the software has been designed to work. Generative AI is more interactive. Students decide what to ask, provide the information needed by the tool, and may go through several rounds of prompts before getting an answer that is useful to them. In an academic setting, this can involve entering assignment questions, draft paragraphs, ideas, or other study-related information into an online AI platform. As a result, students may have to think about issues that are less noticeable when using conventional software, such as whether they are comfortable sharing their information, whether they can rely on responses, and whether the benefits of the tool are worth the cost.

This difference is relevant when looking at why students choose to use AI writing assistance. Ease of use and convenience still matter, but they may not tell the whole story. Value-based Adoption Model (VAM) provides a way of looking at adoption by considering what users gain from technology as well as what they give up or risk when using it. In the case of AI writing assistance, the benefits may include learning support, help with writing, and saving time. At the same time, students may have concerns about privacy and security, the reliability of the information produced, or the cost of accessing certain features. These factors can also be connected. For instance, a student who is uncomfortable with how an AI platform handles submitted information may see less value in using the tool, even when the tool is useful and easy to access. Looking at these factors together is therefore important, particularly when the aim is to understand how different drivers are related to students' use of AI writing assistance.

Drivers of AI Writing Assistance Adoption

The use of generative AI among university students has increased, and researchers have started to look more closely at the reasons behind its use. Different studies have focused on different tools and purposes. Wiangkham and Vongvit (2024) examined the adoption of ChatGPT in higher education and used several MCDM methods to assess the factors involved. Sasikumar and Sunil (2023) focused specifically on chatbot selection for academic writing. Their results showed that accuracy, ease of use, and reliability were among the factors considered by students. In another study, Radulescu and Radulescu (2025) examined the use of generative AI in academic research and discussed functionality, data security, and cost. These studies do not point to one common factor behind AI use. Instead, the factors considered by students seem to depend partly on what they use the tool for and what they expect from it. The performance of the tool is one concern, but students may also think about whether it is easy to use, whether they can afford it, and what happens to the information they enter.

Privacy is one issue that students may think about when using generative AI for their studies. Unlike some of the software normally used for university work, AI tools allow users to enter their own text and information into the system. A student may, for example, paste an assignment question, part of a draft, or some ideas into the tool to get suggestions or feedback. This makes the handling of the information entered into the platform an issue worth considering. Ellucian (2026) noted that data protection remains a concern as universities make greater use of AI in

teaching and learning. Chan and Hu (2023) reported a similar concern among students. Their study found that students were aware of privacy, ethical, and data protection issues when using generative AI, although they also recognised that these tools could be useful for their studies.

Apart from the concerns about privacy, students also have practical reasons for using AI writing tools. One of them is the amount of time they can save when working on academic tasks. Previous studies have linked time saving and better productivity with the use of information technologies (Vieriu & Petrea, 2025; Khamesi et al., 2024). For writing tasks, students can also use AI to get comments, suggestions, or ideas while preparing an assignment. Miranda et al. (2025) found that this type of support can help students feel more confident in their academic work. Cost is another point that students may have to think about. Although many AI tools can be used for free, some of the more advanced functions require a subscription. Students therefore may choose to stay with the free version if the additional functions do not seem necessary for their studies. This issue can be more noticeable in developing countries, where financial constraints may affect the choice between free and paid AI services (Miranda et al., 2024; Aldreabi et al., 2025). Overall, the previous studies cover both sides of the issue: students can benefit from the help provided by AI, but they also have to consider what they are comfortable sharing and whether the available benefits are worth the cost.

Looking across the previous studies, students appear to consider several things when using AI writing assistance. Ease of use, usefulness, reliability, learning support, security and privacy, and cost have all been discussed in the literature, but they have not received the same level of attention. Ease of use, usefulness, and reliability, for example, have been examined in several studies, while security and privacy, cost and value, and learning support are less often considered together in studies of AI writing assistance. Another issue is the relationship between these factors. Many studies focus on identifying which factors students consider or on ranking them, but this does not tell us much about whether one factor may be connected to or influence another. This is relevant because students' views of one aspect of an AI tool may depend on other aspects of the same tool. The present study therefore considers eight drivers identified from the literature and examines them in two ways: EWM is used to determine the weight based on variation in the responses, while DEMATEL is used to examine the relationships among the drivers. The eight drivers selected for the study are shown in Table 1.

Table 1: Identified Drivers and Supporting Literature

ID	Driver	Description	Sources
D1	Ease of Use	Easy to learn and operate without extensive technical skills	Sasikumar & Sunil (2023); Radulescu & Radulescu (2025)
D2	Accessibility	Accessible anytime and anywhere via digital platforms	Wiangkham & Vongvit (2024); Radulescu & Radulescu (2025)
D3	Security & Privacy	Protects user data and ensures confidentiality of submitted content	Chan & Hu (2023); Wu et al. (2024); Ellucian (2026); Radulescu & Radulescu (2025)
D4	Trust & Reliability	Perceived as dependable and consistent in outputs	Sasikumar & Sunil (2023); Radulescu & Radulescu (2025)

ID	Driver	Description	Sources
D5	Accuracy & Quality	Provides grammatically correct and relevant writing suggestions	Sasikumar & Sunil (2023); Radulescu & Radulescu (2025)
D6	Time Saving & Productivity	Helps complete writing tasks faster and more efficiently	Vieriu & Petrea (2025); Khamesi et al. (2024)
D7	Cost & Value	Provides good value relative to cost or subscription fees	Miranda et al. (2024); Aldreabi et al. (2025); Radulescu & Radulescu (2025)
D8	Learning Support & Motivation	Supports learning by providing feedback, explanations, and motivation	Miranda et al. (2025); Vieriu & Petrea (2025).

Decision-Support Techniques for Technology Adoption Evaluation

Although previous studies have identified a number of factors related to AI adoption, there is still less understanding of how these factors relate to one another. Most studies focus on identifying the factors that influence students' use of AI or on ranking them based on their responses. This tells us what factors are present but gives less indication of how the factors may influence each other. For example, a student's concern about privacy may be related to how much value they see in using an AI tool, while the perceived value of the tool may also depend on the support it provides for learning. Looking at the factors separately may therefore overlook some of these relationships. A clearer picture can be obtained by considering both the weight of each factor and the way the factors are connected. This provides the basis for using EWM and DEMATEL in the present study to examine the eight identified drivers of AI writing assistance adoption.

MCDM methods provide a useful way to look at this issue from a different angle. In particular, the Entropy Weight Method (EWM) can be used to assign weights to the criteria based on the variation in the respondents' ratings. A criterion with greater variation provides more information for distinguishing between the criteria and, as a result, receives a higher EWM weight (Zhu et al., 2020). The method has been used in a range of areas, including risk assessment, environmental evaluation, and educational technology, partly because it does not require subjective weighting by the researcher. However, EWM has its limits. The weights are derived from differences in the data and do not show whether one criterion influences another. Thus, a higher EWM weight should not automatically be taken to mean that the criterion has greater influence within the adoption process. This distinction is important in the present study because understanding the factors involved in AI writing assistance adoption requires not only looking at differences in the respondents' ratings but also considering how the factors are related to one another.

DEMATEL was introduced by Gabus and Fontela (1972) to study the relationships between different factors. In this study, it is used together with EWM because EWM only gives the weight of each criterion based on the variation in the responses. DEMATEL, on the other hand, looks at how the criteria are related and whether one criterion has more influence on another. It considers both direct and indirect relationships between the criteria. The DEMATEL results divide the criteria into two groups, namely Cause and Effect. A criterion is included in the Cause group when its influence on the other criteria is greater than the influence it receives. In

comparison, a criterion is placed in the Effect group when it receives more influence from the other criteria than it gives to them (Si et al., 2018). This distinction is useful for the present study because the eight AI writing assistance drivers may not have the same type of relationship. Some drivers may influence several other factors, while some may mainly be affected by them. Therefore, DEMATEL provides additional information that cannot be obtained from the EWM weights alone.

EWM and DEMATEL provide different types of information, so using them together can be useful when several adoption factors need to be considered. EWM shows how much the responses vary across the criteria, while DEMATEL looks at the relationships between those criteria. Although both methods have been used in different areas of decision-making, their combined use in studies of AI writing assistance adoption appears to be limited. To the best of the authors' knowledge, there is also no study that has used EWM and DEMATEL together to examine AI writing assistance adoption among undergraduate students. Previous studies have generally focused either on ranking adoption factors or on examining the relationships between them. Looking at only one of these aspects leaves part of the picture unexplored. For this reason, the present study brings the two methods together to examine both the differences in students' responses and the relationships among the eight adoption drivers. This approach allows the findings from one method to be considered alongside those from the other when interpreting students' adoption of AI writing assistance.

Methodology

This study employs a quantitative, decision-support research design to evaluate the drivers of AI writing assistance adoption among undergraduate students. Eight drivers were identified through a systematic review of the information systems and educational technology literature on AI adoption, as presented in Table 1. These drivers served as the evaluation criteria for both EWM, and the DEMATEL analyses described in this section

Criteria Selection

For this study, eight drivers were adapted through a systematic review of the literature on AI writing assistance adoption and AI-related MCDM studies. The description of the adapted and adopted drivers presented in Table 2.

Table 2: Identified Drivers and Descriptions

Driver	Description
D1: Ease of Use	AI writing tools are easy to learn and operate without extensive technical skills
D2: Accessibility	AI writing assistance can be accessed anytime and anywhere through digital platforms
D3: Security & Privacy	AI writing tools protect users' data and ensure confidentiality of submitted content
D4: Trust & Reliability	Students perceive AI writing tools as dependable and consistent in their outputs

D5: Accuracy & Quality	AI tools provide grammatically correct, coherent, and relevant writing suggestions
D6: Time Saving & Productivity	AI writing assistance helps students to complete tasks faster and more efficiently
D7: Cost & Value	AI writing assistance provides good value relative to cost or subscription fees
D8: Learning Support & Motivation	AI tools support learning by providing feedback, explanations, and motivation

Data Collection and Screening

A structured questionnaire was administered online via Google Forms to undergraduate students at UiTM CNS, Seremban Campus, who had prior experience using at least one AI writing assistance tool for academic tasks. The questionnaire comprised three sections: (a) demographic and screening items; (b) Likert-scale driver evaluation items ranging from 1 (Strongly Disagree) to 5 (Strongly Agree), which served as the input data for the EWM analysis; and (c) pairwise influence rating items ranging from 1 (low influence) to 3 (high influence), which served as the input data for the DEMATEL analysis.

Unlike subjective weighting methods that depend on expert judgment, EWM derives criterion weights directly from the variability of respondents' ratings (Zhu et al., 2020). Its validity therefore depends on the quality and consistency of respondents' evaluations rather than on their domain expertise, making it appropriate for use with experienced end-users as the primary data source. For DEMATEL, although the method is traditionally associated with expert panels, recent studies have demonstrated its applicability with experienced end-users as respondents in technology adoption contexts, where users possess direct and substantive experience of the system being evaluated (Bi et al., 2024). Additionally, unlike traditional research that needs massive sample sizes, DEMATEL prioritizes deep system knowledge over sheer numbers. Therefore, keeping the sample small and limited to daily users was necessary to maintain data validity.

Entropy Weight Method (EWM)

EWM was implemented through the following three steps.

Step 1: Normalization. Given the decision matrix $X = [x_{ij}]$, where $i = 1, \dots, n$ respondents, i.e., $n = 27$ and, $j = 1, \dots, m$ criteria, i.e., $m = 8$. Each rating is normalized, where:

$$p_{ij} = \frac{x_{ij}}{\sum_{i=1}^n x_{ij}}$$

For example, Respondent 1 rated D3 (Security and Privacy) as 4, and sum of D3 was 89, thus $p_{1,3} = \frac{4}{89} = 0.0449$.

Step 2: Entropy calculation. The entropy value of each criterion (e_j) is computed as:

$$e_j = -k \sum_{i=1}^n p_{ij} \ln(p_{ij}); k = \frac{1}{\ln(n)}$$

Where $k = \frac{1}{\ln(n)} = \frac{1}{\ln(27)} = 0.3034$.

Step 3: Calculating Weight. The final objective weight for each criteria are computed as:

$$d_j = 1 - e_j$$

$$w_j = \frac{d_j}{\sum_{j=1}^m d_j}$$

The higher the weight, the higher discriminatory power among respondents' ratings.

DEMATEL Analysis

DEMATEL was implemented through the following four steps.

Step 1: Direct-relation matrix. Each respondent rated the degree of direct influence of every driver on every other driver, using a scale of 1 (low) to 3 (high), with diagonal values set to zero. These ratings were averaged across all 27 respondents to form the direct-relation matrix A .

Step 2: Normalisation. Matrix A was normalised by the maximum row sum to obtain matrix X :

$$X = \frac{A}{\max \left(\sum_j a_{ij} \right)}$$

Step 3: Total-relation matrix. The total-relation matrix T , capturing both direct and indirect influence, was computed as:

$$T = X(I - X)^{-1}$$

where I is the identity matrix. The row sum (R_i) and column sum (C_i) of T represent the total influence given and received by each driver, respectively.

Step 4: Cause-Effect classification. Prominence and net relation values were computed as:

$$D + R_i = R_i + C_i, D - R_i = R_i - C_i$$

Drivers with $D - R_i > 0$ were classified as Cause drivers; those with $D - R_i < 0$ were classified as Effect drivers.

Integration of EWM and DEMATEL

To synthesize the statistical dispersion obtained from EWM with the causal prominence derived from DEMATEL, the final integrated weight (W_j^{final}) was calculated for each adoption driver using the following formulation:

$$W_j^{\text{final}} = \frac{w_j^{\text{EWM}} \times N(D + R)_j}{\sum_{j=1}^m w_j^{\text{EWM}} \times N(D + R)_j}$$

Where $N(D + R)_j$ represents the normalized DEMATEL prominence score relative to the system total ($\sum D + R$).

Results and Discussion

This section presents the findings derived from the Entropy Weight Method (EWM) and the Decision-Making Trial and Evaluation Laboratory (DEMATEL) analyses, followed by the final integrated ranking of the eight adoption drivers.

Respondent Profile

The study focused on students who were already familiar with AI writing tools because the analysis required respondents to judge the relationships among the selected adoption drivers. From the initial 164 undergraduate students at FSKM, UiTMCNS, only those who reported using AI writing tools on a daily basis were retained for the analysis. This resulted in 27 respondents. Students who did not use AI tools or used them only occasionally were not included, as their limited experience may have made it difficult for them to assess the relationships between the different drivers. The decision to focus on daily users also means that the study does not capture the views of students who rarely use or do not use AI writing tools. However, the selected respondents had regular experience with these tools and were therefore in a better position to provide informed assessments for the DEMATEL analysis.

The profile in Table 3 shows that ChatGPT was used by all 27 respondents (100.0%), followed by Google Gemini (63.0%), QuillBot (55.6%), and Grammarly (51.9%). Many respondents used more than one tool, with general-purpose tools such as ChatGPT and Gemini being used alongside writing-focused tools such as QuillBot and Grammarly. In terms of their main uses, improving grammar and writing quality and generating ideas were the most frequently reported tasks, both at 81.5%. These results show that the respondents were using AI at different points in their academic writing, rather than for a single purpose. Their regular use of several AI writing tools provides a relevant basis for examining how they view the different factors involved in AI writing assistance adoption.

Table 3: Respondent Profile and AI Tool Usage Characteristics (N = 27)

Characteristic	Category	Frequency (n)	Percentage (%)
Faculty / Field	Computer and Mathematical Sciences (FSKM)	27	100
Usage Frequency	Daily / Task-Continuous	27	100
AI Writing Tools Used (<i>Multiple responses allowed</i>)	ChatGPT	27	100
	Google Gemini	17	63
	QuillBot	15	55.6
	Grammarly	14	51.9

Characteristic	Category	Frequency (n)	Percentage (%)
Primary Task Applications (Multiple responses allowed)	Grammar Improvement & Sentence Refinement	22	81.5
	Idea Generation & Brainstorming	22	81.5
	Paraphrasing & Vocabulary Enhancement	18	66.7
	Structuring & Coherence Check	14	51.9

EWM Results

The Entropy Weight Method (EWM) was executed to compute objective weight allocations based on the dispersion of evaluations among the 27 daily AI writing tool users. In information theory, lower entropy values (e_j) indicate higher information dispersion and variability across user responses, thereby yielding a higher objective weight (w_j^{EWM}) and greater discriminatory power.

Table 4 shows that there was a clear difference in the EWM weights for the eight drivers. Security and Privacy (D3) had the highest weight at 0.3414, followed by Learning Support and Motivation (D8) at 0.1654 and Cost and Value (D7) at 0.1276. D3 also had the highest standard deviation (1.2030), meaning that the respondents gave more varied ratings for this factor. As a result, D3 recorded the lowest entropy value (0.9789) and the highest divergence value (0.0211), which gave it the highest EWM weight. D3, D8 and D7 together accounted for 63.44% of the total EWM weight.

For the other drivers, Trust and Reliability (D4) and Accuracy and Quality (D5) received weights of 0.1099 and 0.1054, respectively. The weights for Ease of Use (D1), Accessibility (D2), and Time Saving and Productivity (D6) were much lower, at 0.0510, 0.0497, and 0.0496. These three drivers also had smaller standard deviations, particularly D6 (0.6202). This indicates that the respondents' ratings were more similar for these factors. In contrast, their ratings for Security and Privacy were more widespread. It should be noted that the EWM weight does not directly show how important a driver is to the students. The weight is calculated from the variation in the responses. A higher weight means that there was more variation in the ratings and, therefore, the criterion provided more discriminatory information in the EWM calculation. Thus, the first rank of Security and Privacy should be understood in terms of the differences in the respondents' ratings, rather than as evidence that students considered it more important than the other drivers.

Table 4: Weights and rank of all drivers using EWM

Driver	Mean	SD	e_j	d_j	w_j^{EWM}	Rank
D1: Ease of Use	4.4815	0.6427	0.9968	0.0032	0.0510	6
D2: Accessibility	4.5556	0.6405	0.9969	0.0031	0.0497	7
D3: Security & Privacy	3.2963	1.2030	0.9789	0.0211	0.3414	1
D4: Trust & Reliability	3.8519	0.8182	0.9932	0.0068	0.1099	4
D5: Accuracy & Quality	3.9259	0.8286	0.9935	0.0065	0.1054	5

D6: Time Saving & Productivity	4.3333	0.6202	0.9969	0.0031	0.0496	8
D7: Cost & Value	3.8889	0.8916	0.9921	0.0079	0.1276	3
D8: Learning Support & Motivation	4.2222	1.0127	0.9898	0.0102	0.1654	2

Note: SD-standard deviation

Security and Privacy (D3) had a much higher EWM weight than the other drivers in Table 4, with a value of 0.3414. On the other hand, Ease of Use (D1) and Time Saving and Productivity (D6) had much lower weights, at 0.0510 and 0.0496. However, the lower weights for D1 and D6 do not mean that these aspects were not relevant to the respondents. Both had high mean scores, which shows that the students generally agreed that AI writing tools were easy to use and could help them save time. The main difference can be seen in the spread of their responses. The ratings for D1 and D6 were quite close to each other, while the ratings for D3 varied much more between the respondents. Since EWM gives a higher weight when there is greater variation in the data, D3 obtained a much larger weight.

The respondents in this study were daily users of AI writing tools, so their experience with basic functions such as accessing the tools and using them for writing may already be quite familiar. This could be one reason why their responses to ease of use and time saving were relatively similar. Security and Privacy were different. Some students may be more careful about entering assignment materials, personal information, or other academic content into an AI platform, while others may not have the same level of concern. This difference is reflected in the higher variation of the responses. For this reason, the EWM ranking should not be read as meaning that Security and Privacy is the most important factor for students. The result mainly shows that the responses for this factor were more varied and provided more discriminatory information in the EWM calculation. For FSKM, UiTMNS, this issue may still be worth looking at, especially in providing students with clearer guidance on the type of academic or personal information that can be entered into AI writing tools. At the same time, the high mean scores for Ease of Use and Time Saving and Productivity show that students still viewed these practical benefits positively, even though they received lower EWM weights.

DEMATEL Results

While EWM isolates the objective weight of individual adoption factors based on statistical dispersion, it treats criteria as independent units. To determine how these factors structurally interact within the decision-making process of UiTMNS undergraduates, DEMATEL was applied. Table 5 presents the complete DEMATEL structural metrics and classification for all eight adoption drivers evaluated by UiTMNS undergraduates.

Table 5 presents the DEMATEL results for the eight drivers. Four drivers were placed in the Cause group, namely Cost and Value (D7), Trust and Reliability (D4), Learning Support and Motivation (D8), and Security and Privacy (D3). The other four drivers, Ease of Use (D1), Accessibility (D2), Accuracy and Quality (D5), and Time Saving and Productivity (D6), were classified as Effect drivers. Among the Cause drivers, D7 recorded the highest D-R value at 1.1637, followed by D4 at 0.7874, D8 at 0.7134, and D3 at 0.5236. This means that these four drivers had a greater overall influence on the other drivers than the influence they received from them. Cost and Value therefore had the strongest net causal relationship in the model. This does not necessarily mean that cost was the main reason students used AI writing tools, but it shows that cost and value were more influential in their relationships with the other

factors considered in this study. This may be related to the fact that students can choose between free and paid AI services, with the usefulness of additional features being one consideration when deciding whether a paid option is worthwhile.

Learning Support and Motivation (D8) also showed a positive net relation (0.7134), while its prominence value (D+R) was 40.7891. The result indicates that D8 was closely connected with the other drivers and, at the same time, had a greater outward influence than inward influence. Trust and Reliability (D4) showed a similar pattern, with a positive D–R value of 0.7874. In contrast, Ease of Use (D1) had the highest prominence value (41.5450), but its D–R value was negative (-1.0224). This means that although ease of use was highly connected with the other drivers, it was more influenced by them than it influenced them. Accessibility (D2) showed the same pattern, with a D–R value of -1.1786. Overall, the DEMATEL results show that drivers do not all play the same role in the model. Some factors, particularly Cost and Value, Trust and Reliability, Learning Support and Motivation, and Security and Privacy, have stronger outward relationships, while others are more affected by the relationships among drivers.

Table 5: DEMATEL Structural Prominence, Net Relation, and Causal Groupings

Driver	Ri	Ci	D+R	D-R	Group
D1: Ease of Use	20.2613	21.2837	41.5450	-1.0224	Effect
D2: Accessibility	19.3416	20.5202	39.8618	-1.1786	Effect
D3: Security & Privacy	19.1930	18.6694	37.8623	+0.5236	Cause
D4: Trust & Reliability	19.4537	18.6663	38.1201	+0.7874	Cause
D5: Accuracy & Quality	19.7105	19.7763	39.4868	-0.0658	Effect
D6: Time Saving & Productivity	19.9394	20.8604	40.7998	-0.9211	Effect
D7: Cost & Value	20.2667	19.1030	39.3696	+1.1637	Cause
D8: Learning Support & Motivation	20.7512	20.0379	40.7891	+0.7134	Cause

Four drivers were placed in the Effect group, namely Accuracy and Quality (D5), Time Saving and Productivity (D6), Ease of Use (D1), and Accessibility (D2). Among them, Accessibility had the lowest D–R value (-1.1786), followed by Ease of Use (-1.0224) and Time Saving and Productivity (-0.9211). Although D1 and D2 were classified as Effect drivers, they still had relatively high D+R values of 41.5450 and 39.8618. This means that both factors had many connections with the other drivers in the model. Their negative D–R values only show that the influence they received was greater than the influence they gave to the other factors. The result for Time Saving and Productivity (D6) was similar, with a D–R value of -0.9211. Accuracy and Quality (D5), however, were almost balanced, with a value of -0.0658. The difference between the influence received and given by D5 was therefore much smaller than for the other Effect drivers. This may indicate that students' views about the accuracy and quality of AI-generated output were closely linked with the other factors considered in the study.

The lower position of D1, D2 and D6 should also be considered together with the EWM results. These three drivers received relatively small EWM weights because the respondents' ratings were more similar. At the same time, their DEMATEL results show that they were connected to the other drivers, particularly Ease of Use. For students who already use AI writing tools every day, basic aspects such as ease of access, ease of use and time saving may already be part of their normal experience with these tools. They may still value these aspects, but differences in these factors were less noticeable among the respondents. Hence, the results for the Effect

group mainly show where these drivers sit within the relationships among the eight factors, rather than indicating that they are less useful to students.

Integrated EWM–DEMATEL Evaluation and Structural Driver Hierarchy

Table 6 presents the final ranking after combining the EWM and DEMATEL results. Security and Privacy (D3) remained the top-ranked driver, with an integrated weight of 0.325. Learning Support and Motivation (D8) came next at 0.1696, followed by Cost and Value (D7) at 0.1263. This is in line with the EWM ranking in Table 4, where these three drivers also occupied the first three positions. All three were also classified as Cause drivers in the DEMATEL results. Cost and Value (D7), in particular, had the highest D–R value of 1.1637, showing that it had the strongest net influence among the eight drivers.

The changes were more noticeable, although still small, among the lower-ranked drivers. Accuracy and Quality (D5) remained in fifth place and Ease of Use (D1) remained sixth. Time Saving and Productivity (D6) moved up from eighth in the EWM ranking to seventh in the integrated ranking, while Accessibility (D2) moved from seventh to eighth. D6 had a higher D+R value than D2 (40.7998 compared with 39.8618), which indicates that it was more closely connected with the other drivers. This difference was reflected in the final ranking.

Overall, combining the two results did not change the general pattern. Security and Privacy (D3), Learning Support and Motivation (D8), and Cost and Value (D7) remained the three highest-ranked drivers. Ease of Use (D1), Time Saving and Productivity (D6), and Accessibility (D2) remained towards the lower end of the ranking. The integrated ranking is useful for comparing the driver's using information from both analyses, but it should not be treated as a direct ranking of what students consider important. In particular, the high position of D3 is partly related to the variation in its EWM responses and its Cause position in DEMATEL.

Table 6: Driver's Rank and Group using EWM and DEMATEL

Driver	EWM Method		DEMATEL Method			EWM-DEMATEL	
	EWM Weight (w_j^{EWM})	Rank	Prominence (D+R)	Net Relation (D–R)	Causal Group	Integrated Weight (w_j^{final})	Final Rank
D1: Ease of Use	0.051	6	41.545	-1.0224	Effect	0.0533	6
D2: Accessibility	0.0497	7	39.8618	-1.1786	Effect	0.0498	8
D3: Security & Privacy	0.3414	1	37.8623	0.5236	Cause	0.325	1
D4: Trust & Reliability	0.1099	4	38.1201	0.7874	Cause	0.1053	4
D5: Accuracy & Quality	0.1054	5	39.4868	-0.0658	Effect	0.1046	5
D6: Time Saving & Productivity	0.0496	8	40.7998	-0.9211	Effect	0.0509	7

D7: Cost & Value	0.1276	3	39.3696	1.1637	Cause	0.1263	3
D8: Learning Support & Motivation	0.1654	2	40.7891	0.7134	Cause	0.1696	2

Discussions on EWM-DEMATEL Findings

Security and Privacy (D3) received the highest EWM weight (0.3414) and was ranked first in the integrated results. D3 was also classified as a Cause factor in the DEMATEL analysis. The EWM result is mainly related to the spread of the responses. D3 had the largest standard deviation among the eight drivers, indicating that the respondents were less consistent in their ratings of security and privacy. This is different from factors such as Ease of Use and Time Saving and Productivity, where the responses were more similar. For students using AI writing tools, concerns about privacy may differ depending on what they are willing to enter into an AI platform and how they perceive the handling of their information. The DEMATEL result gives a different view of D3. Its positive D–R value (0.5236) places it in the Cause group, meaning that D3 had a greater influence on the other drivers than the influence it received from them. This does not mean that security and privacy was the main reason for using AI writing tools. Rather, it indicates that this factor had a stronger outward relationship with the other drivers in the model. Similar concerns have been reported in previous studies, where privacy, ethical issues, and data protection were identified in relation to students' use of generative AI (Chan & Hu, 2023; Ellucian, 2026; Wu et al., 2024). The combination of the EWM and DEMATEL results is worth noting. The responses differed most for Security and Privacy, while the DEMATEL analysis also placed it among the factors that influence the other drivers. For the students in this study, security and privacy were therefore not simply another feature of an AI writing tool. Their responses show that students had different views on this issue, and its relationship with the other adoption drivers was also stronger than for some of the other factors.

Learning Support and Motivation (D8) ranked second and was classified as a Cause factor. Students may be looking to AI writing tools for more than help with producing a piece of writing. The tools can also be used when they need ideas, feedback, or directions while working on an assignment. This is broadly consistent with Miranda et al. (2025) and Nguyen et al. (2024), who reported positive associations between AI writing support, students' self-efficacy, and engagement. Cost and Value (D7) ranked third and was also classified as a Cause factor. It recorded the highest net causal score in the DEMATEL analysis. The cost of using AI tools is therefore worth considering, particularly where some functions are only available through paid plans. For students, choosing between a free version and a subscription may depend on whether the additional features are actually useful for their academic work. Previous studies have also noted the tendency of students and other users to rely on free-tier AI services because of financial constraints (Miranda et al., 2024; Aldreabi et al., 2025). The results for D8 and D7 point to two fairly practical considerations in students' use of AI writing assistance: whether the tool helps them with their learning and whether what they get from it is worth paying for.

Ease of Use (D1) and Accessibility (D2) were ranked sixth and eighth, respectively, in the integrated results, and both were classified as Effect drivers. Interestingly, the two criteria had the highest mean agreement scores, while their standard deviations were relatively small. Most of the respondents therefore gave similar and positive responses to these two aspects of AI writing tools. This also helps explain their lower EWM weights, since there was little difference

in the responses for these criteria. The DEMATEL results add another point to this finding. Both D1 and D2 were placed in the Effect group, meaning that changes in these criteria are more closely associated with the other drivers in the model than with direct causal influence on them. Since all respondents were daily users of AI writing tools, their familiarity with the tools may partly explain why ease of use and accessibility did not stand out in the results. A similar pattern was reported by Pitts and Motamedi (2026), who found that perceived ease of use was not a significant predictor of students' intention to use AI chatbots after other factors were taken into account. In the present study, this does not mean that ease of use and accessibility are unimportant. Rather, the results indicate that these two aspects may have less influence on the differences in adoption decisions among students who are already familiar with AI writing tools.

Although the EWM-DEMATEL analysis provides useful insights into the relationships among the AI adoption drivers, the findings should be considered in light of the characteristics of the respondents. The study involved 27 daily users of AI writing tools from FSKM at UiTM CNS, Seremban Campus. Since these students are studying in a technology-related field, their experience with digital technologies may differ from that of students from other faculties. In particular, they may be more familiar with software applications and may have greater awareness of issues related to cybersecurity and data privacy. This could partly explain why ease of use was not a major concern among the respondents. Their responses may therefore not fully represent students from non-technical disciplines, who may have different levels of digital experience and different concerns when using AI writing tools. Future studies could extend the analysis to students from other faculties and compare the resulting causal structures. Such comparisons would help determine whether Security and Privacy remains a prominent driver of AI writing assistance adoption across different student groups.

Conclusion and Recommendations

This study examined eight drivers related to the use of AI writing assistance among 27 undergraduate students at FSKM, UiTM CNS, Seremban Campus. The findings show that the drivers did not play the same role in the analysis. Security and Privacy (D3) was ranked first in the final results and was also classified as a Cause factor. Learning Support and Motivation (D8), Cost and Value (D7), and Trust and Reliability (D4) were also in the Cause group. The other four drivers, namely Ease of Use (D1), Accessibility (D2), Accuracy and Quality (D5), and Time Saving and Productivity (D6), were classified as Effect factors.

Security and Privacy (D3) was the most noticeable result. It received the highest EWM weight because the students' ratings for this factor varied more than the ratings for the other drivers. Thus, the result should not be taken to mean that privacy was the main concern for every student. D3 was also classified as a Cause factor in the DEMATEL analysis. Cost and Value (D7) had the highest D-R value, followed by Trust and Reliability (D4), Learning Support and Motivation (D8), and Security and Privacy (D3). This shows that these factors had more influence on the other drivers than they received from them. The remaining factors were more influenced by the relationships among the drivers.

The results also show that students' use of AI writing tools is not simply related to ease of use or saving time. Other matters, such as learning support, cost, trust, and the information shared with the AI platform, also need to be considered. This may be relevant to FSKM and UiTMNS when supporting students who use AI for academic work. Besides providing access to AI tools,

students should have clear guidance on their appropriate use. In particular, they should know what personal or academic information is suitable to share with AI platforms and how AI-generated content should be used in their own work.

There are some limitations to this study. The sample was small, with only 27 students, and all respondents were daily users of AI writing tools from one faculty and one campus. Students who rarely used AI or did not use it were not included. The findings therefore may not represent the views of other groups of students or the wider UiTM population. Future studies could involve students from different faculties and universities and include users with different levels of AI experience. This would allow further comparison of whether factors such as privacy, cost, learning support, and trust have similar relationships among different groups of students.

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