Applied Quantitative Analysis, Vol. 5 No. 1 (2025) https://doi.org/10.31098/quant.3554

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Research Paper

Prompt Engineering, AI, and e-Catalog in Proposal Writing: A PLS-SEM Approach

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Received : June 23, 2025	Revised : July 16, 2025	Accepted : September 08, 2025	Online : September 08, 2025

Abstract

This study investigates what influences individuals' confidence in their ability to develop compelling grant proposals, with a special emphasis on the moderating effect of previous proposal-writing experience. It evaluates four main factors: the use of emerging AI technologies, proficiency in prompt engineering, digital literacy levels, and the functionalities provided by the e-Catalog system on the BIMA platform. Applying a quantitative method and analyzing data through Applying a quantitative method and analyzing the data using Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS 3, the study found thatwith SmartPLS 3, the research found that none of the four independent variables (X_1–X_4) had a statistically significant direct influence on perceived proposal-writing competence ($p > 0.05$). In contrast, prior experience in crafting proposals significantly influenced the outcome variable ($\beta = 0.438$, $p < 0.01$). These results emphasize that while digital tools and AI skills may support the process, they are insufficient in building self-assurance in grant writing without substantial practical experience. Therefore, initiatives aiming to improve grant-writing proficiency should emphasize experiential learning and applied practice. This research contributes to the broader conversation on digital governance by underscoring the value of experience in enhancing bureaucratic expertise and individual professional capacity.

Keywords: *Grant Writing Competence, AI In Proposal Development, Digital Capability, BIMA E-Catalog, Practical Experience*

INTRODUCTION

Every year, the Ministry of Higher Education, Science, and Technology of Indonesia (Kemdiksaintek) organizes a competitive grant program for research and community service aimed at improving the quality and impact of higher education. This national initiative promotes not only innovation and scientific inquiry but also encourages lecturers to engage in community-based solutions that address real societal needs. To participate, lecturers must fulfill several administrative and academic requirements, including holding a valid National Lecturer Identification Number (NIDN) and having an active SINTA (Science and Technology Index) score as a measure of publication productivity and research engagement.

Despite the growing demand for high-quality proposals, many lecturers continue to face challenges in preparing documents that meet evaluative standards and align with funding requirements. These difficulties persist even as the digital era provides access to a wide array of technological tools designed to enhance academic productivity. In particular, Artificial Intelligence (AI) tools, such as Deepseek, Blackbox, and Neverask, have emerged as transformative platforms that can assist researchers in drafting more structured, coherent, and compelling proposals. However, the effective use of these tools hinges upon a relatively new yet essential skill: Prompt Engineering Literacy, or the ability to construct precise and goal-oriented inputs to optimize AI

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outputs (Maharjan, 2024; Cain, 2024; Park, 2023).

Simultaneously, the Indonesian Ministry has developed the BIMA (Belmawa Integration Management Application), a web-based system that not only collects proposal submissions but also integrates an e-catalog of research clusters, partner institutions, and previously funded proposals. This e-catalog serves as a crucial resource for benchmarking, aligning topics with national priorities, and increasing the strategic value of proposal submissions. While both Prompt Engineering and e-Catalog utilization have the potential to significantly enhance proposal quality, their successful application depends on the digital literacy of lecturers. Existing studies highlight the importance of digital competencies in higher education, yet few have explored how these specific tools intersect in the context of competitive grant writing in developing countries. Moreover, although AI is increasingly integrated into academic writing and research support (Dwivedi et al., 2023), there is limited empirical evidence on its impact when mediated by user experience, particularly among Indonesian lecturers.

This study aims to fill that gap by examining the relationships between Prompt Engineering Literacy, AI tool usage, e-Catalog familiarity, and writing experience in shaping the quality of grant proposals. Anchored in the Digital Literacy Framework and the Technology Acceptance Model (TAM), this research contributes both theoretically, by refining our understanding of AI integration in academic workflows, and practically, by offering actionable insights for improving proposal success rates in Indonesia's higher education system (Kang, 2023; Méndez-Domínguez, 2023).

LITERATURE REVIEW

In the digital era, the integration of artificial intelligence (AI) in academic processes has become a global trend, including in the preparation of research proposals and community service. Proposal grant competitions, such as those organized by Indonesia's Ministry of Higher Education, Science, and Technology (Kemdiksaintek), demand high-quality documents to obtain funding. This literature study aims to explore the role of AI, especially prompt engineering, digital literacy, and the use of e-catalogs in improving the quality of grant proposals. These findings will support the theoretical framework of the article that has been designed, as well as identify research gaps that need to be filled.

The use of AI in academic writing has been recognized as a tool that increases efficiency and creativity. AI-based tools such as GPT-3 and similar applications (e.g., Deepseek and Blackbox) are capable of generating coherent text drafts, identifying research gaps, and systematically structuring documents. In the context of grant proposals, AI can help lecturers save time at the initial drafting stage, allowing for a focus on substantive aspects such as methodology and social impact.

However, the effectiveness of AI largely depends on the user's ability to provide clear instructions. Research shows that 72% of academic AI users have difficulty generating relevant outputs due to ambiguous instructions. This confirms the importance of prompt engineering as a critical skill. Higher education institutions that provide prompt engineering training experienced a 40% increase in the quality of proposals submitted (Soori, 2023; Taye, 2023; Chiu, 2023)

Prompt engineering is defined as the technique of designing precise instructions to guide AI to produce outputs as per user needs. In the context of grant proposals, this includes the ability to articulate grant-specific research objectives, methodologies, and criteria into an AI-understandable language. For example, instructions such as "Create a research background on the use of AI in higher education in Indonesia" are more effective than general requests such as "Write a research background"(Khosravi, 2022; Bhutoria, 2022; Yilmaz, 2023; Halaweh, 2023).

E-catalogs, such as those integrated in the BIMA application of the Ministry of Education and Science, act as a structured data repository that facilitates access to relevant information. Electronic catalogs improve the efficiency of reference searches with tagging features, keyword-based filters, and automated recommendations. In the context of grant proposals, the e-catalog allows lecturers to explore funded research topics, current trends, and successful proposal formats. Digital literacy includes not only technical skills using AI tools or e-catalogs, but also a critical understanding of evaluating technological outputs. High digital literacy correlates with the ability to identify AI biases, verify reference sources, and adapt technology to contextual needs.

In Indonesia, the challenges of digital literacy are still significant. Data from the Ministry of Communication and Information Technology shows that only 32% of lecturers have advanced digital skills. This has implications for the low optimal use of AI and e-catalogs. Digital literacy training that is integrated with prompt engineering and e-catalog is believed to be a solution (Mendes, 2023; Han, 2024; Swertz, 2022; Sollis, 2023; Wang, 2024).

Table 1. Innovation vs. Previous Research

Aspects	Previous Research	Contributions to This Article
Utilization of AI	Fast content generation	AI + e-catalog for compliance and contextual relevance
Prompt Engineering	Generic technical skills	Prompt engineering to assist in the preparation of grant proposals
E-Catalog	Passive database	Active system integrated with AI (*compliance prompting*)
Digital literacy	Ability with adaptation and adoption of digital technology in general	contextualized prompt engineering literacy and synergy with digital infrastructure such as BIMA e-catalog

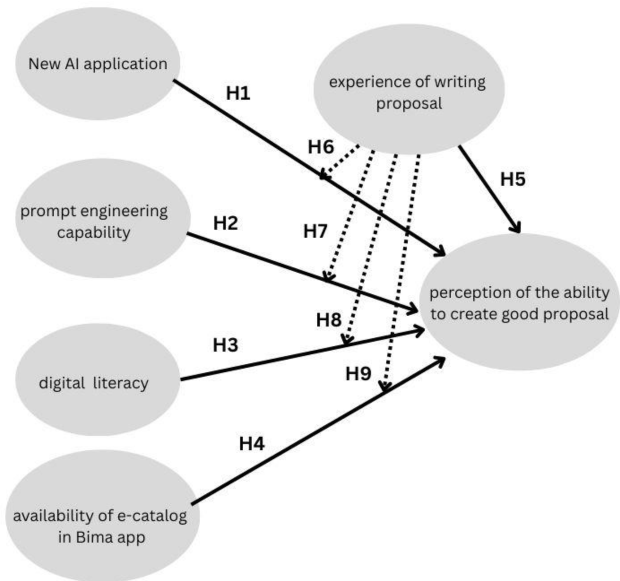

Figure 1. Initial Research Model

RESEARCH METHOD

Research Design and Approach

This study employed a quantitative explanatory research design to investigate the influence of digital competencies. specifically, the use of AI-based applications, prompt engineering literacy, digital literacy, and access to the e-Catalog within the BIMA application, on lecturers' perceived ability to craft high-quality grant proposals. In addition, the study examined the moderating role of prior experience in grant proposal writing to determine how it might strengthen or weaken the direct effects of those factors.

Population and Sampling Technique

The target population of this study consisted of Indonesian university lecturers who have experience in or an interest in submitting proposals to the national grant scheme managed by the Ministry of Education, Culture, Research, and Technology. A purposive sampling technique was applied, with the following inclusion criteria:

1. Active lecturers with a valid National Lecturer Identification Number (NIDN),
2. Familiarity with the grant application process,
3. Active membership in an online professional group related to research grants (e.g., "Grup Hibah DIKTI").

A total of 37 respondents participated in the study. Data were collected using a structured questionnaire distributed through an online platform, enabling a wide reach across geographic regions.

Instrument Development

The primary research instrument was a structured questionnaire developed using a 5-point Likert scale, ranging from:

1. 1 = Strongly Disagree,
2. to 5 = Strongly Agree.
3. The questionnaire consisted of 30 items that measured the following constructs:
4. Independent Variables (X)
   X_1 – AI Application Use (5 items): Assesses the extent to which AI tools (e.g., Deepseek, Blackbox, Neverask) are utilized to assist in proposal writing.
   X_2 – Prompt Engineering Literacy (5 items): Measures the respondent's ability to formulate effective prompts to maximize AI output quality.
   X_3 – Digital Literacy (5 items): Evaluates the respondent's competency in using digital technologies for academic purposes.
   X_4 – e-Catalog Availability within BIMA (5 items): Assesses respondents' awareness and use of BIMA's e-Catalog feature as a resource for grant proposal alignment.
5. Dependent Variable (Y):
   Perceived Ability to Develop High-Quality Proposals (5 items): Captures respondents' confidence and perceived competence in writing proposals that meet grant standards.
6. Moderating Variable (M):
   Experience in Writing Grant Proposals (5 items): Measures the extent and influence of experience in enhancing proposal writing performance and use of digital tools.

All items were developed based on the theoretical constructs and were evaluated for content validity through expert judgment. The instrument design was guided by existing frameworks in digital literacy (Ng, 2012) and AI-assisted academic writing (Dwivedi et al., 2023).

Data Analysis Technique

The data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) via the SmartPLS 3.0 software, which is suitable for predictive models, small-to-medium sample sizes, and formative or reflective constructs. The analysis process included

1. Measurement Model Assessment:
   Convergent Validity: Assessed using Average Variance Extracted (AVE > 0.50),
   Reliability: Measured by Cronbach's Alpha and Composite Reliability (CR > 0.70).
2. Structural Model Assessment:
   Evaluated based on path coefficients, significance levels (p-values < 0.05), R^2, and f^2 values.
3. Moderation Analysis:
   The interaction effect of grant writing experience (M) on the relationship between independent variables (X_1–X_4) and the dependent variable (Y) was tested using product indicator approaches.

The variables used are as follows:

1. New AI applications (X_1) → The extent to which new AI applications can assist in drafting grant proposals.
2. Prompt Engineering (X_2) Capability → Ability to create effective instructions for AI to produce quality output.
3. Digital Literacy (X_3) → Level of understanding and skill in using digital technologies, including AI and e-catalogs.
4. The role of e-Catalog in the BIMA Application (X_4) → The availability of references and resources within the BIMA application that support the writing of grant proposals.
5. Perception of the Ability to Make a Good Grant Proposal (Y) → The extent to which an individual feels capable of crafting a good grant proposal with the support of the above factors.
6. Experience in Writing Proposals (M) → A person's previous experience in writing grant proposals can strengthen or weaken the influence of independent variables on dependent variables.

Based on the predetermined construct, the relationships between variables can be formulated in the following hypothesis. Relationship of Independent Variables (X) to Dependent Variables (Y)

H1: The use of new AI applications (X_1) has a positive effect on the perception of the ability to make good grant proposals (Y).

H2: Ability in prompt engineering (X_2) has a positive effect on the perception of ability to make a good grant proposal (Y).

H3: Digital literacy (X_3) has a positive effect on the perception of the ability to make good grant proposals (Y).

H4: The availability of e-Catalog in the BIMA application (X_4) has a positive effect on the perception of the ability to make good grant proposals (Y).

H5: Experience writing Proposals (X5) has a positive effect on the perception of the ability to make a good grant proposal (Y).

If the experience of writing a grant proposal is used as a moderation variable, then:

H6: The experience of writing grant proposals (M) reinforces the relationship between the use of new AI applications (X_1) and the perception of the ability to create good grant proposals

(Y).

H7: The experience of writing a grant proposal (M) reinforces the relationship between prompt engineering ability (X_2) and the perception of ability to create a good grant proposal (Y).

H8: The experience of writing grant proposals (M) strengthens the relationship between digital literacy (X_3) and the perception of ability to create good grant proposals (Y).

H9: The experience of writing grant proposals (M) strengthens the relationship between the availability of e-Catalog in the BIMA application (X_4) and the perception of the ability to create a good grant proposal (Y).

FINDINGS AND DISCUSSION

The respondents in this study are lecturers throughout Indonesia whose data we obtained through questionnaires shared online. A total of 43 respondents filled out the questionnaire. The demographics of respondents by gender are as follows: 14 people (32.6%) are male, and 29 (67.4%) people are female. Based on the last education, the demographics of respondents are as follows: 26 people (60.4%) have a master's degree, and 17 people (39.5%) have a doctoral degree. Based on age, the demographics of the respondents are as follows: 1 person (2.3%) is under 30 years old, 8 people (18.6%) are 30-39 years old, 13 people (30.2%) are 40-49 years old, 16 people (30.2%) are 50-59 years old, 5 people (11.6%) are over 60 years old.

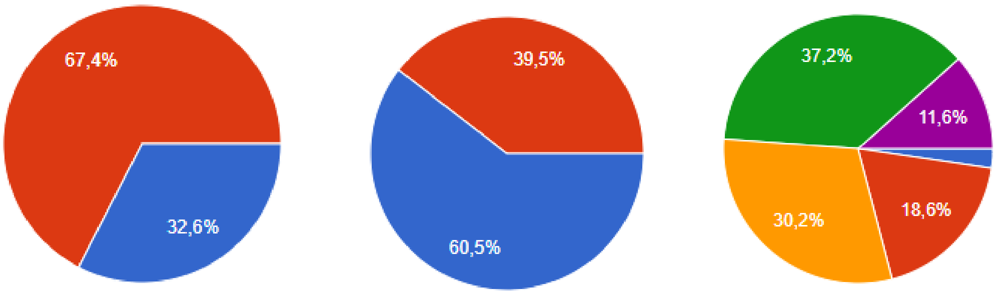

Figure 2. Respondent demographics by gender, Recent education, and age

Based on the experience of participating in grant competitions, the demographics of respondents are as follows: 19 people (44.2%) have received funding and more than once, 12 people (27.9%) have received grants 1 time, 9 people (20.9%) have never won grants, and 3 people (7%) have never participated in competitions. Based on the frequency of using AI in academic activities, the distribution of respondents is as follows: 3 people (7%) very often, 12 people (27.9%) often, 15 people (34.9%) sometimes, 8 people (18.6%) rarely, and 5 people (11.6%) never use AI. Based on the understanding of promot engineering, the distribution of respondents is as follows: 12 people (27.9%) are understanding, 25 people (28.1%) are very understanding, and 6 people (14%) do not understand. Based on the experience of using e-catalogs, the distribution of respondents is as follows: 6 people (14%) have used it several times, 25 people (58.1%) have only known about e-catalog, and 12 people (27.9%) have never used e-catalog.

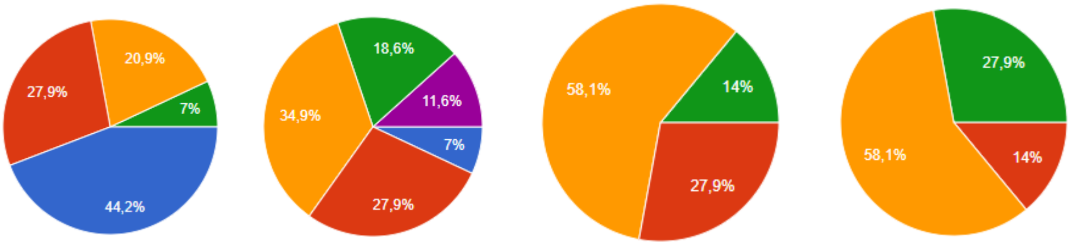

Figure 3. Distribution of respondents. Based on experience participating in grant competitions, the use of AI, understanding prompt engineering, and the use of e-catalogs.

Measurement Model

The results of the outer loading analysis showed that most indicators had values above 0.7, which signifies a strong relationship with the latent variables they measured. Some indicators on the New AI Application (X1) variable, such as X1.2 (0.967), X1.4 (0.932), as well as indicators on the Prompt Engineering Capability (X2) variable, such as X2.2 (0.945), have very high outer loading values, suggesting that these indicators are excellent gauges for latent variables. The same can also be seen in the variables Digital Literacy (X3) with X3.5 (0.915) and the Availability of e-Catalog in the BIMA Application (X4) with X4.4 (0.953). In addition, in the variable Perception of the Ability to Make Good Grant Proposals (Y), the Y1 indicator (0.965) also showed a very strong relationship.

Meanwhile, there are several indicators with an outer loading value between 0.6 to 0.7, such as indicators on the variables of Grant Proposal Writing Experience (M5 = 0.764) and Perception of Ability to Make Good Grant Proposals (Y1 = 0.965). Values within this range are still acceptable, especially in exploratory research, but may be considered for improvement to improve model reliability.

Table 2. Outer Loadings

Indicators	New Ai Application (X1)	Prompt Engine Capable (X2)	Digital Literacy (X3)	Available of E-Catalog (X4)	Writing Proposal Experience (M)	Perception Ability Create a Proposal (Y)
M1					0.890	
M2					0.937	
M3					0.956	
M4					0.947	
M5					0.764	
X1.1	0.847					
X1.2	0.967					
X1.3	0.888					
X1.4	0.932					
X1.5	0.901					
X2.1		0.894				
X2.2		0.945				
X2.3		0.921				
X2.4		0.932				
X2.5		0.866				
X3.1			0.879			

Indicators	New Ai Application (X1)	Prompt Engine Capable (X2)	Digital Literacy (X3)	Available of E-Catalog (X4)	Writing Proposal Experience (M)	Perception Ability Create a Proposal (Y)
X3.2			**0.899**			
X3.3			**0.897**			
X3.4			**0.910**			
X3.5			**0.915**			
X4.1				**0.896**		
X4.2				**0.839**		
X4.3				**0.885**		
X4.4				**0.953**		
X4.5				**0.949**		
Y1						**0.965**
Y2						**0.962**
Y3						**0.956**
Y4						**0.958**
Y5						**0.847**

In the analyzed data, no indicators were found with an outer loading value below 0.6, which indicates that each indicator has made a good enough contribution in explaining its latent variables. Overall, the results of this outer loading show that the model used has good measurement quality, with most indicators showing strong convergent validity. If there is a need to improve the reliability of the model, an evaluation can be carried out on indicators with lower values to determine whether revision or deletion is necessary. However, based on the results obtained, this model is quite adequate in describing the relationship between the indicator and the latent variable measured.

Table 3. Construct Reliability and Validity

Constructs/Items	Cronbach's Alpha	rho_A	Composite Reliability	Average Variance Extracted (AVE)
New AI Aplc	0.946	0.955	0.959	0.824
Prompt Eng Capable	0.949	0.955	0.961	0.832
Digital Literacy	0.942	0.944	0.955	0.810
Avail of e-Catalog	0.945	0.960	0.958	0.819
Writing Prop Exp	0.941	0.946	0.956	0.813
Percept Ability to Create a Proposal	0.966	0.967	0.974	0.881

The results of the construct reliability analysis showed that all variables had an excellent level of reliability and validity based on Cronbach's Alpha, rho_A, and Average Variance Extracted (AVE) values. Based on evaluation standards, a Cronbach's Alpha value ≥ 0.9 reflects very high reliability, while a range of 0.7 – 0.9 indicates good to adequate reliability, and a value below 0.7 indicates low reliability. Meanwhile, rho_A is generally considered adequate if it is worth more than 0.7, although it does not have an absolute limit. the AVE ≥ 0.5 indicates that more than 50% of the variance of the indicator can be explained by latent variables, so the convergent validity is considered good, while the AVE value below 0.5 indicates weak convergent validity.

Based on the results of the analysis, the New AI Application variable (X1) has a Cronbach's Alpha of 0.946, indicating very strong reliability, supported by a rho_A of 0.955, which further confirms the reliability of the construct. An AVE value of 0.824 indicates that more than 82% of the variance of the indicator can be explained by latent variables, so the convergent validity of these variables is excellent. Similar is also seen in the Prompt Engineering Capability (X2) variable with Cronbach's Alpha of 0.949, rho_A of 0.955, and AVE of 0.832, indicating that the indicators in this construct are very consistent in measuring latent variables.

Furthermore, the Digital Literacy (X3) variable has Cronbach's Alpha 0.942, rho_A 0.944, and AVE 0.810, indicating that this construct has excellent convergent reliability and validity. Similar results were also seen in the e-Catalog Availability variable in the BIMA Application (X4) with Cronbach's Alpha 0.945, rho_A 0.960, and AVE 0.819, indicating that the indicators in this variable have a very high internal consistency. The variables of Grant Proposal Writing Experience (M) had Cronbach's Alpha 0.941, rho_A 0.946, and AVE 0.813, which suggests that most of the variance in the indicator can be explained by latent variables well.

Meanwhile, the variable Perception of the Ability to Make Good Grant Proposals (Y) recorded the highest Cronbach's Alpha, at 0.966, with a rho_A of 0.967, which further corroborated the reliability of this construct. An AVE value of 0.881 indicates the highest convergent validity compared to other variables, which means that most of the variance of the indicator can be explained by the latent variable.

Overall, all variables in the study had Cronbach's Alpha above 0.9, indicating very high reliability, as well as rho_A ranging from 0.94 to 0.96, which further strengthened the reliability of the construct. In addition, an AVE above 0.7 for all variables indicates that the latent variable can explain the variance of the indicator very well. Therefore, the model shows excellent reliability and validity, so there is no need for revision or removal of indicators, since all constructs have met high measurement standards.

Table 4a. Discriminant Validity

Fornell-Larcker Criterion	New AI Application (X1)	Prompt Eng Capable (X2)	Digital Literacy (X3)	Available of E-Catalog (X4)	Writing Prop Exp. (M)	Percept_ Ability to Create a Proposal (Y)
New AI Aplc (X1)	0.908					
Prompt Eng Capable (X2)	0.838	0.912				
Digital Literacy (X3)	0.704	0.853	0.900			
Avail of e-Catalog (X4)	0.516	0.615	0.521	0.905		
Writing Prop Exp (M)	0.371	0.516	0.538	0.345	0.902	
Percept Ability to Create a Proposal (Y)	0.560	0.683	0.712	0.532	0.740	0.939
Heterotrait-Monotrait Ratio (HTMT)						
New AI Aplc (X1)						
Prompt Eng Capable (X2)	0.886					
Digital Literacy (X3)	0.742	0.899				
Avail of e-Catalog (X4)	0.547	0.648	0.555			
Writing Prop Exp (M)	0.394	0.544	0.567	0.364		
Percept Ability to Create a Proposal (Y)	0.585	0.710	0.743	0.552	0.773	

Table 4b. LIFE

Inner VIF Values	Percept_ Ability to Create a Proposal (Y)
New AI Aplc (X1)	3.554
Prompt Eng Capable (X2)	7.487
Digital Literacy (X3)	4.674
Avail of e-Catalog (X4)	2.248
Writing Prop Exp (M)	1.711

The results of the discriminant validity analysis confirmed that each variable in the model had significant differences from the others, indicating that the construct used had met adequate measurement standards. The evaluation of discriminant validity was carried out through three main methods, namely the Fornell-Larcker Criterion, the Heterotrait-Monotrait Ratio (HTMT), and the Variance Inflation Factor (VIF).

According to the Fornell-Larcker Criterion, discriminant validity can be said to be fulfilled if the square root of the Average Variance Extracted (AVE) of a construct is greater than its correlation to other latent variables in the model. The results of the analysis showed that the square root value of AVE of each variable was higher than its correlation with other constructs. For example, the New AI Application variable has the square root of AVE of 0.908, Prompt Engineering Ability of 0.912, Digital Literacy of 0.900, Availability of e-Catalog in BIMA Application of 0.905, Experience of Writing Grant Proposals of 0.902, and Perception of Ability to Make Good Grant Proposals of 0.939. Thus, this model has met the Fornell-Larcker criteria, which show that each construct is more effective in explaining its own indicators compared to its relationship to other constructs.

In addition, the validity of the discriminant was also tested using the Heterotrait-Monotrait Ratio (HTMT), which compares correlations between different constructs with correlations within the same construct. The results of the analysis showed that all HTMT values in the model were below the 0.90 threshold, with a range of values between 0.3125 to 0.7843. Based on the criteria used, the HTMT value ≤ 0.90 indicates excellent discriminant validity, while the HTMT value ≤ 0.90 is still acceptable in some research contexts. Because all HTMT values in this study remain below 0.90, it can be concluded that each latent variable has conceptual clarity, and there is no problem of multicollinearity between constructs.

As a complement, the Variance Inflation Factor (VIF) analysis was also carried out to ensure that there was no multicollinearity between latent variables. VIF is used to assess the degree of interconnectedness between constructs in the model, with the criterion that a VIF value of < 3.3 indicates the absence of significant multicollinearity. The results of the analysis showed that all VIF values in the model were below this threshold, meaning that there was no excessive association between latent variables, except for the Prompt Engineering Capable (X2) of 7.487. Thus, each variable in the model remains unique and does not experience overlap that could interfere with the discriminant validity.

Table 5. Result of Testing Hypothesis

Testing Hypothesis	**Original Sample**	**T Statistics**	**P Values**	**Result**
H1: New AI Aplc -> Percept Ability to Create a Proposal	0.060	0.318^{ns}	0.375	No
H2: Prompt Eng Capable ->Percept Ability to Create a Proposal	0.117	0.393^{ns}	0.347	No
H3: Digital Literacy -> Percept Ability to Create a Proposal	0.222	0.967^{ns}	0.167	No

Testing Hypothesis	Original Sample	T Statistics	P Values	Result
H4: Avail of e-Catalog -> Percept Ability to Create a Proposal	0.202	1.258ns	0.104	No
H5: Writing Prop Exp -> Percept Ability to Create a Proposal	0.439	2.650**	0.004	Yes
H6: Writing Prop exp moderate X1 to Y	0.038	0.159ns	0.437	No
H7: Writing Prop Exp moderate X2 to Y	0.254	0.667ns	0.252	No
H8: Writing Prop Exp moderate X3 to Y	-0.174	0.553ns	0.290	No
H9: Writing Prop Exp moderate X4 to Y	-0.271	1.676*	0.047	Yes
Note(s): n =5,000 subsample; ***p < 0.001; **p < 0.01; ns: not significant (one-tailed test)				

Path Coefficient Analysis and Hypothesis Testing

Path coefficient analysis was used to evaluate the direct influence between latent variables in the research model. The path coefficient value ranges from -1 to +1, where a value close to +1 indicates a strong positive relationship, while a value close to -1 indicates a strong negative relationship. If the value is close to 0, then the relationship between the variables is considered weak or insignificant.

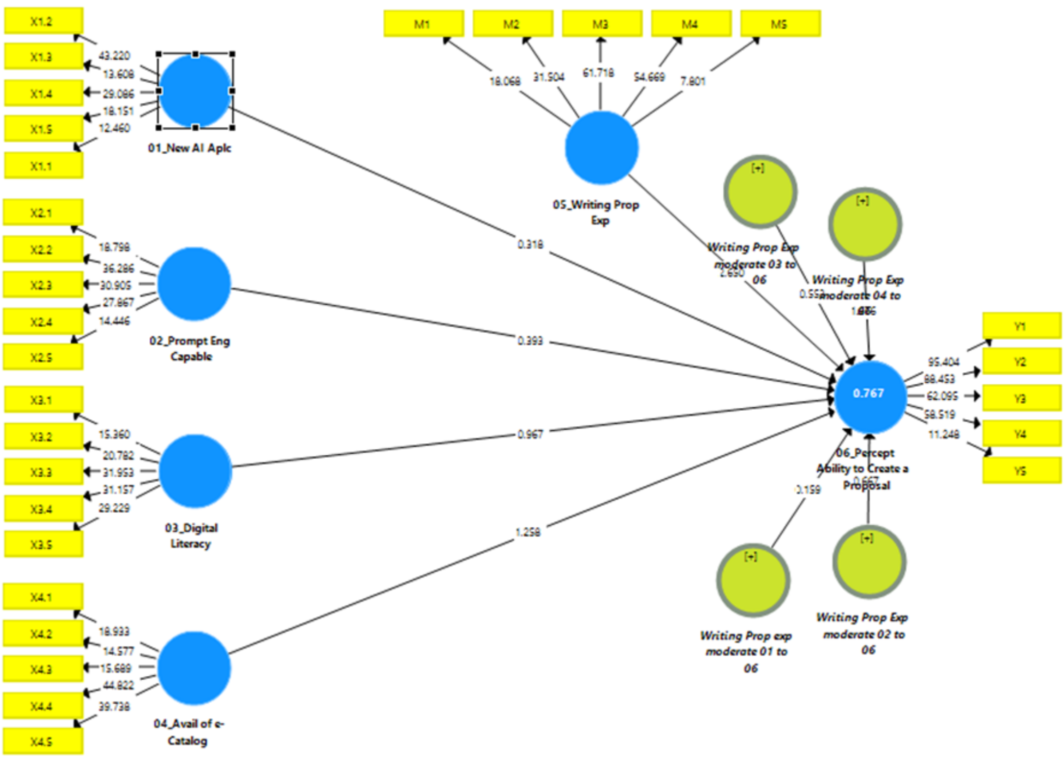

Figure 4. Structural Model (Result Model)

Hypothesis testing is carried out by looking at t-statistical values and p-values to determine statistical significance. The criteria used to accept a hypothesis are as follows:

i. The hypothesis is accepted if the t-statistic > 1.96 at a significance level of 5% (α = 0.05).
ii. The hypothesis is accepted if the p-value < 0.05.

The results of the analysis showed that some relationships in the model had a significant influence, while others did not. Here are the results of the analysis in detail:

1. The Influence of AI Applications on the Perception of Ability to Write Competitive Grant Proposals. The path coefficient of 0.060, with p-value = 0.375, indicates no significant influence on the direction of positive influence. This indicates that the higher the utilization of AI applications, the greater the perception of the ability to write quality grant proposals.
2. The Effect of Prompt Engineering Ability on the Perception of Ability to Write Competitive Grant Proposals
   With a path coefficient of 0.117 and a p-value = 0.347, this relationship is not significant in a positive direction. This means that the better the prompt engineering skills, the higher a person's confidence in preparing grant proposals.
3. The Influence of Digital Literacy on the Perception of Ability to Write Competitive Grant Proposals
   The path coefficient value is 0.222, and the p-value = 0.167, indicating that this relationship is not significant at a significance level of 5%. This means that digital literacy does not affect the perception of the ability to write grant proposals
4. The Effect of the Availability of the e-Catalog in the BIMA Application on the Perception of Ability to Write Competitive Grant Proposals
   The path coefficient is 0.202, p-value = 0.104, indicating an insignificant relationship. In other words, the existence of e-Catalog in the BIMA application does not have a direct impact on the perception of the ability to write competitive grant proposals.
5. The Effect of Grant Proposal Writing Experience on the Perception of Ability to Write a Competitive Grant Proposal
   The highest path coefficient in this model, which is 0.439, and p-value = 0.004, shows a very significant relationship. This confirms that the more experience in writing grant proposals, the more the perception of ability to write competitive grant proposals.
6. The Influence of AI Applications on the Experience of Writing Grant Proposals (Experience of Writing Proposals as a Moderation Variable)
   With a path coefficient of 0.038 and a p-value = 0.437, this result shows that it does not moderate
7. The Effect of Prompt Engineering Skills on Grant Proposal Writing Experience (Proposal Writing Experience as a Moderation Variable)
   The path coefficient of 0.254, with p-value = 0.252, shows an insignificant relationship. This means that the higher the prompt engineering ability, the more experience in writing a grant proposal is not moderated by the experience of writing a proposal.
8. The Effect of Digital Literacy on the Experience of Writing Grant Proposals (Experience of Writing Proposals as a Moderation Variable)
   The path coefficient of -0.174, with p-value = 0.290, shows an insignificant relationship, although not as strong as the other variables.
9. The Effect of the Availability of e-Catalog in the BIMA Application on the Experience of Writing Grant Proposals (Experience of Writing Proposals as a Moderation Variable)
   The path coefficient of -0.271, with p-value = 0.047, suggests that this relationship is significant. Thus, Experience in writing Proposals is a moderating variable.

Table 6. R2, R2 adjusted and Q2

	R2	R2 adj	Q^2 (=1-SSE/SSO)
Percept_ Ability to Create a Proposal (Y)	0.767	0.704	0.634

R^2 (R-Square), R^2 Adjusted, and Q^2 (Predictive Relevance) analysis aim to assess the extent to which independent variables are able to explain dependent variables as well as measure the model's overall predictive strength. R^2 indicates the proportion of variability of dependent variables that can be explained by independent variables, with the following interpretation categories: R^2 value ≥ 0.67 is considered strong, $0.33 \leq R^2 < 0.67$ is categorized as moderate, and $R^2 < 0.33$ is considered weak. Meanwhile, R^2 Adjusted is a version that has been adjusted to be more accurate in estimating the model's predictive capabilities, especially when the number of independent variables increases. In addition, Q^2 (Predictive Relevance) is used to measure the extent to which the model has predictive relevance to dependent variables. If the Q^2 value > 0.35, then the model has high predictive ability, while if $0.15 < Q^2 \leq 0.35$, the predictive ability is moderate, and if $0.02 < Q^2 \leq 0.15$, then the predictive power is relatively weak.

The results of the analysis showed that the Perception of Ability to Write Competitive Grant Proposals (Y) had an R^2 of 0.767, which means that 76.7% of the variation in this variable can be explained by the factors of AI Application, Prompt Engineering Ability, Digital Literacy, Availability of e-Catalog in BIMA Application, and Grant Proposal Writing Experience. An Adjusted R^2 value of 0.704 indicates that after considering the number of predictive variables, the model still has good predictive capabilities. In addition, a Q^2 value of 0.634 indicates that the model has high predictive power, so independent variables in the model can significantly influence an individual's perception of writing a quality grant proposal.

For the variable of Grant Proposal Writing Experience (M), an R^2 value of 0.532 was obtained, which indicates that 53.2% variation in grant proposal writing experience can be explained by the factors of AI Application, Prompt Engineering Ability, Digital Literacy, and Availability of e-Catalog in BIMA Application. An Adjusted R^2 value of 0.514 indicates that after adjustments, the model still has moderate to strong predictive capabilities. Meanwhile, a Q^2 value of 0.349 indicates that the model has moderate to high predictive power in explaining the experience in writing grant proposals.

Overall, the results of the analysis show that this model has good predictive power, especially in explaining the Perception of Ability in Writing Competitive Grant Proposals. A positive and sufficiently high Q^2 value indicates that this model has good predictive relevance, so it can be used as a basis for further research as well as a reference in decision-making related to factors that affect an individual's ability to prepare a quality grant proposal.

CONCLUSIONS

This study critically evaluates how various dimensions of digital capabilities affect the Perception of the Ability to create a Good Grant Proposal, emphasizing the role of proposal writing experience as a moderation variable.

The H1 to H4 hypothesis tests the direct influence of four main variables, New AI Applications, Prompt Engineering Capabilities, Digital Literacy, and Availability of e-Catalogs in BIMA Applications, on the perception of proposal drafting capabilities. The results showed that none of the four variables had a statistically significant effect. These findings indicate that the existence of digital tools and AI innovations alone is not enough to increase user confidence in carrying out complex administrative tasks such as writing proposals. This shows that there is a gap between the provision of digital technology and the effectiveness of its use by employees.

Hypothesis H5 shows that Experience in Writing Proposals has a significant influence on the perception of the ability to draft proposals. This underscores the importance of hands-on experience as a key factor in the successful implementation of digital management.

Hypotheses H6 to H9 examine the role of experience moderation on the relationship between digital capabilities (X_1–X_4) and dependent variables. Of the four moderation hypotheses, only H9 was statistically significant, namely, the experience of moderating the relationship between the availability of e-Catalogs and the perception of the ability to prepare proposals. These findings emphasize that digital infrastructure will provide greater strategic value when used by individuals with direct experience and engagement. Practically, the study offers several implications for stakeholders:

1. For lecturers, the findings emphasize the importance of experiential learning, such as workshops, mentoring, and hands-on grant writing sessions, to build competence beyond merely using digital tools.
2. For universities and research institutions, the results highlight the need to design professional development programs that integrate AI usage with real-world proposal writing experiences.
3. For policy-makers and grant program developers, the study suggests that digital platforms like BIMA's e-Catalog should not only function as static repositories but also be actively leveraged in training modules and integrated into the grant application pipeline.

LIMITATION & FURTHER RESEARCH

This study is subject to several limitations that should be acknowledged when interpreting the findings. First, the data were collected solely from Indonesian university lecturers, which limits the generalizability of the results to broader educational or international contexts. Different countries may employ distinct systems, digital infrastructure, and evaluation standards for grant proposal development, potentially influencing the relationship between digital competencies and perceived proposal-writing ability.

Second, the sample size was relatively small (n = 37), and recruitment was conducted via purposive sampling through online academic groups. As such, the sample may not fully represent the diversity of grant applicants in Indonesia, particularly those in remote or underrepresented institutions with limited access to digital resources.

Third, the study relied on self-reported data, which may be subject to social desirability bias or inaccuracies in respondents' assessment of their own digital skills and proposal-writing competence. Future research could benefit from incorporating objective performance-based measures or triangulating survey data with document analysis of submitted proposals.

Fourth, the study used a cross-sectional design, limiting the ability to establish causal relationships. Longitudinal studies could offer more robust insights into how digital skill development and experience accumulation over time influence grant-writing confidence and success rates.

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