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Would Lecturers Use AI-Based Software to Write Scientific Article? A Quantitative Approach in Indonesia

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ABSTRACT

AI-based (artificial intelligence) software utilization is increasingly widespread, including in education. On the one hand, AI-based software offers advantages for producing quality writing, such as converting voice into text, summarizing paragraphs, and improving grammar. There are pros and cons to each argument. Interestingly, permission or prohibition on using software is only for students, not lecturers. Moreover, lecturers should write quality scientific articles productively so that AI-based software can facilitate writing. Therefore, this research explores the driving and inhibiting factors that are thought to influence the use of AI-based software to assist lecturers in writing scientific articles. Following its goals, this research identified the potential factors through six hypotheses and tested them using PLS-SEM. This research recruited 110 lecturers in Indonesia as respondents to express their quantitative perceptions. It found that Product Quality (QLT) and Security (SEC) factors influence lecturers' use of AI-based software in scientific writing. However, four other variables (Motivation/MOT, Supporting Ability/SUP, Subjective Norms/NOR, and Individual Ability/ABL) had no influence. The finding exposed software quality has a vital role in engaging lecturers' intention to use AI-based software considering its characteristics to satisfy their needs: usefulness, easiness, accuracy, and efficiency. Also, lecturers are concerned with information security since AI-based software captures personal data, including user behavior during its usage. This research promotes practical implications for universities to regulate AI-based software, considering its benefits have been recognized by lecturers. However, its misuse can lead to the university's credibility in research and should be mitigated.

1. INTRODUCTION

Artificial Intelligence-based (AI-based) software is used in various sectors and domains to help human work, including education [1]. An example of AI-based software usage is student failure detection based on the learning management system (LMS) data track record [1, 2]. It actualized in the ChatGPT and Bard (now Gemini) software [3, 4], which students widely use to complement the teacher's role in discussing subject matter [2]. Students also use the software to write content in scientific articles to be submitted to journals or conference proceedings. Moreover, there are also several AI-based software to help the process of writing scientific articles [5, 6], for example, correcting English grammar [7, 8], searching articles for literature reviews [3], and converting voice into text. Students commonly can leverage AI-based software [9], considering their limited writing experience and the need to get high grades.

AI-based software usage can be controversial and debatable if the user is a lecturer. People have a perception that lecturers should have more adequate competence and experience. It has been a subjective prestige for lecturers to be more independent in writing articles without the help of software. It looked at the AI-based software usage to assist writing is considered a degradation of abilities, irresponsible, and unethical. Moreover, Shen et al. [10] mentioned a study in 2023 that claimed that reviewers identified 63% of fake abstracts created by ChatGPT. It signalized limited human ability to detect whether lecturers wrote scientific articles. Also, Dashti et al. [11] emphasized that scientific writing is only valid when performed manually by researchers (including lecturers). Separately, Zou and Huang reveal doctoral students' opinion that stated these disadvantages since using ChatGPT: breeding laziness, weakening higher-order thinking, impairing writing ability, and demotivating writing learners [12]. Extremely, overuse of AI-based software may lead plagiarism and a lack of accurateness [7].

However, many lecturers think AI-based software is only helpful because they have performed research essence processes. AI-based software can support lecturers with limited English proficiency and translating references [13, 14]. Hence, writing processes are negotiable to be assisted by AI-based software. In addition, AI-based software usage supports technology's general principle to assist people in doing anything more efficiently [5]. AI-based software usage has become a trending technology that should increase productivity. Specifically, Zou and Huang told several benefits from ChatGPT to facilitate the brainstorming, outlining, and thinking development efficiently [12].

These pros and cons underlie this research to explore the factors influencing lecturers using AI-based software for writing scientific articles. This research took the specific case of writing scientific articles because this is currently a trending and debatable topic among academics. AI-based software is generally considered commonplace in society, but not for writing scientific articles among lecturers. Lecturers must be an example for students when writing quality scientific articles so that the behavior of using AI-based software is questionable. Specifically, several people think AI-based software for writing scientific articles is plagiarism [7].

To address these pros and cons, this research offers a solution by identifying factors influencing lecturers' intentions to use AI-based software. Factor identification reflects a landscape that describes the software adoption process and reveals what causes context-specific use for scientific writing among lecturers. Moreover, factor identification also becomes a reflection for stakeholders to determine policies relevant to the landscape. The pros and cons can be addressed long-term by determining the allowed and prohibited cases following the current behavior.

This research can contribute theoretically and practically. After identifying influencing factors, its results can contribute theoretically to knowledge about software adoption based on the positivist paradigm and contemporary cases. In addition, the identification results can provide input to universities and lecturer professional associations to formulate clear regulations for using AI-based software.

This research consists of several chapters. Section 1 portrays the introduction of this research with the background, problem boundaries, and objectives. Section 2 narrates literature reviews that outline fundamental theories to support the research and hypotheses generation process, while Section 3 reveals the methodology used to obtain research data. Sections 4 and 5 unveil the testing results and discussions, respectively. Finally, Section 6 contains the conclusion following the research objectives, while Section 7 promotes the relevant suggestions for future research.

2. LITERATURE REVIEW

2.1 AI-based software

The use of AI-based software in the education sector has become widespread, especially as the impact of two milestones. The first milestone was the COVID-19 pandemic, which encouraged information technology (IT) [15] to automate business processes in educational institutions. IT has shifted from automation to artificial intelligence to speed up manual work and even help cognitive thinking. As the pandemic gradually subsides, education stakeholders have realized the great benefits of using artificial intelligence to help their respective jobs. Several examples of research have revealed the use of Artificial Intelligence (AI), such as detecting the possibility of failing [1], detecting the possibility of cheating, image recognition [16], personalized-recommender systems for students [17], and preparing future lecture schedules. Through large-scale and various data, Salas-Pilco and Yang highlighted promising predictive models with many benefits for universities, such as detecting student failure [2]. It replaces human cognitive thinking, which consumes more time.

The second milestone was the proliferation of various AI applications with generative types that allow direct interaction between humans and the software interface. AI-based software enables new promising opportunities and challenges in education practices [18]. ChatGPT [3, 5] is a popular generative AI application that provides an interaction model using natural human language to explore knowledge of simple interaction processes. Natural human language allows a broad segment of users to utilize it to improve academic knowledge. Furthermore, academics (lecturers and students) can find discussion partners who help search for knowledge [2, 19] based on the availability of the AI-based software database. Several cases show that AI-based software is misused to cheat during exams or lecture assignments. Schönberger [3] portrayed many universities adjusting the culture of examination to anticipate their students' cheating behavior due to ChatGPT misuse. However, AI-based software also offers large-scale transfer and sharing of knowledge, which helps increase the knowledge and competence of academic activities, including lecturers.

2.2 Software adoption

Software adoption is the process of humans using software to gain benefits and fulfill their needs and purposes. Software adoption becomes a crucial process after software testing and release, but it must be addressed during development. It often happens since the software development team works on the analysis stage to deployment and maintenance while the business unit ensures the software is well-adopted. Mass-produced software (not in-house or custom-based) has gone through a feasibility study, but specific segments/groups may fail to adopt it. Adoption failure derives from a gap between past feasibility studies with current conditions and unique segment characteristics.

As part of technology, software adoption can also rely on theories related to technology adoption and acceptance to explain the systematics of the adoption process. Theories related to technology adoption and acceptance that have a high reputation and have been widely relied on to reveal the software adoption process are TAM (Technology Acceptance Model, including version 2), TOE (Technological-Organization-Environment) model, UTAUT (Unified Theory of Acceptance and Use of Technology, include version 2), TPB (Theory of Planned Behavior), and the Motivation Theory. Moreover, Ventakesh [20] has proposed an update for UTAUT by considering AI-based software characteristics. These theories became a foundation for this research to develop relevant premises and arguments in estimating the factors contributing to lecturers' intentions to use AI-based software to write scientific articles. This research argues that existing theories must be synthesized and not taken raw and entirely from one theory to ensure comprehension of the scope of the alleged factors and rationalization of their interrelationships.

For comparison, other studies have revealed the processes of adopting AI-based software with different user contexts. Pillai and Sivathanu assessed chatbot's adoption as a type of AI-based software using TAM, specifically perceived ease of use, perceived usefulness, perceived trust, perceived intelligence, and anthropomorphism as influencing factors. Chatterjee et al. [21] also synthesized TAM and TOE to examine factors influencing AI adoption in manufacturing and production firms.

2.3 Hypotheses generation

As a product that its users utilize, AI-based software must have product quality that states the software's ability to meet the goals and needs of users. This concept aligns with ISO 25010, which describes a software quality model including usability, functionality, reliability, portability, efficacy, and maintainability. Efficiency relates to the fast processing of tasks, while reliability relates to precise results. Bringula [22] in 2023 also underlined effectiveness as software quality attribute that was owned by ChatGPT, a popular AI-based software. The importance of software quality has also been recognized through technology and acceptance models: TAM, UTAUT, and MPCU. As a manifestation of software quality, perceived usefulness in TAM empirically contributes to the intention, as empirically proven by Binowo et al. [15]. Also, Schönberger [3] underlined ChatGPT's usefulness (as an AI-based software) to support scientific work as a part of software quality. Moreover, practically, AI-based software can compose an initial draft of an article following the instructions [7]. Usability also becomes fundamental elements in software quality since it emerges and assure the software user to engage with the software. Xu et al. [23] revealed usability as contributing factors in adopting the AI-based software. Separately, Niloy et al. agreed them by declaring that ease of access (part of usability aspect) encourages ChatGPT usage [24]. In contrast, Phuoc [25] in 2022 found that software complexity had negative influence on the intention to use software so that software easiness as part of usability became more essential. From global perspective, International Organization for Standardization recognized usability as software quality attribute in ISO 25010 [26]. Therefore, this research suspects a correlation between the quality of AI-based software products and usage intentions as postulated from TAM and ISO. It is manifested by **Hypothesis 1 (H1)**: the quality of AI-based software products positively affects lecturers' intentions to use them to write scientific articles (**QLT→INT**).

This research also suspects that the user's motivation influences the intention to use AI-based software. It aligns with the Motivation Model theory, which divides motivation into two perspectives: intrinsic and extrinsic [27]. Intrinsic motivation is related to the desire to do something based on personal interest and satisfaction. Meanwhile, extrinsic motivation is related to external triggers that cause people to work. This research suspects that productivity targets, the desire to receive awards, and quality targets for scientific articles are external triggers for a lecturer to use AI-based software to assist in writing scientific articles. They had similarities with business needs, as spoken by Borges et al. [28], as one of two key motivations for AI adoption. This premise is represented by **Hypothesis 2 (H2)** with UTAUT and Motivation Model as initial theories: Lecturers' motivation influences their intention to use AI-based software for writing scientific articles (**MOT→INT**).

Financial support and digital literacy also influence the process of using software. These two things are supporting abilities that influence someone's use of software. In the context of this research, someone with the financial ability to buy or subscribe to software should have the intention to use the software compared to someone who does not have the financial ability. This research also argued financial support represent relationship between price value with intention to use AI-based software as proven by Gansser and Reich [29] in 2021. The same premise applies to digital literacy and the ability to use software, so this research proposes the variable supporting ability as a factor that encourages using AI-based software for writing scientific articles. Hence, Social Influence, Facilitating Conditions, and Price Value from UTAUT became baseline in this correlation. This correlation is actualized as **Hypothesis 3 (H3)**: Supporting ability positively influences the lecturer's intention to use AI-based software for writing scientific articles (**SUP→INT**).

The existence of AI-based software raises pros and cons, as mentioned in the introduction. Pros and cons were also found by Bringula [22] in 2024 after performing an experiment on text mining analytics to compare positive versus sentiment about ChatGPT usage from academics' perspective. His finding show that positive sentiment got more frequency than negative one. Therefore, this research suspects that official organizational rules, community culture, and colleague recommendations influence a lecturer's interest in using AI-based software. The TAM, TPB, and TRA frameworks also recognize these external trigger factors. Also, Bernabei et al. [9] found that AI-based software users were influenced by their society to use it. It was in line with findings from Gansser and Reich [29] and Alhwaiti [30] that social influence affects the intention to use AI-based software. This research groups these three as Subjective Norm variables (refer to UTAUT and TAM theories) and puts them in **Hypothesis 4 (H4)**: Subjective norm influences lecturers' intentions to use AI-based software to write scientific articles (**NOR→INT**).

One of the interesting issues related to the use of AI-based software is security. It becomes a logical consequence because algorithms in AI-based software utilize data originating from the identity of the application owner and behavior while using the application. It also becomes a risk [19, 31] that can reduce someone's intentions if AI-based software cannot protect personal data or data leaks. Moreover, the public has heard much news about data being misused through AI-based applications. Many software users do not want others to know that they are using the application or what their behavior is like while using it. On the other hand, the software's success in ensuring security for protecting personal data can encourage a person's credibility and intention to use AI-based software. Also, Pillai and Sivathanu [32] found that AI-based software users' trust has a vital role in their intention to use it for adoption processes. It relates strongly to the ethical principles of AI in K-12 education from Jobin et al. [33], as reminded by Adams et al. [34] in 2023. This premise underlies **Hypothesis 5 (H5)**: AI-based software's ability on security influences lecturers' intentions to use it for writing scientific articles (**SEC→INT**).

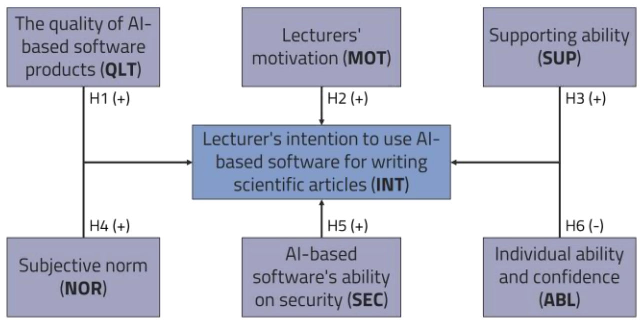

Figure 1. Hypotheses framework

The final variable that can influence a person's intentions is the individual's ability and self-confidence regarding competence in writing scientific articles. Considering the function of AI-based software as a tool for writing scientific articles, this research argues that lecturers with good writing skills tend to have little intention of using AI-based software. It is a logical consequence of someone who wants to be independent without relying on technology if they have adequate competence. The scope of competency here includes English language skills, writing skills, and an understanding of research methodology. Therefore, this research formulates **Hypothesis 6 (H6)**: Individual ability and confidence negatively affect a lecturer's intention to use AI-based software (**ABL→INT**).

Finally, this research elaborates all hypotheses into a framework (see Figure 1). It comprises seven variables that will be decomposed into several indicators in Methodology section.

3. METHODOLOGY

This research implemented classification from Saunders et al. [35] with each layer to define categorization from Philosophies to the Time-Horizon type. In Philosophies, it was Positivism because this research constructed participants' belief and perception [36]. The knowledge were elaborated from the postulated hypotheses at the beginning to be tested in the end of the research as a signal of the Deductive approach, while this research also applied a Survey as a strategy. Figure 2 visualizes its research categorization.

Following its goals as stated in the Introduction, this research explored the causative factors through a survey strategy. It covers identifying the driving and inhibiting factors for people when they stop using software in an office environment. This research tailored the quantitative approach in these main phases: (1) Instrument generation from related theories in literature review, (2) Primary data collection (including respondent recruitment and data capturing), and (3) Results processing and interpretation. Using the codification technique, it performed the content analysis method to elaborate primary data into identified patterns. Each respondent's statement was classified into the same categories and extracted to perceive causative factors by comparing, contrasting, and synthesizing.

Following its goals, this research identified the potential factors through hypotheses formulated in Section 2. It actualized the hypotheses testing in a quantitative approach using PLS-SEM due to its reliability in verifying suspected relationships among variables, especially for individual perception. Moreover, PLS-SEM utilization for hypotheses has been implemented successfully in other AI-based software or application adoption, such as Pillai and Sivathanu [32] in 2020, Chatterjee et al. [21] in 2021, Gansser et al. [29] in 2021, and Phuoc [25] in 2022. Moreover, Pillai et al. and Chatterjee et al. performed TAM quantitatively while Gansser actualized UTAUT. These experiences indicate PLS-SEM's ability to emphasize objective interpretation following statistical principles, especially when this research adapting TAM and UTAUT. PLS-SEM utilization facilitate this research to objectively determine whether a factor empirically influences to lecturer's intention to use AI-based software.

This research tailored the quantitative approach in these main phases: (1) Research instrument production following the formulated hypotheses; (2) Primary data collection using an online questionnaire; and (3) Data testing with the PLS-SEM procedures and result interpretation.

3.1 Instrument production

This research composed the instruments following related theories referred to entire variables in the hypothesis framework (see Figure 1). The instruments were packaged in a questionnaire with two main parts: demography profiling and perception measurement using the Likert scale. This research has 37 instruments from seven variables. Before releasing the questionnaire to the respondents, this research hosted a pivot testing to ensure its readability. Table 1 exposes the produced instruments with their references.

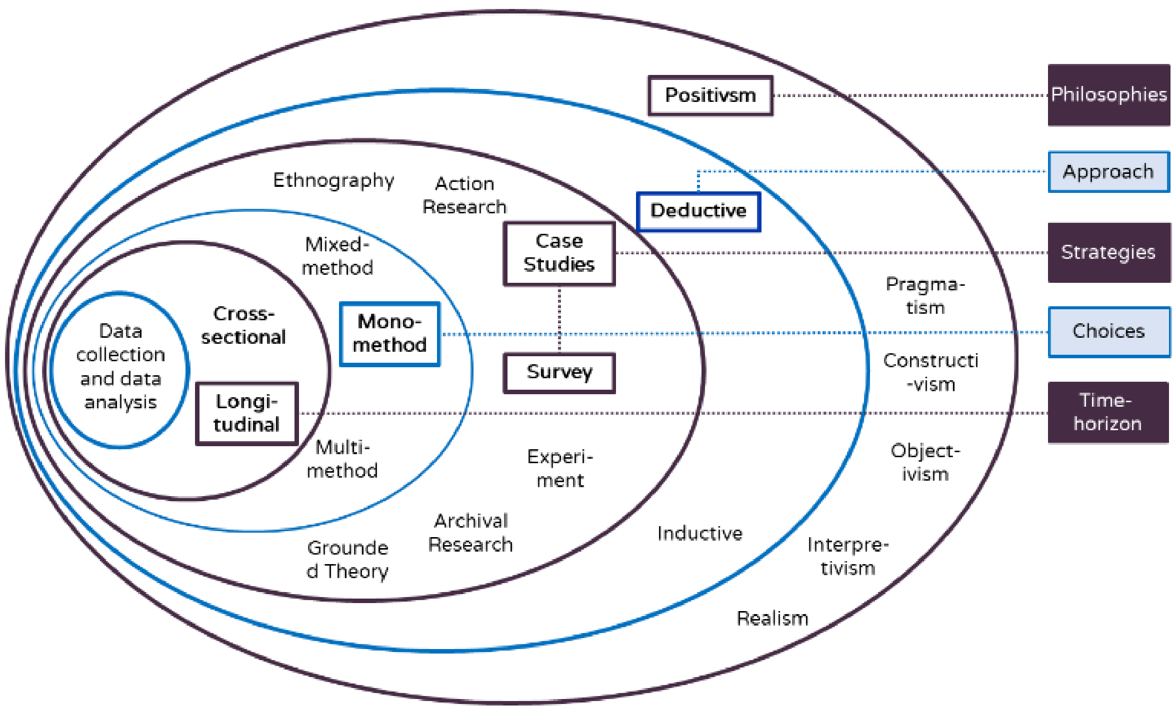

Figure 2. Research classification following its paradigm, adapted from Saunders et al. [35]

Table 1. List of instrument

Variable	Indicator	Statement
Product Quality (QLT); Sources: [3, 7, 9, 15, 20, 22, 25, 29, 31, 32, 37]	QLT.01	AI-based software helps scientific article writing quickly.
	QLT.02	AI-based software helps scientific article writing with correct results.
	QLT.03	AI-based software has a good reputation.
	QLT.04	AI-based software is useful in writing scientific articles.
	QLT.05	AI-based software suits my job as a lecturer.
	QLT.06	AI-based software is easy to use.
Motivation (MOT); Sources: [28]	MOT.01	I have a relatively high scientific article writing productivity target (two or more articles per year).
	MOT.02	I want to get an award for my scientific article writing productivity.
	MOT.03	I have targets writing quality scientific articles (e.g., correct grammar, easy-to-understand sentences, complete content).
Supporting Ability (SUP); Sources: [29]	SUP.01	I have the financial ability to buy or subscribe to AI-based software in the context of writing scientific articles.
	SUP.02	I have adequate digital literacy skills to use AI-based software.
	SUP.03	I can use AI-based software in the context of writing scientific articles.
Subjective Norms (NOR); Sources: [9, 29, 30]	NOR.01	The place where I work provides formal/legal permission for lecturers to write with the help of AI-based software.
	NOR.02	My workplace admits the culture of using AI-based software in writing scientific articles.
	NOR.03	Lecturer colleagues (same or different institutions) recommend using AI-based software in writing scientific articles.
Security (SEC); Sources: [12, 19, 32, 37, 38]	SEC.01	AI-based software used for writing scientific articles keeps information confidential.
	SEC.02	AI-based software used for writing scientific articles prevents data leakage.
	SEC.03	The AI-based software for writing scientific articles does not propagate my behavior or habits.
Individual Ability (ABL); Proposed directly by authors.	ABL.01	I can speak English adequately in writing scientific articles in English.
	ABL.02	I can speak Indonesian adequately in writing scientific articles in Indonesian.
	ABL.03	I have an adequate understanding of the standards and formats for writing scientific articles.
Intention (INT); Sources: [20, 29, 32]	INT.01	If not pressed, I intend to use AI-based software to write scientific articles.
	INT.02	In urgent circumstances (e.g., time constraints), I intend to use AI-based software to write scientific articles.
	INT.03	I can improve my skills in this field by using AI-based software to write scientific articles.

Table 2. Respondents' profile

Category	Field	Frequency
Teaching background	Computer domain	77 (70.00%)
	Non-computer domain	29 (26.36%)
	Choose to be hidden	4 (3.64%)
Publication records last three years	0 to 2	14 (12.73%)
	3 to 5	36 (32.73%)
	6 to 8	15 (13.64%)
	9 or more	45 (40.91%)
H-index in Google Scholar	0 to 5	60 (54.55%)
	6 to 10	39 (35.45%)
	11 or more	10 (9.09%)
Location	Jabodetabek	20 (18,18%)
	West Java non-Jabodetabek	56 (50,91%)
	Java provinces non-West Java non-Jabodetabek	11 (10,00%)
	Sumatera provinces	9 (8,18%)
	Sulawesi provinces	6 (5,45%)
	Other provinces	4 (3,64%)
	Choose to be hidden	4 (3,64%)
Gender	Male	63 (57,27%)
	Female	47 (42,73%)

3.2 Data collection

This research collected primary data from lecturers in Indonesian higher education. They were recruited through convenience/accidental sampling during August 2023. The sample was selected based on the availability and willingness of lecturers in Indonesia to participate in this research without any intervention to deliberately determine the gender proportion of writing experience and scientific field. Voluntarism is essential considering the relatively large number of questions that must be filled in and the characteristics of PLS-SEM, which require relatively low data adequacy compared to CB-SEM. The demographic composition in Table 2 occurs organically. However, the author argues that the sample size of 110 with the proportion of each attribute is representative by considering the involvement of lecturers in various provinces, the diversity of the frequency of productivity in writing scientific articles, and the diversity of scientific fields.

After inputting their profile, they used a five-point Likert scale to express their perception following the instruments. Since its hypotheses framework had six paths, this research targeted 60 persons as a minimum sample due to considering Hair et al. [39] formulation. Initially, this research got 112 respondents who completed the questionnaire filling. After data checking, 110 was valid and indicated this research qualification was beyond the targeted minimum sample number. Based on the respondent's profile (Table 2), this research has successfully captured a sample from diverse backgrounds. Moreover, this research captured Grammarly as their most favorite AI-based software for scientific writing (85.14%), followed by ChatGPT as consulting service (55.14%).

4. RESULTS

4.1 Inner and outer testing

This research converted the collected data from categorical data in the Likert scale into numerical data (1 to 5). SmartPLS version 3 processed those data using the PLS algorithm after the hypotheses model emerged (see Figure 3). This research performed two tests for outer model analysis: reliability and validity. The reliability test calculated the Composite Reliability (CR) values with a minimum reliability value requirement of 0.70 [28]. Validity testing follows the average variance extracted (AVE) value with a minimum value requirement of 0.50 [28] using the Fornell-Lacker criteria. This research found that five indicators obtained a value of less than 0.7, so they needed to be eliminated. The system replayed the PLS algorithm to recheck the calculation of the reliability value after eliminating the five. The recalculation results show that all indicators have a CR value of more than 0.7, so all variables' reliability has been confirmed. Table 3 summarizes the calculations for outer and inner test values.

Indicators in the Inner model or structural model test are R-square (R2), predictive relevance (Q2), and effect size f2 [28, 29]. This research only used the INT variable as a variable influenced by other variables. Because the R-square value for the INT variable reaches 0.508, the model meets the minimum requirement of 0.20. Meanwhile, the Q2 value was only obtained when the INT variable reached 0.282, which means it meets the requirements for a positive value. Finally, this study measures the f2 value in all variables except INT. Only the QLT and SEC variables meet the rule of 0.02, while the other four are below 0.02. These results indicate that only the QLT and SEC variables impact the INT variable. Table 3 displays detailed results of R2, Q2, and f2 values.

4.2 Hypotheses testing

Determination of the acceptance of Hypotheses refers to the values: path coefficient, Sample Mean (SM), Standard Deviation (SD) T-statistics value, and the P Values from the bootstrapping operation results using SmartPLS 3 with 5000 subsamples [28]. Hair et al. [39] stated that the condition for a hypothesis to be accepted is <0.050, so only hypotheses H1 and H5 were accepted. These two hypotheses state that quality and security each influence lecturers' intentions to use AI-based software to write scientific articles. Thus, four variables have no proven influence: motivation, support ability, subjective norms, and individual ability. Table 4 summarized the related calculations.

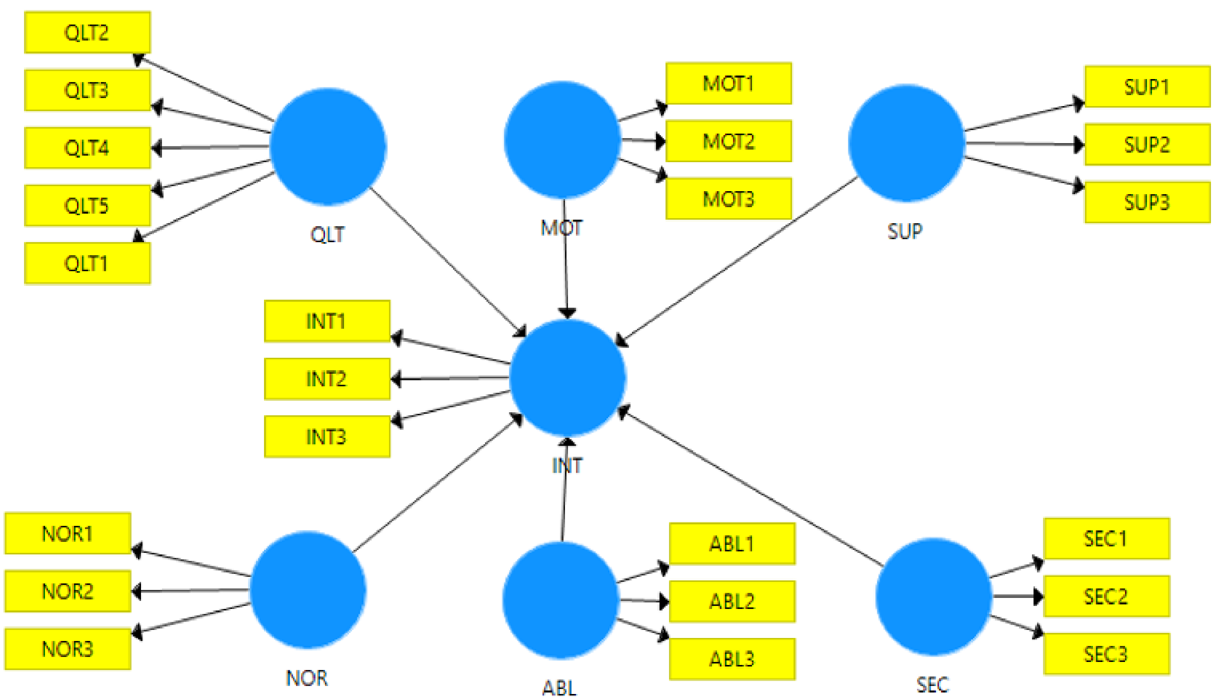

Figure 3. Emerged model in smart PLS

Table 3. Summary of Fornell-Lacker and other related metrics

Metrics	QLT	MOT	SUP	NOR	ABL	SEC	INT
Fornell-Lacker							
QLT	.806						
MOT	.360	1.000					
SUP	.258	.030	.964				
NOR	.428	.249	.161	.754			
ABL	.283	-.044	.605	.117	.862		
SEC	.375	.292	.291	.211	.269	.893	
INT	.685	.310	.274	.295	.251	.423	.829
CR	.881	1.000	.963	.797	.897	.922	.814
AVE	.650	1.000	.929	.568	.743	.798	.687
R2	-	-		-	-	-	.508
Q2	-	-	-	-	-	-	.282
f2	.467	.004	.007	.001	.000	.045	-

Table 4. Summary of hypotheses testing

Hypothesis	SM	SD	T-Statistics	P Value	Result
H1 (QLT→INT)	.582	.099	6.011	.000	**Accept**
H2 (MOT→INT)	.053	.080	.624	.267	**Reject**
H3 (SUP→INT)	.060	.116	.657	.256	**Reject**
H4 (NOR→INT)	.003	.079	.229	.409	**Reject**
H5 (SEC→INT)	.169	.070	2.428	.008	**Accept**
H6 (ABL→INT)	.015	.101	.042	.483	**Reject**

5. DISCUSSION

5.1 Theoretical implications

Based on quantitative calculations, this research found that two variables influence lecturers' intentions to use AI-based software in writing scientific articles. The two variables are quality (QLT) and security (SEC). Proving that the Quality variable (QLT) is a contributor indicates that software quality theory and its components are valid empirically. The results of this research align with several previous studies relating to contributing factors.

Software quality has a wide range of definitions, including aspects of benefit, efficiency, effectiveness, accuracy, and usability [26]. The beneficial aspects proven in this study were in line with Salvagno's statement in the study by Salvagno et al. [7], while the effectiveness and accuracy sharpened Bringula's statement in the study by Bringula [22]. Meanwhile, the usability aspect has the same results as Xu et al. [23] and Nolay et al. [24]. It confirms that aspects of usefulness and reusability play a significant role in software adoption, especially AI-based software. Usefulness signalizes software ability to fulfill users' needs and requirements. Software ability to fulfill them correlated strongly with competition among similar software to achieve its product continuity. Hence, AI-based software will enrich its scope following future enhanced requirements. Specifically for usability, AI-based software currently relies on an interface that offers interaction using natural language to increase the users experience when communicating with the software and its users. It encourages the increasing role of the ability aspect as part of software quality.

Security was another contributing factor that denotes lecturers had strong attention to obtain information security protection, especially personal data protection. This finding strengthens the previous research that performed by Yu [38], Bringula [22], and Xu et al. [23]. They had mentioned information security as crucial determinant when academician (teachers and students) to use ChatGPT. They put information leakage as threat that reduce academicians' intention. However, this research converted it into software's ability (and its operator capability) to protect the users' information security. By converting it, this research attempts to capture users' direct concern and requirements about information security as shown in SEC.01 until SEC.03 (see Table 1). Although take different perspective, it generated similar landscape with previous research.

On the other hand, the four rejected factors (Motivation, Subjective Norms, Ability, and Support) have explanations and arguments as interpretations of statistical test results. As the rejected variable, the Ability shows that there is no significant difference in influence between people who have scientific writing skills and those who do not. Both characteristics have a relatively high intention of utilizing AI-based software in scientific writing. It indicates that AI-based software is open to various groups with various skill levels. Even when people already have scientific writing skills, they feel it is okay to continue using AI-based software because it delivers the expected benefits. This research suspects that AI-based software provides excellent benefits. This significant benefit is the recommendations on techniques for writing scientific articles, which lecturers still need even though they have had many writing experiences.

Another rejected variable is Support (SUP). This research suspects that many indicators in the questionnaire do not construct a sufficient correlation pattern to use AI-based software for writing scientific articles. For example, at the beginning of this research, suspects that financial support was suspected as a contributing factor for purchasing AI-based software licenses. However, this indicator must be proven by considering the relatively cheap price and many similar products. Moreover, AI-based software with a free package provides sufficient benefits. Therefore, this research showed a blurry difference between those who subscribe and those who use the free version. Other indicators related to the SUP variable are digital literacy skills and technical abilities to operate the software. This research argues that AI-based software has good user experience and usability (easy and practical). Thus, digital literacy and the technical ability to operate software do not influence intentions.

Another interesting phenomenon is the non-acceptance of the Subjective Norm variable in lecturers' intentions when writing scientific articles using AI-based software. It proves that currently, lecturers are not affected by the regulations set by institutions regarding using AI-based software to assist in writing scientific articles. However, it could be influenced by the fact that the institution does not set regulations regarding its use. Without regulations, lecturers do not have a legal reference for using or not using them. AI-based software usage relies on the lecturer's rationalization and ethics in distinguishing between permitted and prohibited. In the future, attitudes and intensity may change when regulations allow or prohibit it. Interestingly, the lecturers saw that the surrounding environment (fellow lecturers or the community) also had no influence. This research suspects that this is due to the use of AI-based software, which has already become widespread, so lecturers ignore the attitudes of the surrounding environment when deciding to use AI-based software.

Another variable whose correlation with Intention is rejected is Motivation (MOT). It showed that the three indicators of Motivation (personal demands for productivity, institutional demands for productivity, and personal demands for producing quality work) are not automatically directly proportional to the intention to utilize AI-based software in writing scientific articles. This situation happened because of the diversity of lecturers' characters in Indonesia based on their inclination towards institutional duties. Some lecturers are interested in research, so they set targets for publication. However, some lecturers were interested in teaching or organizational assignments, so they did not have publication productivity targets except to fulfill the minimum annual publication quantity standards. This situation has the impact of not forming a positive correlation between lecturer motivation and intention to use AI-based software. This research suspects that in the future, it will be necessary to group lecturer characteristics (as mentioned previously) to ensure the influence of specific motivation only on lecturers who have passion for the research.

Finally, this research also advocates the academic institution to formulate and legalize a guideline for AI-based software. It helps lecturers to distinguish which activities that can be supported by AI-based software or not. It also gives legal certainty as narrated also by Gupta and Bhaskar [40] in 2020. Separately in 2023, Zou and Huang [12] and Salvagno et al. [7] agree it can balance productivity and fairness in academic publication.

5.2 Practical implications

First implication was related with the acceptance of H1 (QLT→INT). In implementing AI systems, the software must still have the quality to fulfill user needs and/or objectives. Specifically, its indicators were valid and increased the lecturer's behavior to utilize AI. They empirically characterized software quality attributes that influence its use by lecturers. In writing typed scientific articles in the future, similar applications must pay attention to these four things as part of the quality of the software built to attract user intentions and maintain business continuity. Therefore, this finding implies that software developers in the AI industry should prioritize product quality attributes to satisfy users since software quality has a fundamental impact on ensuring user's intention at the present and continuity to use in the future.

Another accepted variable is Security, a hot issue in software development and artificial intelligence. Recently, society has become increasingly aware that security in using software, especially those based on artificial intelligence, is mandatory. The public demands guarantees that the use of software has adequate information security protection. This premise is proven when using AI-based software to write scientific articles. Using AI-based software to write scientific articles does not use personal data, so recognizing its behavior does not cause privacy violations. However, the use of software that uses an account causes the potential for misuse of personal data in the account by the application owner. Moreover, using an account with a Single Sign-On system or API access to several general accounts (for example, Google) can potentially cause data leaks that need to be anticipated. Therefore, software developers should also ensure information security compliance with requirements and regulations, especially personal data protection. Academic institutions should also build academicians' awareness of information security to balance AI-based software's benefits with related risks.

6. CONCLUSIONS

Following its goals, this research identified the potential factors by testing six hypotheses with 110 lecturers in Indonesia. By validating their quantitative perception, this research empirically revealed that Product Quality (QLT) and Security (SEC) influence lecturers' use of AI-based software in scientific writing. The finding exposed software quality has a vital role in engaging lecturers' intention to use AI-based software considering its characteristics to satisfy their needs: usefulness, easiness, accuracy, and efficiency. Also, lecturers are concerned with information security since AI-based software captures personal data, including user behavior during its usage. In contrast, four other variables (Motivation/MOT, Supporting Ability/SUP, Subjective Norms/NOR, and Individual Ability/ABL) had no influence. This research promotes practical implications for universities to regulate AI-based software, considering its benefits have been recognized by lecturers. However, its misuse can lead to the university's credibility in research and should be mitigated.

7. RECOMMENDATIONS

Future research should expand the respondents' participation to improve profile diversity. With more diverse respondents, this research can escalate representativeness and feasibility. This research also suggests more comprehensive qualitative feedback from experts, such as psychologists and philosophers, through focus group discussions to escalate the findings' validity. Their participation can enrich the interpretation of the adoption process from a multi-disciplinary. Also, this research also promotes comparison studies about AI-based software adoption by segregating respondents into two or more classes, such as digital literacy or research experience. It enables insight into specific segments for formulating the necessary regulations.

Another recommended research topic is the classification and evaluation of various types of AI-based software in writing scientific articles following the ethical corridor. Considering the increasingly powerful features and services of AI-based software in writing scientific articles. For example, using it for grammar correction still gets positive sentiments, while idea generation until manuscript finalization gets negative sentiments. Also, several educational institutions have created guidelines for using AI to write scientific articles. This reaction phenomenon has become exciting by emphasizing its influence on productivity and ethical compliance.

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