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UNLOCKING AI POTENTIAL: EFFORT EXPECTANCY, SATISFACTION, AND USAGE IN RESEARCH

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ABSTRACT

Aim/Purpose	This study investigates the key factors influencing the adoption and use of artificial intelligence (AI) applications among researchers, focusing on effort expectancy, satisfaction, perceived ease of use, and perceived usefulness, which shaped attitudes and drove AI adoption as a research assistant.
Background	AI tools have rapidly become game-changers in academic research, transforming tasks such as literature retrieval, writing, editing, and data analysis. Despite their potential, barriers like high effort expectancy, inconsistent user satisfaction, and ethical concerns regarding over-reliance and plagiarism continue to hinder widespread adoption. A pressing gap exists in understanding how AI impacts the efficiency and integrity of academic research workflows.
Methodology	A quantitative approach using structural equation modeling (SEM) was employed. Data was collected from 120 active researchers who use AI tools for academic tasks, including literature reviews, writing support, and data visualization.
Contribution	This study contributes to the understanding of how key factors, such as effort expectancy and satisfaction, affect AI adoption in academic research. It emphasizes the importance of reducing cognitive load and improving user satisfaction to promote widespread AI adoption. It also underscores the

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	importance of intuitive AI design and institutional support in shaping researchers' engagement with AI tools, which could enhance productivity and research outcomes.
Findings	The findings reveal that effort expectancy, satisfaction, perceived ease of use, and perceived usefulness significantly influence attitude and actual use of AI tools, with attitude serving as a key mediator. The model demonstrated moderate to high explanatory power ($R^2 = 0.409$ to 0.459) and predictive relevance ($Q^2 = 0.171$ to 0.409), highlighting the substantial role of effort expectancy and satisfaction in shaping perceived ease of use and usefulness. These findings emphasize the importance of reducing cognitive load and improving user satisfaction to encourage the adoption of AI tools in research.
Recommendations for Practitioners	Institutions and AI developers should focus on reducing the learning curve of AI tools by enhancing their intuitiveness and providing targeted training and technical support. Ethical AI use should also be promoted to address concerns about over-reliance and plagiarism. Institutions should foster a culture that normalizes AI integration in research practices.
Recommendations for Researchers	Researchers should be informed of the long-term effects of AI adoption on research quality and integrity and how institutional support can foster positive attitudes toward AI tools in academic research.
Impact on Society	The broader adoption of AI tools in academic research could enhance productivity and efficiency, leading to more breakthroughs in various fields and benefiting society by accelerating research and innovation. Additionally, AI can democratize access to research resources, particularly for underfunded institutions and early-career researchers, by enabling broader participation in cutting-edge research and fostering equity and diversity in academic contributions.
Future Research	Future studies should focus on the role of user experience in AI adoption, particularly how different user groups interact with AI tools. Longitudinal studies could provide insights into how attitudes toward AI change as users become more familiar with the tools.

Keywords	artificial intelligence, research assistance, AI adoption, effort expectancy, perceived ease of use, satisfaction, academic research, technology acceptance

INTRODUCTION

The field of scientific research is now being changed by artificial intelligence (AI) as it reduces the time and effort needed by researchers by automating jobs and enhancing research methods. Post-graduate and budding researchers especially benefit from AI as it offers timely assistance in solving the challenges posed by academic research. AI tools can expedite literature research by rapidly identifying gaps in the current literature, summarising important findings, and collecting integral information from large pools of articles and journals (Santiago et al., 2023). According to Santiago et al. (2023), artificial intelligence (AI) also makes data analysis easier, enabling researchers to handle big data sets quickly and find hidden patterns. AI tools like ChatGPT have been gaining popularity in bibliometric studies as they speed up research output, doing the heavy lifting for researchers handling demanding work (Watrianthos et al., 2023). AI tools can also help researchers navigate the daunting task of completing literature reviews by assisting them in specifying important findings and pertinent hypotheses faster. AI can also aid researchers with data analysis, a field that frequently calls for specialized knowledge and expertise. Automated analysis of large datasets allows researchers to gain deeper insights into their topics and achieve more robust and reliable results (Watrianthos et al., 2023).

Beyond technical efficiency, AI tools hold the potential to democratize access to advanced research capabilities, reducing disparities between experienced and novice researchers by offering scalable, user-friendly solutions. Recent studies emphasize that AI not only aids novice researchers in analysis but also fosters more personalized learning experiences for researchers, helping them improve critical elements of their research, including writing and data visualization (Soodan et al., 2024; Watrianthos et al., 2023). AI can assist with writing production as one can write and edit a variety of academic pieces. To secure research funding, some researchers even use AI to draft grant proposals (Khalifa & Albadawy, 2024). However, there are growing concerns about the potential pitfalls of AI as a research assistant tool. Besides reducing critical thinking, AI-generated content can sometimes be inaccurate or biased, raising the risk of researchers blindly accepting untrustworthy information (Kamoun et al., 2024; Sekli et al., 2024). In addition, Watrianthos et al. (2023) found that while AI tools like ChatGPT excel in data retrieval and synthesis, there are notable gaps in how these tools address specific academic challenges, such as interpreting complex theoretical frameworks or ethical considerations. Additionally, AI may inadvertently encourage academic dishonesty, such as plagiarism in academic writing (Husain, 2024; Kamoun et al., 2024).

While AI tools offer immense potential in streamlining processes, they also pose ethical dilemmas requiring scrutiny. For starters, despite the advantages of AI as a research assistance tool, a critical research gap remains in understanding the reasons behind their adoption and sustained use in academic settings (Santiago et al., 2023). Understanding the factors driving their adoption and sustained use is essential to harness these tools responsibly while mitigating their risks. Effort expectancy, researcher satisfaction, perceived ease of use, perceived usefulness attitude, and actual use are crucial factors that influence technology acceptance but are still little explored in the context of AI research tools, especially for early career researchers (Marzuki et al., 2023; Musyaffi et al., 2024). While some sources discuss in-depth the over-reliance on AI tools and possible negative impacts on critical thinking and creativity, they do not thoroughly explore how these concerns relate to effort expectancy, perceived usefulness, or researcher attitudes (Chan & Zhou, 2023; Marzuki et al., 2023; Santiago et al., 2023). In other words, there is a need for an understanding of how effort expectancy and satisfaction influence AI adoption and can inform developers to create tools that are more intuitive and accessible.

Recent studies also highlight the limited research on how individual user characteristics, such as experience with technology, affect AI adoption (Watrianthos et al., 2023). This lack of comprehensive studies examining the user-centered aspects of AI adoption is particularly important for novice researchers who may face additional challenges due to their limited experience and knowledge in dealing with the complexities of AI integration. To promote the effective integration of these tools to support them, it is critical to understand how expected effort, perceived ease of use, and other user-related factors impact the decision to adopt AI-powered research support. This study aims to fill this gap by examining these factors through a user-centered lens, focusing on the adoption and sustained use of AI research assistance tools among researchers. By doing so, it aims to provide actionable insights for improving AI integration in academic research, contributing not only to individual researcher success but also to the broader advancement of knowledge creation.

The objective of this study is to investigate the interconnected roles of effort expectancy, satisfaction, perceived ease of use, perceived usefulness, and researcher attitudes in determining the adoption and usage of AI tools as research assistance.

LITERATURE REVIEW

THE ROLE OF AI IN RESEARCH: BALANCING EFFICIENCY AND INTEGRITY

Artificial intelligence (AI) has become a crucial tool in academic research by streamlining processes and improving productivity. AI tools assist researchers with tasks ranging from literature review to proofreading and data analysis. This section will first explore how AI contributes to research efficiency, followed by the potential pitfalls of AI in terms of research integrity.

Enhancing research efficiency

AI tools have changed how researchers conduct literature reviews by reducing time and manual effort. AI tools like ChatGPT can interpret the context of search queries to deliver more relevant results (Heintz et al., 2022; Khalifa & Albadawy, 2024), which reduces the time required to filter through large amounts of research (Sekli et al., 2024). A study suggests that AI tools can be useful in mapping academic trends and publication patterns (Watrianthos et al., 2023). However, users need time to get used to and become familiar with these tools, and the presence of the learning curve associated with different AI platforms can be challenging (Kamoun et al., 2024).

As writing assistance, AI tools like QuillBot and ChatGPT have become valuable for drafting academic papers. These tools help improve grammar, coherence, and clarity in writing, supporting researchers – especially novice ones – through the complex process of developing high-quality academic work (Milad & Fayez, 2024). AI tools can also suggest improvements to sentence structure, aiding the overall flow and readability of texts. On the same line, AI-driven proofreading and editing tools have become essential in reducing errors and improving the consistency of academic texts. These tools automatically detect typos, grammatical issues, and stylistic inconsistencies (Li, 2023). However, researchers have highlighted that AI tools, while useful, must be integrated carefully into the writing process to avoid compromising the academic voice (Soodan et al., 2024). Recent studies also show that AI proofreading tools may miss context-specific errors, particularly when processing nuanced academic language (Watrianthos et al., 2023). Researchers must recognize that AI tools may miss context-specific issues or subtle errors, necessitating human oversight to ensure accuracy (Husain, 2024; Sekli et al., 2024).

AI also plays a pivotal role in data visualization, allowing researchers to process large datasets and generate clear, insightful visual representations. Tools that use AI can detect patterns, create graphs, and recommend appropriate statistical analyses, which are crucial for presenting research findings effectively (Milad & Fayez, 2024; Zhou et al., 2024). However, researchers need a solid understanding of data interpretation principles to ensure that AI-generated visualizations are used correctly and convey the intended message (Ngo et al., 2024; Sekli et al., 2024). Additionally, AI tools in data visualization require continuous refinement to better handle large, complex datasets, as Soodan et al. (2024) noted in their analysis of AI's role in research.

Alongside its contributions to efficiency, the use of AI highlights important questions about ethical considerations in research practices, which will be highlighted in the next part.

Maintaining research integrity

While AI greatly enhances efficiency, AI tools introduce many ethical challenges that require careful consideration. The widespread use of AI in academic writing raises potential concerns regarding plagiarism. AI tools like ChatGPT can inadvertently generate content that closely copies existing work, risking unintentional plagiarism if not carefully reviewed. Another concern of AI use in research is the potential for over-reliance, which can lead to reduced critical thinking and problem-solving skills. While AI tools can automate routine tasks, there is a risk that researchers may become too dependent on these tools, accepting AI-generated results without sufficient scrutiny (Rabbianty et al., 2023).

Researchers are encouraged to acknowledge the use of AI in their work to promote transparency and maintain ethical standards (Husain, 2024; Kamoun et al., 2024). Institutions should implement standardized citation guidelines for AI tools used in research to ensure transparency. Moreover, institutions must provide clear guidelines on AI use to avoid ethical violations, as suggested by Watrianthos et al. (2023). AI developers should incorporate alerts or reminders within tools to flag potential plagiarism or over-reliance on generated content. Human review remains crucial to ensure that AI-generated content does not undermine the originality of the researcher's contributions (Sharadgah & Sa'di, 2022). It is important to use AI as a supplement to, rather than a replacement for, human intellectual engagement (Sekli et al., 2024). Researchers must remain actively involved in validating and interpreting AI-generated outputs to ensure that their work maintains academic rigor and integrity. As highlighted by Soodan et al. (2024), striking this balance is critical to preserving the intellectual depth of academic research in AI-supported environments.

Given these dualities of efficiency and integrity, it becomes essential to examine the factors that influence researchers' adoption and sustained use of AI tools.

ARTIFICIAL INTELLIGENCE (AI) AS RESEARCH ASSISTANCE

AI has become a transformative tool in academic research, offering support in areas such as article retrieval (Polyportis, 2023), writing, editing (Heintz et al., 2022), and data presentation. However, the adoption of AI is influenced by several key factors, including effort expectancy (Alzahrani, 2023), satisfaction (Wedari et al., 2022), perceived ease of use, perceived usefulness (Shyr et al., 2024; Wedari et al., 2022), and attitude (Geddam et al., 2024; Huang, 2021). Understanding these factors helps explain how researchers engage with AI-driven research assistance.

Effort expectancy in using artificial intelligence (AI) as research assistance

A crucial factor influencing researchers' openness to adopting artificial intelligence (AI) tools is their perceived effort expectancy – the amount of work they anticipate will be needed to effectively incorporate AI into their research process (Nazari et al., 2021). This concept includes the perceived ease of use and the cognitive demands of navigating various AI technologies for tasks like literature searching, drafting, proofreading, editing, referencing, and data visualization. When researchers expect that using AI tools will require minimal effort and present few obstacles, they are more inclined to adopt and engage with these tools in their workflows (Geddam et al., 2024).

An expectation of low effort fosters a positive perception of ease of use, encouraging researchers to explore the full potential of AI tools and recognize their benefits. When tools are easy to operate, researchers are less likely to view them as cumbersome, making the adoption process smoother and enhancing the perceived usefulness of the technology (Geddam et al., 2024). Consequently, effort expectancy plays a central role in shaping attitudes toward the use of AI tools for research, directly impacting adoption rates (Nazari et al., 2021).

However, despite these benefits, initial unfamiliarity with AI interfaces can create a higher cognitive load during the learning phase, especially for new users (Sekli et al., 2024). This learning curve can challenge researchers, making it essential for institutions and developers to offer adequate support and training. By fostering a positive attitude towards AI tools, enhancing transparency, and encouraging active engagement, researchers can maximize the efficiency, productivity, and quality of their work, leveraging AI as a robust research aid. As such, H1 and H2 are postulate as follows:

H1: There is a relationship between effort expectancy and the perceived usefulness of AI-driven research assistance.

H2: There is a relationship between effort expectancy and the perceived ease of use of AI-driven research assistance.

Satisfaction in using artificial intelligence (AI) as research assistance

The specific use of artificial intelligence (AI) in the field of research depends highly on individual needs and preferences, making the notion of satisfaction highly idiosyncratic. Generally, AI tools can significantly enhance the research experience by streamlining tasks, improving efficiency, and allowing researchers to focus on more complex aspects of their work. Studies, such as that by Watrianthos et al. (2023), indicate that satisfaction is higher when AI tools offer features like personalized feedback and adaptive responses. This effect is particularly evident in AI applications for writing and data analysis, where the tools can adjust to the user's input, resulting in a smoother and more efficient research process.

Generally, satisfaction levels tend to increase when researchers perceive AI tools as useful for advancing their research goals. One such instance is where AI can be especially beneficial to non-native English speakers by helping them improve clarity and communication in their writing (Heintz et al., 2022). Saqr et al. (2024) found that in e-learning contexts, satisfaction with AI tools is closely linked to their perceived usefulness and ease of use, highlighting that researchers are more likely to feel satisfied if they find these tools beneficial and easily integrated into their workflows. Similarly, Huang (2021) reported that the perceived usefulness of AI tools has a strong correlation with satisfaction; researchers tend to be more content with AI tools when they view them as effective in enhancing their productivity and outcomes. Conversely, if AI tools are challenging to use or perceived as less beneficial, satisfaction levels may decline, underscoring the importance of ensuring AI tools are both practical and easy to operate for maximum adoption.

Furthermore, perceived ease of use plays a significant role in shaping satisfaction with AI tools. When researchers find AI tools simple to navigate, they experience less cognitive load, resulting in a more positive overall experience. Studies, such as Khlaisang et al. (2021), suggest that ease of use not only directly impacts satisfaction but also reinforces the perceived usefulness of the tools, creating a positive feedback loop that further enhances researcher satisfaction. As such, H3 and H4 are postulate as follows:

- **H3**: There is a relationship between satisfaction and the perceived usefulness of AI-driven research assistance.
- **H4**: There is a relationship between satisfaction and the perceived ease of use of AI-driven research assistance.

Easiness and the usefulness of using artificial intelligence (AI) as research assistance

Research consistently shows a strong link between perceived ease of use and perceived usefulness of AI-driven technologies. When researchers find these tools easy to integrate into their research workflows and intuitive to navigate, they are more likely to see them as genuinely beneficial for enhancing research productivity. Researchers tend to adopt and use AI tools regularly when these tools offer simple interfaces and clear guidance (Soodan et al., 2024; Watrianthos et al., 2023).

Studies have demonstrated that well-designed AI systems can enhance both ease of use and perceived usefulness in e-learning and research environments (Huang, 2021). Huang's (2021) study identified ease of use as a mediating factor, suggesting that when users find AI systems accessible and easy to engage with, they tend to perceive them as more valuable, which positively influences their overall attitude toward using these tools.

The perceived usefulness of AI-powered research tools also significantly affects researchers' attitudes toward adopting them (Kashive et al., 2021). For instance, research on ChatGPT's acceptance in educational contexts found that perceived usefulness was a major predictor of sustained usage (Min et al., 2019). While ease of use did not directly impact usage, it influenced both perceived usefulness and attitudes, ultimately promoting AI integration in research.

Additionally, studies on AI in blended learning environments reveal that ease of use directly influences learning attitudes (Huang, 2021; Kashive et al., 2021). When researchers find AI tools easy to operate, they are more likely to maintain a positive attitude towards them. Perceived usefulness further influences satisfaction and shapes attitudes toward these tools, fostering a constructive view of their role in research and learning.

Therefore, when an AI-driven tool is user-friendly and requires minimal training, researchers are more likely to view it as both easy to use and valuable for improving research efficiency. This creates a beneficial cycle: as researchers find AI tools easier to use, they identify additional ways these tools can enhance their work, reinforcing usefulness and encouraging sustained adoption and integration into their research routines. As such, H5, H6 and H7 are postulate as follows:

- **H5**: There is a significant relationship between perceived ease of use and perceived usefulness of AI-driven research assistance.
- **H6**: Perceived usefulness significantly influences the attitude towards using AI-driven research assistance.
- **H7**: Perceived ease of use significantly influences the attitude towards using AI-driven research assistance.

Attitude to use and the actual use of artificial intelligence (AI) as research assistance

Research indicates that positive attitudes toward artificial intelligence (AI) are often associated with a higher likelihood of actual use (Mohmed & Elballat, 2024). For instance, researchers who believe AI tools can enhance their research efficiency and effectiveness are more inclined to incorporate them into their workflows. This draws parallels with the findings that emphasize the importance of perceived usefulness in shaping researcher attitudes and subsequent usage behavior (Lee et al., 2023). A study by Nazari et al. (2021) indicates that students with higher self-efficacy levels are more likely to engage with these tools, exerting more effort and dedication in their writing tasks. This relationship underlines the importance of fostering a positive attitude towards AI tools, as students who perceive these technologies as user-friendly are more likely to integrate them into their writing processes. Furthermore, the context in which AI-driven research assistance tools are introduced can significantly impact researcher attitudes and actual usage. In environments where there is strong institutional support for AI adoption, researchers are more likely to have positive attitudes and engage with these tools (Chan & Zhou, 2023; Geddam et al., 2024). Conversely, in settings where there is limited support or resources for AI integration, researchers may develop negative attitudes, resulting in lower actual usage rates. As such, H8 is postulated as follows:

- **H8**: There is a significant relationship between attitude and the actual use of AI-driven research assistance.

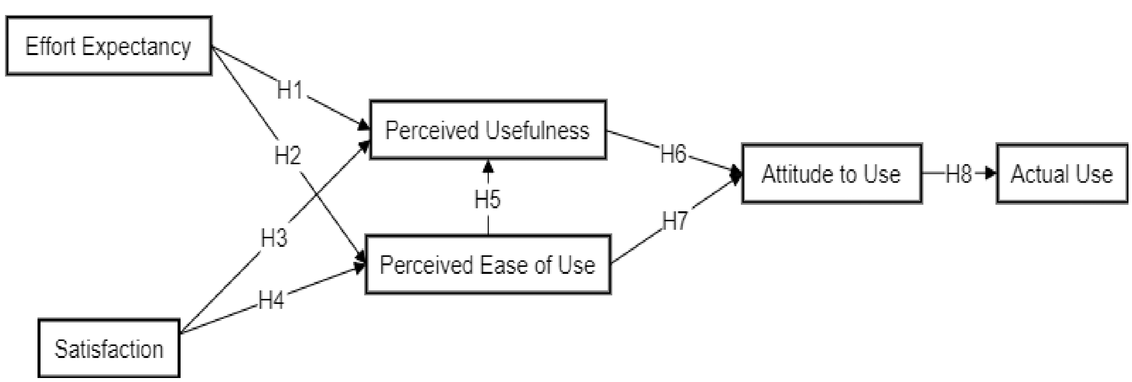

Figure 1. Conceptual framework of AI-powered research assistance

METHODOLOGY

SAMPLE

This study employed a quantitative survey research design targeting postgraduate students as novice researchers who are members of the Doctorate Support Group (DSG). DSG is a non-governmental organization (NGO) dedicated to assisting postgraduate students throughout their research journey. The organization currently has approximately 108,800 members, comprising a diverse range of stakeholders, including students and experts worldwide.

To ensure a robust analysis, volunteer sampling was strategically chosen due to the diverse composition of the DSG community. Given the dispersed nature of the DSG community, volunteer sampling was chosen as it aligns with the study's objectives to capture diverse user experiences with AI tools, as Cohen et al. (2018) suggested. Volunteer sampling is appropriate in this context as it allows for the inclusion of willing participants who have direct experience with AI-driven research tools, aligning with the study's focus on understanding their adoption. This approach is also practical given the online nature of DSG's networks and the difficulty of random sampling in this dispersed population.

To determine an appropriate sample size for valid data representation, the A-priori Sample Size Calculator for SEM was utilized (Soper, 2021). This calculation considered the number of observed variables (n=27) and latent variables (n=6) in the model, an anticipated effect size of .5, a significance level of .05, and a statistical power of .95 (Memon et al., 2020). The minimum required sample size to detect an effect was calculated at n=58, with a recommended sample size of n=88. However, increasing the sample size helps reduce the impact of outliers (Weisburd et al., 2022). Therefore, the sample size was expanded to strengthen the validity of the research findings by n=120. This decision aligns with Cohen et al. (2018), who emphasize the importance of larger samples in reducing the impact of variability in volunteer-based sampling.

To maximize participation, the survey was distributed via DSG platforms with reminders sent at regular intervals, ensuring accessibility across devices. Recruitment involved distributing an online survey through DSG's official platforms (Facebook) with a clear statement of voluntary participation. Participation was further facilitated by designing the survey to provide accessibility to multiple devices (computers, laptops, smartphones, and tablets). These measures ensured a diverse and representative sample of DSG members while minimizing barriers to participation.

ETHICAL CONSIDERATION

This study adhered to stringent ethical protocols to ensure the privacy, confidentiality, and rights of all participants. Additionally, ethical concerns specific to AI use, such as potential biases in AI-generated outputs and risks of over-reliance, were carefully considered. In alignment with relevant data protection laws and institutional guidelines, no personally identifiable information (PII) was collected or processed. All data were anonymized and stored securely to prevent unauthorized access. Specific measures were implemented to safeguard against potential risks unique to AI tools, such as data breaches and misuse of sensitive information. Participants were provided with a comprehensive informed consent form, which outlined the study's objectives, their right to withdraw at any stage, assurances regarding the confidentiality of their responses, and details on the ethical implications of AI use in research.

Participation in the study was entirely voluntary, with no incentives provided to avoid any undue influence on responses. Efforts were made to minimize potential risks, and participants were assured that their data would only be used for research purposes. Additionally, steps were taken to ensure inclusivity and accessibility. The survey was designed to be user-friendly and accessible across multiple devices, including computers, laptops, and smartphones. Clear instructions and contact information for the research team were provided in case participants had any questions or concerns. This approach aimed to foster trust and transparency throughout the data collection process.

Instrumentation

All questionnaire items were adapted deductively from the literature based on the operationalized research variables. Effort expectancy (5 items) was adapted from Alzahrani (2023), satisfaction and perceived ease of use (4 items each) from Venkatesh and Davis (2000), perceived usefulness (6 items) from Davis (1989), attitude (4 items) from Ajzen (1991), and actual use (4 items) from Venkatesh et al. (2012) (The questionnaire is in the Appendix). A 5-point Likert scale (1-strongly disagree to 5-strongly agree) was employed for all items to enhance respondent practicality and minimize rejection.

To ensure the validity of the adapted instruments, a two-step validation was employed, which is the expert review based on content and language and reliability testing. First, the instruments were reviewed by experts in educational technology (three panels) and language (two panels) so that all the items could be understood by the participants. The experts evaluated the instruments to ensure that each item accurately captured the intended construct. All items are reviewed by experts and revised according to the comments and recommendations from them. The final version of items by each variable can be found in the Appendix.

Next, the instrument underwent reliability testing using a pilot study. A small sample of postgraduates (30 samples) from Doctorate Support Groups (DSG) completed the survey, and the data were analyzed to assess internal consistency. The instrument exhibited excellent reliability, collectively with Cronbach's alpha of .907. Each of the variables also demonstrated strong reliability: effort expectancy (.777, acceptable), satisfaction (.862, good), perceived usefulness (.982, excellent), perceived ease of use (.932, excellent), attitude (.912, excellent), and actual use (.962, excellent) (Chua, 2020).

With the instrument used, as in the Appendix, data was collected and underwent further convergent and discriminant validity (discussed in the Data Analysis section) as part of the measurement model analysis. Convergent validity was established with Average Variance Extracted (AVE) values exceeding 0.70 for all constructs, while discriminant validity was confirmed through the Fornell-Larcker criterion. These steps ensured that the instrument was both valid and reliable for measuring the constructs in this study.

Data Collection

Data was collected using Google Forms as its capability for data extraction into various types of files and distributed through the Doctorate Support Group (DSG) community. The questionnaire link can run on computers, laptops, smartphones, and tablets to reduce the bias for data collection via an online questionnaire. Initial information on volunteer participation and rights to reject and withdraw statements were also stated in the first line of the instrument's introduction. Participation was voluntary, with no incentives provided to avoid influencing responses.

Participants were provided with introductory statements that explained the purpose of the study, assured confidentiality and anonymity, and outlined their right to withdraw from the study at any time. The online survey remained open until sufficient responses were obtained. To maximize participation and minimize non-response bias, multiple reminders were sent through DSG's platforms. The distribution strategy ensured that a diverse set of members representing various disciplines and research backgrounds had the opportunity to participate.

Efforts were made to ensure data quality by filtering out incomplete or duplicate responses during the data cleaning phase. This approach resulted in a final sample size of 298 valid responses, which surpassed the minimum requirement determined by statistical power analysis. The comprehensive and systematic approach to data collection provided a robust dataset for subsequent analysis.

Data Analysis

The data collected via the questionnaire were imported into the statistical software package IBM® SPSS® Statistics version 25 for evaluation. The study utilized partial least square structural equation modeling (PLS-SEM), a type of multivariate analysis conducted using SmartPLS™ 4. This analysis was conducted in two parts: (i) measurement model and (ii) structural model. Particularly for structural model analysis, four main criteria were evaluated in order to evaluate the hypothesis and map out each respective relationship in the figure by the following cut-off value as in Table 1.

Table 1. Cut-off value for structural model analysis

Dimensions	Benchmark
1. Regression weight, β	0 and ±1.0
2. Total effect size, R^2	0.25, 0.50, 0.75 weak, moderate, large (Hair et al., 2014) 0.19, 0.33, 0.67 weak, moderate, good (Chin, 2010)
3. Effect size, f^2	0.05, 0.20, 0.35 small, moderate, large (Chua, 2020)
4. Predictive relevance, Q^2	>0, 0.02, 0.15, 0.35 low, moderate, high (Chin, 2010)

This section discusses the measurement model analysis and the structural model analysis is conducted and reported in the Results section.

Measurement model

- **Convergent and discriminant validity**
- **Convergent validity**

A smaller loading value (<.70) indicated that the items are less acceptable and cannot be used to measure the variable (Chua, 2020). Based on Figure 2, the loading value of items for all items for each variable achieved a value of more than .70. Hence, all the items were suitable for further analysis.

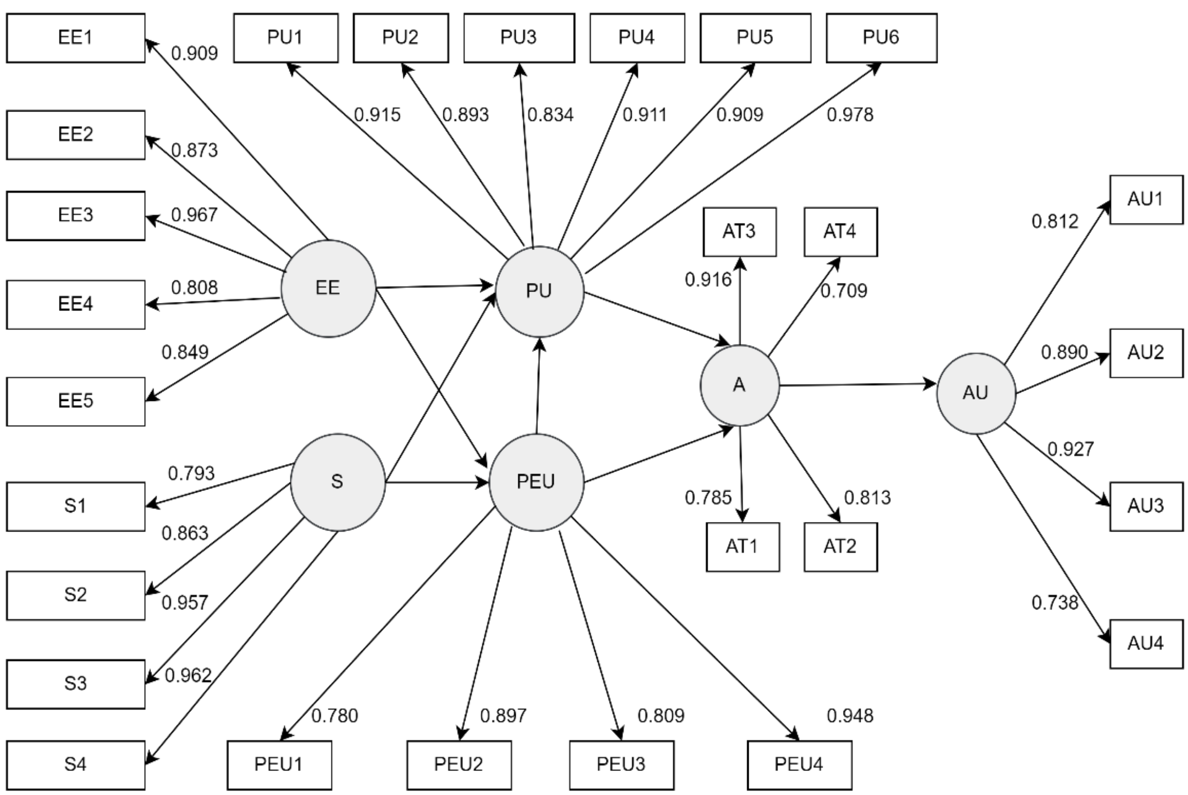

Figure 2. Loading values of variables

EE=effort expectancy, S=satisfaction, PU=perceived usefulness, PEU=perceived ease of use, A=attitude, AU=actual use

The Average Extracted Variance (AVE) illustrated in Figure 3 shows that all six variables achieved a value of >.70, which indicates that the variables explain 70% or more of the variance of the items: effort expectancy (EE) 0.878, satisfaction (S) 0.953, perceived usefulness (PU) 0.815, perceived ease of use (PEU) 0.906, attitude (A) 0.725, and actual use (0.914). Rho-A also shows all the variables have achieved convergent validity by attaining more than >.70 with effort expectancy 0.967, satisfaction 0.981, perceived usefulness 0.903, perceived ease of use 0.945, attitude 0.808, and actual use 0.954.

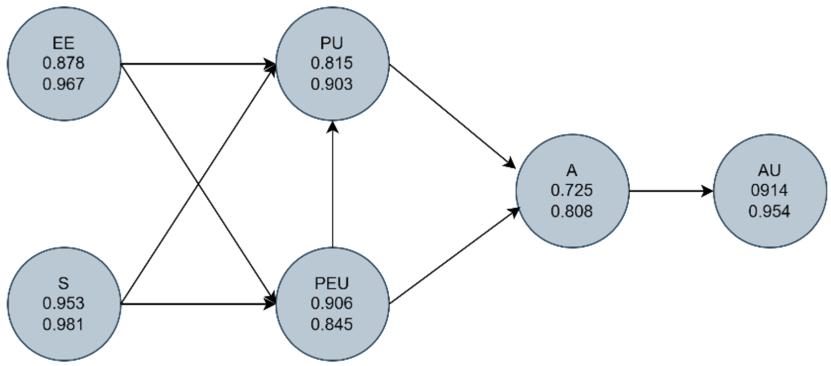

Figure 3. Average extracted variance (AVE) and Rho-A

Composite reliability and Cronbach's alpha validity

Composite reliability (CR) was used to determine the internal consistency, which measured a variable's overall reliability. Chua (2020) stated that a variable had achieved its composite reliability if it obtained >.70. Cronbach's alpha was used to determine the reliability of the items individually in each variable. Cronbach's alpha is achieved if the value is ≥0.70 (Chua, 2020). From Table 2, the composite reliability and Cronbach's alpha reliability are shown to achieve more than .70. Henceforth, the suggested model with its respective relationship is suitable for further structural model analysis.

Table 2. Composite and Cronbach's alpha reliability

Variables	Composite reliability	Cronbach's alpha
Effort expectancy	0.915	.915
Satisfaction	0.956	.956
Perceived ease of use	0.973	.973
Perceived usefulness	0.956	.956
Attitude	0.968	.968
Actual use	0.939	.939

RESULTS

This section presents the findings of the structural equation modeling (SEM) analysis used to assess the relationships between effort expectancy, satisfaction, perceived ease of use, perceived usefulness, attitude, and actual use of artificial intelligence (AI) tools as research assistance. The study tested eight hypotheses using partial least squares structural equation modeling (PLS-SEM) and analyzed the results through path coefficients, R^2 values, and effect sizes.

Structural Model and Hypothesis Testing

The structural model was assessed by examining the path coefficients (β), R^2 values, and effect sizes (f^2). The SEM results in Table 3 support all eight hypotheses, with significant relationships observed between the key constructs. Effort expectancy was found to significantly influence perceived usefulness and perceived ease of use, demonstrating that lower cognitive demands enhance the perceived usefulness and ease of using AI tools. Satisfaction also showed a strong positive relationship with perceived usefulness and perceived ease of use, highlighting the critical role of user experience in technology adoption. Perceived ease of use strongly influences perceived usefulness, indicating that user-friendly AI tools are perceived as more beneficial. Both perceived usefulness and ease of use significantly affected attitudes toward AI adoption. Attitude was identified as a key mediator with a substantial impact on actual use. The following is the summary of all eight hypotheses derived from this study.

H1: Effort expectancy has a positive and significant effect on perceived usefulness ($\beta = 0.847$, $p < 0.001$). This indicates that when researchers perceive AI tools as requiring less effort, they are more likely to view these tools as useful in enhancing their research process.

H2: Effort expectancy also positively influences perceived ease of use ($\beta = 0.847$, $p < 0.001$). This finding suggests that the lower the effort required to use AI tools, the more researchers perceive these tools as easy to use.

H3: Satisfaction positively influences perceived usefulness ($\beta = 0.596$, $p < 0.001$), indicating that researchers who are satisfied with AI tools are more likely to perceive them as useful for their research activities.

H4: Satisfaction positively influences perceived ease of use ($\beta = 0.597$, $p < 0.001$). This suggests that when researchers are satisfied with AI tools, they find them easier to use.

H5: Perceived ease of use has a strong positive effect on perceived usefulness ($\beta = 0.903$, $p < 0.001$). This shows that when researchers find AI tools easy to use, they are more likely to perceive them as useful for their work.

H6: Perceived usefulness positively influences attitude towards AI use ($\beta = 0.491$, $p < 0.001$). Researchers who find AI tools useful are more likely to develop a positive attitude toward using them in their research.

H7: Perceived ease of use also positively influences attitude toward AI use ($\beta = 0.491$, $p < 0.001$). This highlights that when AI tools are easy to use, researchers are more inclined to have a positive attitude toward adopting them.

H8: Attitude towards AI use has a positive and significant effect on actual use ($\beta = 0.676$, $p < 0.001$). This confirms that a positive attitude leads to a higher likelihood of researchers using AI-driven research tools in their work.

The f^2 values in Table 3 indicate the strength of the relationships between constructs:

Effort expectancy on perceived usefulness and perceived ease of use: Large effect ($f^2 = 0.764$)

Perceived ease of use on perceived usefulness: Large effect ($f^2 = 0.400$)

Perceived usefulness and ease of use on attitude: Moderate effect ($f^2 = 0.221$)

Attitude on actual use: Large effect ($f^2 = 0.459$)

These results highlight the significant impact of effort expectancy, perceived ease of use, and perceived usefulness on attitude and actual use of AI tools.

Effect Size (R^2) and Predictive Relevance (Q^2)

R square, R^2 is the coefficient determination, which represents the size of the influence of the total of all independent variables on dependent variables. Chin (2010) indicates that the dependent variables' values of 0.19, 0.33, and 0.67 are weak, moderate, and good models.

The R^2 values (Figure 4) for perceived usefulness ($R^2 = 0.409$), perceived ease of use ($R^2 = 0.433$), attitude ($R^2 = 0.221$), and actual use ($R^2 = 0.459$) indicate that the model explains a substantial proportion of the variance in these constructs, confirming the model's robustness. This is translated with the model explaining 40.9% of the variance in perceived usefulness, 43.3% in perceived ease of use, 22.1% in attitude, and 45.9% in actual use (Figure 4). These values suggest moderate explanatory power for the constructs, with perceived usefulness and perceived ease of use showing the highest levels of explained variance. These findings confirm that the predictors in the model substantially contribute to the explanation of the key dependent variables.

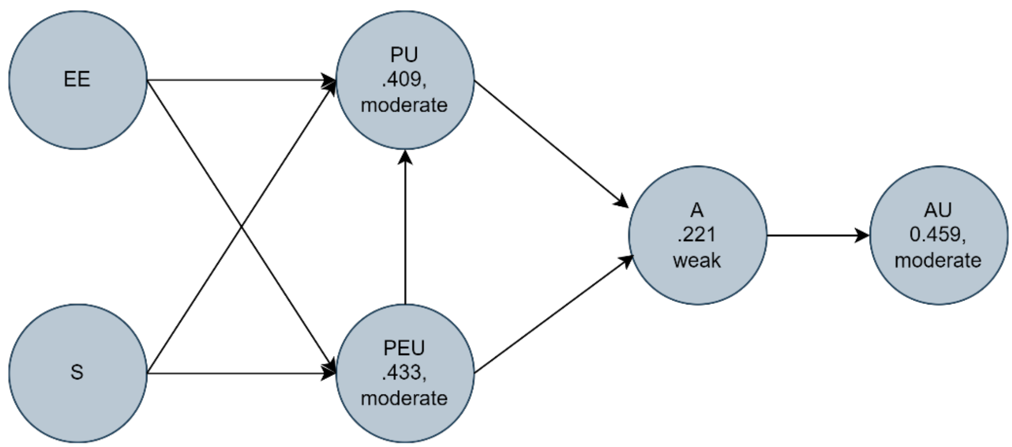

Figure 4. Total effect size, R^2

The model's predictive relevance was assessed using Stone-Geisser's Q^2 values (Figure 5), which demonstrated high predictive power across the key constructs:

- **Perceived usefulness:** $Q^2 = 0.383$ (high predictive relevance)
- **Perceived ease of use**: $Q^2 = 0.383$ (moderate predictive relevance)
- **Attitude**: $Q^2 = 0.171$ (moderate predictive relevance)
- **Actual use**: $Q^2 = 0.409$ (high predictive relevance)

These results highlight the significant impact of effort expectancy, perceived ease of use, and perceived usefulness on attitude and actual use of AI tools. With the actual use ($Q^2 = 0.409$, highly predictive), this means that the extended model with five predictors (effort expectancy, satisfaction, perceived usefulness, perceived ease of use, attitude) can highly predict the actual use of AI tools in the population (N=298).

Furthermore, considering that attitude could also play a role as a dependent variable in SEM for effort expectancy, satisfaction, perceived usefulness, and perceived ease of use, it implies that attitude is able to moderately predict the variables based on the said variables. The same goes for perceived usefulness and perceived ease of use, which could also play a positive role as dependent variables for effort expectancy and satisfaction. It shows that both of them are highly able to predict effort expectancy and satisfaction, respectively. Henceforth, the Q^2 is presented as in Figure 5.

Additionally, Table 3 outlines the detailed statistical outputs for each hypothesis, including significance levels, β coefficients, f^2 values, R^2 values, and Q^2 values.

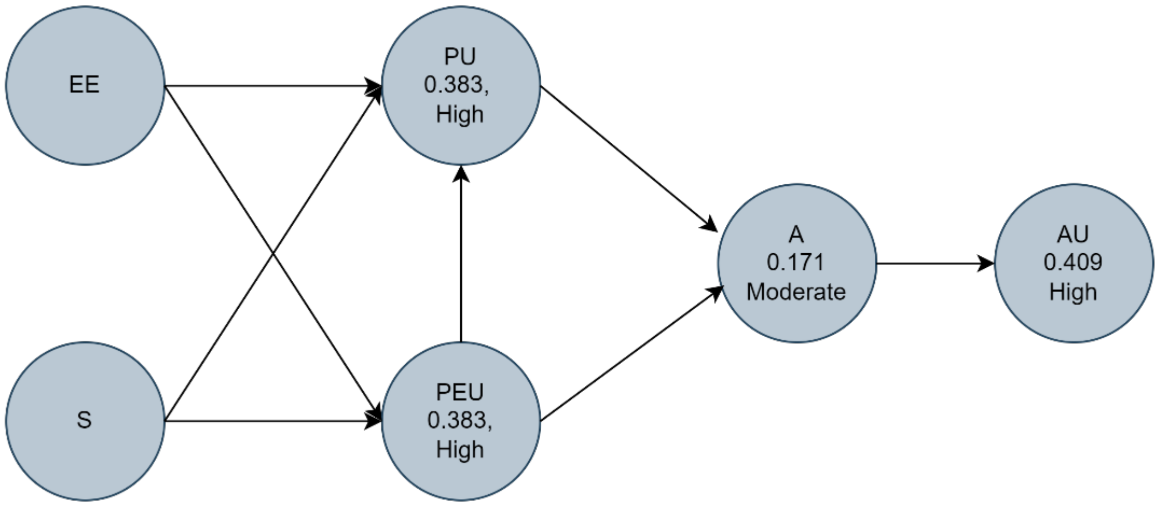

Figure 5. Predictive relevance, Q^2

Table 3. Path coefficients, β, and effect size, f^2

Relationship	Path coefficients, β	Effect size, f^2	Total effect size, R^2	Predictive relevance, Q^2
Effort Expectancy → Perceived Usefulness	.847, accept	.764, large	.409, moderate	.383, high
Satisfaction → Perceived Usefulness	.596, accept	.692, large		
Perceived Ease of Use → Perceived Usefulness	.903, accept	.400, large		
Effort Expectancy → Perceived Ease of Use	.847, accept	.764, large	.433, moderate	.383, high
Satisfaction → Perceived Ease of Use	.597, accept	.692, large		
Perceived Usefulness → Attitude	.491, accept	.221, moderate	.221, weak	.171, moderate
Perceived Ease of Use → Attitude	.491, accept	.221, moderate		
Attitude → Actual Use	.676, accept	.459, large	.459, moderate	.409, high

From the models of Figure 4, Figure 5, and Table 3, this research has obtained the following. External variables have a significant influence, as suggested by Davis (1989). The external variables of effort expectancy and satisfaction, together with the chief variables of perceived usefulness and perceived ease of use and the mediator of attitude, have been found to predict one's adoption and usage of AI tools as research assistance.

DISCUSSION

The findings of this study confirm that several factors, namely effort expectancy, satisfaction, perceived ease of use, perceived usefulness, attitude, and actual use, play significant roles in the adoption and use of AI-driven research assistance tools among researchers. These results are consistent with the Technology Acceptance Model (TAM) and extend the existing literature by emphasizing how AI tools impact the research process, particularly for postgraduate students and early-career researchers.

Effort Expectancy and Its Influence on Perceived Usefulness and Ease of Use

In addition to reducing cognitive demands, effort expectancy plays a pivotal role in shaping users' perceptions of AI tools' overall value, influencing both their initial engagement and sustained adoption. The significant positive relationships between effort expectancy and both perceived usefulness and perceived ease of use highlight the importance of reducing the perceived cognitive load when introducing AI tools to researchers. The finding reinforces the observation of Nazari et al. (2021), who noted that when researchers perceive AI tools as requiring minimal effort to learn and integrate into their workflows, they are more likely to recognize their value and utility in enhancing their research. It can be said that tools that are perceived as requiring less effort to learn and use are more likely to be adopted. This underscores the importance of developing AI tools that prioritize ease of use and integration into existing research workflows. Moreover, the positive impact of effort expectancy underscores the need for practical, user-friendly designs that reduce initial barriers to adoption. The findings also align with Sekli et al. (2024), who emphasized that reducing complexity in AI interfaces can address frustrations, particularly among novice users, and improve adoption rates. This underscores the need for institutions to focus on reducing the complexity of AI tools and providing training and support that lowers the initial learning curve, where users expressed frustration with AI tools requiring advanced technical knowledge.

Satisfaction, Perceived Usefulness, and Ease of Use

Building on the relationship between effort expectancy and perceived usefulness, satisfaction emerges as another critical factor that influences how researchers engage with AI tools. The strong link between perceived ease of use and usefulness underscores the necessity for user-friendly AI tools, highlighting their pivotal role in shaping positive attitudes and driving adoption. Researchers who find AI tools both easy to use and beneficial are more likely to express higher satisfaction levels, leading to continued use of the technology. This finding is consistent with Saqr et al. (2024) and Kashive et al. (2021), who found that user satisfaction significantly impacts technology adoption in educational and research settings. Notably, satisfaction is pivotal for users with limited experience, as Ngo et al. (2024) suggested, whereas inexperienced users reported lower satisfaction due to the perceived complexity of AI tools. Improving satisfaction, therefore, hinges on making AI tools more intuitive and aligning them with researchers' needs, which enhances both perceived usefulness and ease of use. Besides, the strong link between satisfaction and researcher retention suggests that beyond functionality, emotional resonance, such as a sense of accomplishment using these tools, can play a role in one adoption as a research assistant.

The Interplay Between Perceived Ease of Use and Perceived Usefulness

When researchers find AI tools intuitive and easy to use, they are more likely to view them as valuable additions to their workflow. This interplay reinforces positive attitudes toward adoption. The relationship between perceived ease of use and perceived usefulness is one of the strongest in this study, underscoring the importance of designing user-friendly AI tools. When researchers find these tools easy to operate, they are more likely to view them as valuable for improving research efficiency, whether in terms of writing, data analysis, or literature retrieval. This confirms the findings by Kashive et al. (2021), who noted that perceived ease of use often acts as a mediator, enhancing the perceived benefits of AI tools in academic contexts. In the case of research assistance, the easier the tool is to use, the more likely researchers are to adopt it as part of their routine workflow (Kamoun et al., 2024). Furthermore, tools like ChatGPT have been shown to enhance productivity when the interface is simple and intuitive, as Sekli et al. (2024) suggested, where perceived ease of use was a significant determinant of sustained usage, aligning with research demands. It can be said that, from the lens of developers, they may benefit from focusing on contextual help features or embedded tutorials within AI tools, which can immediately address researcher challenges and reinforce both ease of use and perceived usefulness. These perceptions not only shape usability but also significantly influence researchers' attitudes, as discussed next.

Attitude as a Mediator Between Perceived Usefulness, Ease of Use, and Actual Use

Positive attitudes serve as a bridge between perceived usefulness and actual use, driving researchers to incorporate AI tools into their routines. The study confirms that attitude plays a mediating role between perceived usefulness, perceived ease of use, and actual use of AI tools, which is consistent with the Technology Acceptance Model (TAM). For instance, researchers with a favorable attitude toward AI are more likely to use it consistently for tasks such as data visualization and grant writing. Researchers who have positive attitudes towards AI tools, largely influenced by how useful and easy they find them, are more likely to integrate these tools into their research processes (Mohmed & Elballat, 2024). This aligns with findings from Lee et al. (2023), which showed that positive attitudes towards AI tools increased the likelihood of continuous use in research contexts. The results also support the argument by Husain (2024), which highlighted that positive attitudes towards AI tools are often driven by researchers' recognition of their time-saving benefits. As such, fostering a positive attitude through targeted support and training is essential to encourage the actual use of AI tools.

The Impact of Institutional Support on Attitude and Actual Use

Beyond individual factors, institutional support plays a crucial role in shaping positive attitudes, thereby enhancing the overall adoption of AI tools. Institutional support must address common barriers, such as fear of overreliance or ethical concerns, ensuring that researchers feel confident in their ability to use AI responsibly. As suggested by Chan and Zhou (2023) and Geddam et al. (2024), environments where AI tools are actively promoted and supported tend to foster more positive attitudes, resulting in higher usage rates. Conversely, researchers in settings with limited institutional backing may develop negative attitudes toward AI integration, as noted in Sharadgah and Sa'di (2022), where the lack of support negatively impacts researchers' willingness to use AI tools. This finding underscores the need for universities and research institutions to provide not only access to AI tools but also adequate training and resources to support their adoption.

Implications And Contributions

The findings underscore the intertwined roles of effort expectancy, satisfaction, and perceived usefulness in shaping AI adoption. These insights offer actionable implications for developers and institutions alike.

The Theoretical Implications and Contributions

The findings extend the Technology Acceptance Model (TAM) by affirming the importance of effort expectancy, satisfaction, perceived ease of use, perceived usefulness, and attitude in influencing AI adoption. By situating these constructs within the context of academic research, the study highlights the unique challenges faced by postgraduates who are novice researchers in navigating AI tools. Furthermore, the study emphasized the mediating role of attitude and the critical influence of institutional support, contributing to the growing body of literature that connects user experience with technology acceptance. These theoretical insights offer valuable guidance for future research exploring user-centered approaches in technology adoption.

The Practical Implications and Contributions

This study highlights the critical role of AI developers and academic institutions in shaping the responsible adoption of AI tools. Developers must prioritize the creation of tools that reduce cognitive load and enhance usability through simplified, intuitive interfaces (Nazari et al., 2021). These features are especially important for novice researchers who may find complex systems intimidating. Adaptive learning features that provide personalized feedback tailored to user proficiency can significantly improve satisfaction and perceived usefulness. Additionally, ensuring accessibility across devices, integrating multilingual support, and addressing diverse user needs enhances the inclusivity and practicality of AI tools. Ethical safeguards, such as plagiarism detection and bias mitigation mechanisms, should be embedded within AI tools, along with periodic audits by independent ethics committees to ensure compliance with evolving standards (Kamoun et al., 2024; Musyaffi et al., 2024).

From an ethical use perspective, institutions must offer tailored technical support, hands-on training, and accessible resources to help researchers seamlessly integrate AI into their workflows (Saqr et al., 2024). Training initiatives should address varying expertise levels, with a particular focus on early-career researchers. These programs should include mandatory workshops on ethical AI practices, covering topics such as plagiarism detection, critical evaluation of AI outputs, and strategies for mitigating biases (Kamoun et al., 2024). Institutions should consider establishing an AI ethics accreditation program to standardize ethical training and foster responsible AI use. Positive attitudes can also be encouraged through success stories, peer mentorship programs, and case studies of AI's practical benefits.

Researchers, for their part, must embrace opportunities to develop proficiency in AI tools and maintain critical oversight when leveraging AI for routine tasks such as data analysis and literature reviews. Transparent reporting practices should become standard, with researchers including a detailed methodology section describing how AI tools were utilized, thus ensuring transparency and accountability (Nazari et al., 2021). Collaborative feedback mechanisms between researchers and developers can refine AI tools to align with the specific needs of academic users. Such collaborations could lead to the creation of AI functionalities tailored to field-specific requirements and ethical standards.

Incorporating these ethical and practical considerations enhances individual research integrity and contributes to equitable knowledge sharing across borders, fostering inclusivity and allowing wider access to more audiences via cutting-edge research capabilities.

Limitations and Recommendations for Future Works

This study has several limitations that should be acknowledged. First, the sample primarily consisted of postgraduate students and early-career researchers, which may limit the generalizability of the findings to more experienced researchers or those from different disciplines where AI adoption is less prevalent. These sampling limitations might have resulted in findings that present the challenges and perspectives of early adopters, potentially underestimating the barriers faced by more seasoned researchers with deeply ingrained research workflows.

Additionally, while the study focused on the adoption and use of artificial intelligence (AI) tools for research assistance, it did not explore how differences in familiarity with AI technology may influence the perceived ease of use and actual use over time. Variations in prior exposure to AI tools may influence perceived ease of use and actual use over time, potentially skewing the results toward users with similar baseline familiarity. Exploring this factor could have provided deeper insights into the learning curve associated with AI adoption.

Furthermore, the cross-sectional design limits our ability to observe changes in attitudes and usage behaviors as researchers become more accustomed to AI tools. AI adoption is a dynamic process, and as researchers become more accustomed to these tools, their perceptions of ease of use, usefulness, and satisfaction may shift significantly. Longitudinal studies would allow for a more comprehensive understanding of how these factors interact and change with the continued use of AI.

Future research should address these limitations by adopting diverse and stratified sampling techniques to include experienced researchers from a wide range of academic disciplines, such as engineering, social sciences, and pure sciences, where AI adoption behaviors may vary significantly. Longitudinal designs, such as panel studies, could provide valuable insights into how AI adoption behaviors and attitudes evolve over time, particularly as researchers integrate these tools into their workflows. These studies would allow researchers to track the long-term effects of AI on user satisfaction, productivity, and perceived ease of use across different research domains.

Additionally, experimental studies could evaluate the impact of adaptive learning features, such as interactive tutorials and task-based hints, on user satisfaction and productivity. For example, controlled trials could measure the effectiveness of progress reports tailored to user proficiency in reducing cognitive load and fostering engagement. Further, qualitative interviews with researchers could provide rich insights into the broader effects of AI adoption on critical thinking, creativity, and academic integrity, ensuring that these tools enhance, rather than compromise, scholarly practices. Collaborative efforts between developers and academic institutions remain essential to refine AI tools based on user feedback and to establish ethical guidelines that promote responsible and effective use of AI technologies in research.

Future research should explore the broader implications of AI adoption on research quality, focusing on its influence on critical thinking, creativity, and academic integrity. For example, case studies within diverse academic disciplines could provide insights into how AI tools are integrated and their effects on scholarly practices. Research should also evaluate the role of institutional support systems, such as tailored training programs and ethical guidelines, in fostering successful AI adoption. Collaborative initiatives between developers and academic institutions are crucial to refining AI tools, incorporating real-world user feedback, and ensuring ethical standards are upheld. These efforts will promote responsible, effective, and equitable use of AI in research.

CONCLUSION

This study highlights the significant factors that shape the adoption of AI-driven research tools among researchers, focusing on effort expectancy, satisfaction, perceived ease of use, and perceived usefulness. The findings reveal that lower cognitive load and higher satisfaction positively influence researchers' attitudes toward AI, which, in turn, increases actual tool usage. Henceforth, AI-driven research assistance can assist in generating ideas, drafting, revising, and editing, thereby streamlining the writing process and allowing researchers to focus on the content and substance of their work. This insight not only extends the Technology Acceptance Model by highlighting the importance of user experience but also provides actionable guidance for developers and institutions seeking to promote AI adoption.

This research underscores the role of AI tools in leveling the academic playing field, providing researchers from diverse backgrounds with scalable and user-friendly solutions. By mitigating barriers such as technical expertise and resource disparities, AI democratizes access to cutting-edge research capabilities, fostering inclusivity and equity in academic contributions. However, it is essential to balance the use of AI with critical thinking and human insight, as AI-generated content may lack the depth and nuance that come from human reasoning. AI should be viewed as supplemental resources rather than replacements for human judgment and expertise. Over-reliance on AI can limit researchers' creativity and analytical thinking skills. Even though AI is regarded as intelligence in the sense of providing the output, it may not fully understand the context of the research, potentially leading to inaccuracies or inappropriate suggestions; thus, researchers need to be vigilant and critically evaluate AI-generated output. Overall, this study underscores that while AI can greatly enhance research productivity, the successful adoption of these tools depends on a supportive environment that addresses researcher needs, minimizes cognitive loads, and upholds ethical standards. Future research should explore how AI adoption impacts the democratization of research on a global scale, particularly in underprivileged regions, and how tailored support mechanisms can further reduce barriers to entry. Additionally, longitudinal studies are needed to evaluate the long-term effects of AI on research quality, equity, and innovation across diverse academic disciplines.

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APPENDIX: QUESTIONNAIRE

Effort Expectancy	• Using AI-driven research assistance tools in my research would require a lot of mental effort. • I think using AI-driven research assistance tools in my research would require a lot of time and effort to master. • It would be easy for me to become skillful at using AI-driven research assistance tools. • I find AI-driven research assistance tools easy to use • Using AI-driven research assistance tools would require a significant amount of training and support.
Satisfaction	• I am satisfied with the overall performance of the AI-driven research assistance tools in my research. • I am satisfied with the speed at which the AI-driven research assistance tools generate output. • I am satisfied with the level of cost-effectiveness of the.AI-driven research assistance tools. • I am satisfied with the level of innovation built into the AI-driven research assistance tools.
Perceived Usefulness	• Using AI-driven research assistance tools in my research situation needs would enable me to accomplish tasks more quickly. • Using AI-driven research assistance tools in my research situation needs would improve my research quality.

	• I believe that using AI-driven research assistance tools in my research would be a worthwhile investment of my time. • Using AI-driven research assistance tools in my research situation would reduce my workload and save me time. • Using AI-driven research assistance tools in my research situation would make it easier to do my research. • I would find AI- research writing assistance tools in my research situation needs would be useful in my research.
Perceived Ease of Use	• Learning to operate AI-driven research assistance tools is easy for me. • I find it easy to navigate through AI-driven research assistance tools. • I find AI-driven research assistance tools easy to implement. • It is easy for me to utilize AI-driven research assistance tools.
Attitude	• I am willing to invest time in learning how to use AI-driven research assistance tools. • I will recommend that my friends who are involved in research use AI-driven research assistance tools. AI-driven research assistance tools are a good idea. • I am confident that I could become proficient in using AI-driven research assistance tools for my research.
Actual Use	• I use AI-driven research assistance tools in my research process. • I use AI-driven research assistance tools to ease the process of research. • I used the AI-driven research assistance tools as they helped me to analyze large amounts of data quickly and accurately. • I use AI-driven research assistance tools as they speed up the research process.

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