UNIVERSITY OF TURKU
Turku School of Economics

Research on the Impact Factors of User Satisfaction With AI-Assisted Academic Writing Tools

Business Intelligence and Knowledge Management

Master's thesis

Author(s):

Xiaobo Yu

Supervisor(s):

Reima Suomi

10.6.2025

Turku

The originality of this thesis has been checked in accordance with the University of Turku quality assurance system using the Turnitin Originality Check service.

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Number of pages: 108 pages + appendices 9 pages

Date: 10.6.2025

With the rapid development of artificial intelligence technology, AI-assisted academic writing tools have gradually become important auxiliary tools for academic research due to their efficiency and intelligent features. However, users face limitations in functionality, data privacy risks, and ethical issues during actual use, leading to significant fluctuations in user satisfaction. Therefore, optimizing tool performance from both technical and user perspectives to enhance user satisfaction has become a hot topic of common concern in the academic community.

This study is based on the Technology Acceptance Model (TAM) and the Information Systems Success Model (ISSM). It systematically analyzes the core factors affecting user satisfaction with AI-assisted academic writing tools through a combination of qualitative and quantitative methods. The research first employs a semi-structured interview method and uses grounded theory to conduct a three-level coding analysis of the interview data, identifying and refining core dimensions such as system quality, tool adaptability, information quality, ethical compliance, resource equity, user perceived value, user experience, and perceived risk. Based on this, a multidimensional theoretical model encompassing technological factors, institutional factors, user factors, and content factors is constructed, along with corresponding research hypotheses. Subsequently, a questionnaire survey was conducted to collect 408 valid sample data, and structural equation modeling analysis was performed using SmartPLS software to validate the theoretical model and research hypotheses.

The research results indicate that system quality, tool adaptability, information quality, and functional utility have a significant positive impact on user satisfaction. Ethical compliance and resource fairness indirectly positively influence satisfaction by enhancing user trust. Additionally, perceived risk significantly suppresses user satisfaction. Furthermore, the level of user involvement indirectly positively affects user satisfaction by improving perceived ease of use and interaction experience.

Based on the above research conclusions, this study proposes targeted optimization strategies, including strengthening the intelligent features of the tools, particularly the accuracy of content generation, literature recommendation, and logical verification; improving the design of the interactive interface to reduce users' learning and operational costs; enhancing privacy protection and ethical compliance mechanisms by establishing transparent user data management standards and ethical certification systems to increase user trust in the tools; and encouraging educational institutions to formulate relevant usage norms to balance tool efficiency and academic integrity, thereby further enhancing overall user satisfaction and willingness to continue using the tools.

This study expands the theoretical framework for user satisfaction research on AI-assisted academic writing tools, providing theoretical support and practical guidance for tool developers and educational institutions to optimize tool design.

Key words: AI-assisted academic writing tools, user satisfaction, technology acceptance model, information systems success model, privacy protection; ethical compliance.

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1 Introduction

1.1 Research Background

With the rapid development of information technology, the application of AI technology in various fields is continuously deepening, and the research field is no exception. AI-assisted writing tools, due to their efficiency and convenience, have gradually become important assistants in academic research, receiving widespread attention and application. In May 2020, OpenAI released the GPT-3 model, which attracted significant attention in the academic community due to its outstanding natural language processing capabilities. (Danjiang et al., 2020) The model's performance in tasks such as text generation, translation, and answering questions has the potential to significantly enhance the writing efficiency of researchers. Subsequently, many AI-assisted writing tools emerged in China, such as Kimi, Doubao, Wenxin Yiyan, Xunfei Spark, and Tongyi Qianwen, among others. The application of AI-assisted academic writing tools in scientific research not only aids in academic writing but also provides strong support in literature reviews, data analysis, and other areas. Furthermore, with the continuous advancement of AI technology, the functions and performance of AI-assisted writing tools are also constantly improving. Many scholars have begun to focus on the application prospects of AI-assisted academic writing tools and their roles in the academic environment.

In recent years, scholars have conducted in-depth research on the application of AI-assisted writing tools from various perspectives, such as exploring their effectiveness in academic writing, studying their impact on students' writing skills, and analysing the ethical issues and countermeasures related to their use in research work. These studies not only demonstrate the broad application prospects of AI-assisted writing tools but also indicate the high level of attention and importance that society places on this technology. The emergence of AI-assisted writing tools in academic environments has triggered a significant transformation in handling and executing writing tasks. This transformation has not only improved writing efficiency and accuracy but also changed the ways in which academic research is disseminated and shared. This article delves into user satisfaction with AI-assisted academic writing tools and explores different perspectives in recent studies. The analysis includes several aspects, including perceived benefits, challenges, and the broader implications of integrating AI into academic writing practices. Research on user satisfaction is crucial, as it directly affects the effectiveness of these tools and the writing experience of users. Users with high satisfaction are more likely to continue using these tools and benefit from them,

thereby enhancing their writing skills and academic outcomes. Furthermore, understanding user satisfaction helps developers optimize these tools to better meet users' needs and preferences.

Despite the many conveniences brought by AI-assisted writing tools, users also face some challenges in the process of using them. Firstly, the errors and limitations of AI-assisted writing tools may lead to inaccurate research results, thus affecting the quality of academic papers. Secondly, there are doubts about users' dependence on the tool and its applicability at different writing stages. Some studies have pointed out that although AI-assisted writing tools perform well in grammar and formatting proofreading, they are still deficient in content creation and logical reasoning. In addition, AI-assisted academic writing tools still have functional limitations, data privacy risks, and ethical norms in practical application, which not only directly affects users' experience and satisfaction, but also raises concerns about academic ethics. Academic research requires a high level of data security, intellectual property rights, and academic integrity, and users have higher expectations for privacy protection and ethical compliance in the process of using AI-assisted writing tools, and many issues such as the controversy over academic ethics, technical limitations, and cognitive bias of users have not been fully discussed. At the same time, some users are highly satisfied with the efficiency of AI-assisted writing tools, while others are frustrated by the black-box nature of the technology and the lack of personalization. This contradiction highlights the need to systematically deconstruct the key factors affecting satisfaction from the user's perspective. Reasonable use of AI technology-assisted writing can significantly improve the efficiency and quality of academic writing, but at the same time, all parties need to work together to develop relevant policies and norms to ensure the fairness and reliability of academic research.

In summary, user satisfaction with AI-assisted academic writing tools is influenced by various factors, including the tool's functional performance, user experience, and ethical considerations. Future research should further explore these influencing factors and propose corresponding improvement suggestions to enhance the effectiveness of AI tools in academic writing.

1.2 Research Significance

This article summarizes and learns from the research achievements in related fields, and through surveys and data analysis, it studies user satisfaction with AI-assisted academic writing tools and the factors influencing it. It also conducts empirical analysis, which has certain theoretical and practical significance.

Theoretically, firstly, it enriches the research on user satisfaction related to AI-assisted writing tools. Through literature review, it was found that research on AI-assisted writing tools mainly focuses on technical performance, writing efficiency, and tool functionality, with relatively few studies addressing user satisfaction. This paper approaches the topic from the perspective of user satisfaction, analyzing it in conjunction with users' actual experiences to explore the key factors that influence user satisfaction. The research not only fills the gap in the study of user satisfaction in the field of AI-assisted writing tools but also provides a theoretical basis for further optimizing tool design and enhancing user experience.

Secondly, it expands the application of user satisfaction theory in emerging technologies. Past research on user satisfaction has primarily focused on areas such as social media, e-commerce platforms, and online learning systems, with little attention given to the application scenarios of AI-assisted writing tools. This paper introduces user satisfaction theory into the emerging technology of AI-assisted writing tools by constructing and validating a model of the influencing factors of user satisfaction, thereby enriching the application of user satisfaction theory in AI-assisted writing tools and deepening the understanding of user satisfaction across different platforms.

From a practical perspective, firstly, from the user’s point of view, this research can provide strong guidance for the use and improvement of AI-assisted academic writing tools. By analysing user satisfaction and its influencing factors, developers can gain a deeper understanding of the actual needs and pain points encountered by users during the usage process, allowing for targeted optimization of the product to enhance its practicality and user experience. This will help users utilize AI tools more effectively, improve their writing efficiency and academic outcomes, and better address the challenges of academic writing.

Secondly, from a societal perspective, this research contributes to promoting the widespread application of AI technology in the academic field, facilitating the dissemination and sharing of knowledge. As AI-assisted writing tools continue to develop and become more popular, they not only enhance the writing capabilities of individual researchers but also promote innovation and collaboration within the broader academic community. By revealing user satisfaction and needs regarding these tools, the research provides profound insights for various sectors of society on the application of AI technology in academic writing, thereby fostering recognition and acceptance of such tools, and ultimately enhancing overall academic productivity.

The application of AI in the publishing industry also provides important references for its use in academic writing. Shi (2019) explored the innovative practices of artificial intelligence in the Japanese publishing industry, demonstrating the key role of AI in content generation and optimization. AI not only enhances publishing efficiency but also improves content quality, further proving its wide application in writing and content generation. He and Zhang (2018) also pointed out that machine writing has been widely used in the media industry, with AI-generated news articles and advertising copy significantly increasing the speed and quality of content production, which shares a similar logic with the demand for content generation in academic writing. Therefore, AI technology not only drives innovation in the media industry but also provides strong technical support for academic writing.

With the continuous advancement of AI technology, researchers are gradually beginning to explore the specific applications and impacts of these tools in academic writing. Wei et al. (2024) believes that generative AI models like ChatGPT represent a significant innovation of AI in the field of education. These tools can assist in text generation, grammar checking, and information retrieval in academic writing, greatly enhancing academic productivity and simplifying the complexity of academic writing. This provides researchers with more convenient writing support and indicates that AI technology has tremendous potential in improving writing efficiency.

On the other hand, Bi et al. (2024) pointed out that AI-generated content technologies, particularly tools like ChatGPT, demonstrate significant market potential in text, voice, and image generation. The widespread application of AI-generated content tools globally not only promotes the automation of writing and knowledge production but also provides technical support for various types of creation. Especially in academic writing, these tools can greatly simplify the content generation process. Research also shows that innovations in AI-generated content technology have driven the diversification of text generation applications, further promoting the transformation of academic writing methods.

To assess the impact of AI tools on writing quality and efficiency, researchers have employed various experimental design methods. Pereira et al. (2023) studied the effectiveness of AI tools in enhancing the clarity and conciseness of academic writing. The research found that users expressed high satisfaction with the seamless integration of AI during the brainstorming phase, which not only improved the accuracy of the language but also ensured the logical coherence of the text. Meanwhile, Nazari et al. (2021) evaluated the impact of digital writing assistants in higher education through randomized controlled trials. The study indicated that these tools not only

improved writing quality but also significantly reduced the time students needed to complete writing tasks. This finding suggests that AI-assisted tools can provide crucial support in the high-pressure environment of academic writing, helping users efficiently generate high-quality content in a short amount of time.

The research by Alqadi et al. further explored the application of ChatGPT in academic writing, particularly in the entire process from draft generation to final revision. （Alqahtani & Najjar, 2023）The coherent suggestions from ChatGPT greatly aided the writing process. The study found that ChatGPT could not only help students generate ideas in the early stages of writing but also provide real-time feedback during the writing process, thereby enhancing coherence and fluency. Such generative AI technologies have gradually become important tools in academic writing, providing strong support for researchers and students in complex writing tasks.

At the same time, the application of AI-assisted tools is not only limited to improving writing efficiency but also plays an important role in interaction and collaboration. Wang et al. (2023) suggested that intelligent academic services based on ChatGPT can provide functions such as intelligent literature recommendations, academic question answering, and research method consulting. This interactive academic support greatly enhances the user's learning experience. Through interaction with AI tools, users can continuously improve their abilities during the writing process and effectively utilize AI to achieve academic goals.

Overall, AI-assisted writing tools have been widely applied in various fields, especially in academic writing, where their emergence has changed traditional writing methods. These tools not only significantly enhance writing efficiency and quality but also provide comprehensive support from content generation to text polishing. With the continuous development of AI technology, these tools will continue to play a greater role in academic writing, promoting the progress and innovation of academic research.

1.2.1 Research on User Satisfaction with AI-Assisted Writing Tools

In recent years, research on user satisfaction has gradually become an important topic across various fields, especially in the service industry, e-commerce, and information technology. Satisfaction studies provide strong support for the optimization of products and services. Classic user satisfaction research typically focuses on factors such as ease of use, functionality, service quality, and personalized experiences. Previous theories and models, such as Expectation

Confirmation Theory (ECT), Technology Acceptance Model (TAM), and Information Systems Success Model (ISSM), provide a theoretical foundation for satisfaction research, emphasizing the relationship between user expectations, actual experiences, and satisfaction. The evaluation methods for user satisfaction mainly include quantitative and qualitative approaches. Quantitative methods utilize surveys, rating systems, and user feedback data, while qualitative methods gather users' subjective feelings and specific suggestions through interviews and case studies to gain deeper insights into users' actual needs and directions for tool optimization. However, research on the satisfaction of AI-assisted tools, particularly user satisfaction with AI-assisted writing tools, remains relatively limited. Specifically, how to measure the performance of AI tools in different writing contexts and how these tools meet users' specific needs are still weak points in current research.

The study of user satisfaction with AI-assisted writing tools is gradually becoming a focal point of research. Wang (2023) research on college students' satisfaction with social Q&A platforms reveals that personalization and ease of use are key factors in enhancing user satisfaction. This research not only provides insights for optimizing social Q&A platforms but also has certain implications for the study of satisfaction with AI-assisted writing tools, particularly in terms of how AI tools can enhance users' writing experiences through personalized features and convenience. Similarly, Chen Yongwei studied the dual impact of generative AI tools on content generation and user satisfaction. He pointed out that while generative AI tools improve writing efficiency, they also significantly enhance overall user satisfaction by enriching the interaction experience between users and the tools.（Chen, 2023.）This indicates that AI tools help users complete tasks not only through content generation but also by enhancing the user experience through efficient feedback mechanisms. This finding suggests that the level of automation and response speed are important factors affecting user satisfaction, which is particularly evident in the application of AI-assisted writing tools.

In addition, Jia et al, (2024) and others explored user satisfaction with ChatGPT under different usage types, focusing on functionality versus entertainment. The study found that entertainment-oriented users had higher satisfaction with AI tools, while functionality-oriented users were more concerned with the accuracy and timeliness of the content. This research reveals the impact of different user needs on satisfaction, indicating that the functionality, precision, and efficiency of AI tools have a direct effect on user satisfaction in academic writing. Such studies provide new insights for the design and improvement of AI-assisted writing tools. Similarly, Guo Yajun, in his research,

revealed the usability of AI tools like ChatGPT in information retrieval and academic writing through empirical analysis, and delved into the impact of these tools on user satisfaction. The research showed that AI tools not only significantly improved the efficiency of information retrieval but also demonstrated a high level of intelligence in text generation and revision, enabling users to complete academic writing tasks more quickly, particularly excelling in literature reviews and structural optimization. Guo et al. (2024) further pointed out that personalized services and the accuracy of results are key factors in enhancing user satisfaction. When AI tools can respond quickly and accurately to user needs, user experience and satisfaction significantly improve. This provides important directions for optimizing AI-assisted writing tools, especially in enhancing personalization and intelligence levels.

Piao et al. (2024) and others studied the user experience of the generative AI service 'Wenxin Yiyan' among young users. They found that the tool performed well in terms of usability and personalized services, but still had shortcomings in handling complex issues and the accuracy of responses in specific fields. This directly affected users' trust and satisfaction with AI writing tools, highlighting that the gap between technological performance and user expectations is a significant factor influencing user satisfaction. This finding indicates that the intelligence level of AI tools is not only reflected in the speed of content generation but also in how effectively they handle complex tasks and provide accurate feedback.

Yu (2024), through research on AI-assisted online courses, revealed that personalization, usability, and trust are key factors influencing user behavior. The study showed that when AI tools meet users' expectations and academic needs, user satisfaction significantly increases. This research emphasizes the importance of a user-centered design philosophy in enhancing satisfaction. This perspective is also applicable to the design of AI-assisted writing tools, particularly in how to improve the tool's intelligence level to enhance the user experience in meeting personalized needs. Meanwhile, Liang, in her research, proposed that personalized services are a key factor in improving user satisfaction. She pointed out that as the application of artificial intelligence in education becomes increasingly personalized and intelligent, user satisfaction with AI tools continues to rise. (Liang & Liu, 2018.) This research underscores the importance of user-centered design and highlights the significant role of personalized services in enhancing user satisfaction.

However, despite the significant potential of AI-assisted writing tools in enhancing writing efficiency and quality, certain factors may still negatively impact user satisfaction. In her research

on the factors influencing users' continued use of AIGC platforms, Duan et al. (2024) raised the issue of users' dependency on AI tools. The study shows that while AI-assisted writing tools excel in improving writing efficiency, excessive reliance on these tools may weaken users' autonomous learning and writing abilities, thereby affecting their long-term satisfaction. This research indicates that users' dependency on AI tools may lead to a decline in creativity and independent thinking skills, which is particularly important in academic writing. Jin's research further reveals the impact of the gap between users' expectations of generative AI tools in academic writing and their actual experiences on satisfaction. (Jin et al., 2024.) The study indicates that while AI tools can significantly enhance writing efficiency, if they fail to meet users' high expectations regarding accuracy, professionalism, and creativity, user satisfaction often declines. This is crucial for the development of AI-assisted writing tools, as balancing users' high expectations with the actual performance of the tools is key to enhancing satisfaction. Meanwhile, Wang& Feng (2024) analyzed the ethical challenges of using ChatGPT in paper writing, pointing out that although generative AI technology performs excellently in improving writing efficiency, issues regarding the originality and accuracy of the generated content still exist. This poses a threat to the credibility of academic research and affects users' overall satisfaction with AI tools.

Finally, Xiong (2017) discussed the issue of copyright ownership of AI-generated content, pointing out that while users enjoy the convenience of AI-generated content, they still have concerns about the originality and ownership of the content, which may affect user satisfaction. Yang's research further demonstrated that satisfaction is influenced by a combination of factors, including tool usability, functionality, and user experience, providing a broader perspective for satisfaction research on AI-assisted writing tools. (Yang, 2015.)

In summary, user satisfaction research on AI-assisted writing tools encompasses multiple factors, including personalized services, ease of use, accuracy, and users' reliance on the tools. While these tools excel in enhancing writing efficiency and quality, they still need improvement in meeting users' high expectations and handling complex tasks. Future research should continue to focus on how to enhance the intelligence level of AI tools to improve user satisfaction.

1.2.2 Research on the Risks Associated with AI-Assisted Writing Tools

Although AI-assisted writing tools have demonstrated tremendous potential in improving writing efficiency and quality, their limitations have also attracted widespread attention. First, Tian (2024)

conducted an in-depth study on the risks and regulatory challenges associated with generative AI applications, including ethical issues, plagiarism, and data security. She pointed out that in an academic environment, the widespread use of AI tools without proper regulation could undermine academic originality and academic integrity. Tian's research highlights the potential risks of plagiarism and threats to data privacy, particularly in academic writing, where AI-generated content can easily be confused with others' work, leading to academic misconduct. Ling et al. (2023) also explored the ethical challenges of AI-assisted writing tools, particularly regarding the authenticity of content and privacy security issues associated with generative AI tools. He points out that while generative AI tools like ChatGPT excel at improving writing efficiency, there are still concerns about the reliability and authenticity of the content they generate, especially in academic writing, where AI-generated content may not always be accurate, and the sensitive data they process can raise privacy security issues. Chen (2023) focused on other social impacts of AI-generated tools in content creation, such as unemployment, income inequality, and intellectual property disputes. He points out that as AI-assisted writing tools become more widespread, certain professions may be threatened by automation, particularly in the academic field, where researchers may become overly reliant on these tools, thereby weakening their inherent ability for independent thinking and creativity. This phenomenon is also evident in academic research, where over-reliance on AI tools may impact researchers' creativity and originality. Furthermore, Chen (2023) noted that the widespread application of generative AI tools has raised intellectual property and privacy issues. As AI-generated content increases, users face challenges not only in terms of technical limitations but also in protecting content originality and using AI-generated content within legal frameworks. Intellectual property disputes may limit the application of AI-generated content in academic writing, prompting academic institutions to exercise greater caution when promoting AI tools. Vuković et al. (2025) noted in their systematic review of AI technology applications in the financial sector that AI systems lacking explainability mechanisms may trigger severe transparency and accountability crises. Similar risks exist in academic contexts, particularly regarding issues such as unclear originality of AI-generated content and ambiguous responsibility attribution. Additionally, the study also emphasises that without robust governance mechanisms, the widespread deployment of AI technology may exacerbate risks such as 'algorithmic bias'，'data misuse,' and 'regulatory arbitrage.' These issues can be analogised to the unfairness and ambiguity caused by uneven training data or model black boxes in academic writing. In line with this, Dabis and Csáki (2024) conducted a study on the ethical policies adopted by global universities in response to generative AI tools, finding that most top universities have explicitly emphasised in their policies that students

bear ultimate responsibility for AI-assisted generated content, ensuring that the output reflects their independent thinking and academic capabilities. These policies generally emphasise the core values of 'human oversight' and 'accountability mechanisms,' advocating that while allowing the use of AI tools to a certain extent, teachers should prevent academic misconduct through course design and assessment methods, such as adjusting thesis evaluation criteria and requiring disclosure of AI usage. Additionally, the study found that 'transparent use,' 'privacy protection,' and 'copyright ownership' are core issues that universities commonly focus on when establishing AI usage guidelines, and these aspects are crucial for maintaining academic ethics and intellectual property rights.

In the academic field, Lu (2023) explored the impact of generative AI tools on academic adaptation through research on Chinese students studying in the UK. While AI tools provide support in helping international students adapt to academic writing norms, they demonstrate limitations when addressing cultural differences and the complexity of academic requirements. This limitation manifests in the tools' inability to provide precise support tailored to different academic cultural backgrounds. When using AI tools, international students may not fully meet their specific needs, thereby affecting their academic writing performance. Wei et al. (2024) further points out that while AI tools demonstrate significant potential in teaching and research, they also raise issues of information inaccuracy and content bias. Generative AI tools, when unregulated, may generate incorrect information or biased content, which not only undermines the credibility of academic research but may also lead students to overly rely on these tools, thereby weakening their critical thinking and academic abilities. These issues pose significant challenges to the widespread application of AI writing tools, particularly in academic settings, where overreliance on AI tools by students and researchers may have long-term negative consequences. Hoffman et al. (2021) highlights the fragility of trust in AI systems as a critical issue. When AI systems fail to meet user expectations, especially under time pressure, users' trust in the system is prone to collapse. This is particularly important in critical tasks such as academic writing, as any errors in content generation or task execution by AI tools can quickly erode user trust. Cheng et al. (2020) further explored privacy issues in AI chatbots, finding that privacy risks significantly impact user satisfaction. This is highly relevant to the limitations of AI-assisted writing tools, especially in academic settings where confidentiality and data security are paramount. Academic writing often involves sensitive research data, and if AI tools cannot ensure the privacy and security of this data, it will greatly affect users' trust in the tools.

Liu and Cheng (2024) have pointed out that the deep application of AI tools in academic journals faces numerous practical challenges, including technical bottlenecks and limitations in application scenarios. While AI writing tools demonstrate potential in content generation and knowledge services, their functional capabilities remain constrained by the maturity of the technology, making it difficult to meet the demands of all academic writing tasks. For example, AI tools perform inadequately when handling tasks requiring in-depth analysis and critical thinking, meaning that users still need to rely on human intervention for certain complex academic writing tasks.

Shen et al. (2023) discussed the dual nature of large language models such as ChatGPT, pointing out that while these tools can improve writing efficiency, they may also lead to a decline in user creativity, particularly when students become overly reliant on AI tools, potentially losing their ability to write independently. Research indicates that overreliance on AI tools may weaken students' initiative and creativity in writing, which is detrimental to their long-term academic development. Le Phan's research further reveals the limitations of AI tools in English writing. While these tools can significantly improve writing efficiency and quality, they still face technical challenges, especially when handling complex grammar and structure, where AI tools often fail to meet expectations. (Le Phan, 2023.) This indicates that the application of AI-assisted writing tools still faces technical bottlenecks in certain specific areas, requiring further optimization and improvement. Fang et al. (2024) further discussed ethical issues and potential academic misconduct associated with AI in scientific writing, calling on the academic community to consider the impact of AI-generated content on academic publications, particularly the potential for plagiarism in academic research. Additionally, the accuracy and reliability of AI-generated content remain critical issues that require urgent attention. Wu (2024) pointed out that while AI 2.0-era intelligent tools provide efficient academic support for researchers, these tools may also increase instances of academic misconduct, such as plagiarism and fabrication of generated content, while enhancing productivity.

Cheng et al. (2024) studied how universities and research institutions address academic misconduct caused by AI writing tools. The study found that while AI tools offer significant convenience in literature reviews and draft generation, the content they produce often lacks depth and logical coherence, making it easily identifiable as non-original content. As a result, many universities have begun to introduce AI detection systems to identify AI-generated content in papers. Zhao (2024) further emphasized that universities should provide guidance on the use of technology and academic norms to prevent the misuse of AI tools.

In summary, while AI-assisted writing tools enhance efficiency, they also reveal numerous limitations. Over-reliance on AI tools may weaken users' writing abilities, impact academic integrity, and even raise intellectual property and privacy issues. As AI technology continues to advance, balancing tool performance with enhanced user guidance and regulation will become a key research direction for the future.

1.2.3 Research Review

Through a review and analysis of existing literature, it can be observed that research on AI-assisted writing tools has made significant progress in areas such as user satisfaction and improved writing efficiency. However, existing studies still have some limitations, particularly in terms of long-term impacts, user dependency, and satisfaction among specific user groups, which require further in-depth exploration. Specifically, the following limitations and future research directions are identified:

The theoretical models and analytical dimensions used in existing satisfaction studies are relatively limited. Current research on user satisfaction with AI-assisted writing tools primarily relies on the Technology Acceptance Model (TAM) and the Expectancy Confirmation Theory (ECT) (Yang, 2020), but these models are relatively simplistic and lack a deeper analysis of users' actual behaviour and experiences. While some studies have assessed the technical performance and user perceptions of the tools through questionnaires and user feedback, there is limited research on users' actual needs in academic environments. Future research should integrate diverse theoretical models, particularly by incorporating more qualitative research methods, to better understand users' psychological and behavioural patterns during the use of AI tools.

Research on the satisfaction of specific user groups remains insufficient. Current studies primarily focus on conducting satisfaction surveys for all user groups, lacking in-depth analysis of specific groups, particularly users in the academic writing field. Wang (2023) noted in her study on the satisfaction of social Q&A platforms that university students, due to their prolonged usage and high dependency, constitute an important target group for researching mobile app satisfaction. However, research on AI-assisted writing tools, especially targeting groups such as university faculty and graduate students who frequently use writing tools, remains scarce. Such users have more specialised and complex needs for AI tools, and the factors influencing their satisfaction are also more diverse.

Further research is needed to enrich the understanding of the multi-dimensional factors influencing user satisfaction. Current studies primarily focus on technical performance and ease of use when identifying factors influencing satisfaction, while discussions on other potential factors such as data security and ethical issues are relatively scarce. Tian Meng pointed out that the application of AI tools in academic writing not only affects user experience and satisfaction but may also impact user trust due to issues such as data privacy and plagiarism risks. Future research should further enrich the dimensions of satisfaction, not only considering the technical performance of the tools but also delving into their performance in terms of academic norms and ethical issues, particularly how to enhance user trust and satisfaction through reasonable tool design and technological regulation (Tian, 2024.)

In summary, existing research on user satisfaction with AI-assisted writing tools has made some progress, but there are still significant research gaps in areas such as theoretical model construction and user satisfaction studies in academic environments. Future research should focus more on the actual application effects of tools in academic settings. Additionally, combining multi-dimensional factor analysis will help promote the optimization and development of AI-assisted writing tools. This not only helps AI tools better adapt to the needs of academic writing but also provides stronger theoretical support for the regulation and usage standards of such tools.

1.3 Research Content

In response to the research objectives outlined earlier, this paper draws on existing research findings related to the theory of satisfaction with AI-assisted tools in academic writing. It takes AI-assisted writing tools widely used in higher education institutions both domestically and internationally as its research subject. Using a questionnaire survey method, the study identifies the factors influencing users' satisfaction with AI-assisted tools in academic writing, analyses the questionnaire data, and employs the SmartPLS tool for data analysis and structural equation modelling (SEM). The study aims to address the lack of empirical research in the field of AI-assisted writing tool satisfaction. The research content specifically includes the following three aspects:

Firstly, through semi-structured interviews, specific feedback from users during actual use is collected, with a focus on exploring the differences between their expectations and actual experiences of the tool. The interviews revolve around aspects such as the tool's usability, functionality, technical support, and writing efficiency, aiming to uncover the core factors

influencing user satisfaction. Then, the interview data was analysed using grounded theory to gradually identify and confirm the key factors influencing satisfaction, providing a basis for subsequent questionnaire surveys.

Secondly, after identifying the key factors influencing satisfaction, a questionnaire was designed and distributed to further analyse the impact of these factors on user satisfaction using quantitative methods. The questionnaire was designed based on existing theoretical frameworks and combined with interview results to ensure the scientific validity and rationality of the scales. After data collection, SmartPLS software was used to analyse the data, employing structural equation modelling (SEM) to quantify the extent to which each factor influences satisfaction. The core of the study lies in constructing and validating the theoretical model to clarify which factors play a significant role in influencing satisfaction.

Finally, after constructing and validating the theoretical model of how AI-assisted writing tools influence user satisfaction, the study proposed strategies to optimise user satisfaction with AI-assisted writing tools based on the model's analysis results. The study discusses in detail how to enhance user satisfaction by improving tool functionality, enhancing user experience, and strengthening technical support. Specific recommendations include: enhancing the tool's usability, improving the intelligence of writing suggestions, optimising the user interface, and strengthening technical support services. These recommendations provide practical guidance for developers of AI-assisted writing tools to enhance user satisfaction and promote their application and adoption in academic writing.

1.4 Research Method

(1) Literature Review Method

The abundant literature and research findings have laid the theoretical foundation for this study. By summarising existing literature and compiling the latest research findings from the academic community worldwide, this study conducts a comprehensive analysis and review of relevant research both domestically and internationally. Through the preparation of a literature review, it refines relevant arguments and evidence based on existing research.

(2) Interview Method

The interview method is an effective way to obtain information through direct communication, helping researchers gain a deeper understanding of the interviewees' true feelings and behaviours. In this study, semi-structured interviews were conducted with academic writers who have used AI-assisted writing tools to obtain user satisfaction and experience feedback during actual use. The interviews focused on key factors such as tool functionality, usability, and user support, helping researchers identify the core factors influencing user satisfaction. This study was designed by combining literature reviews and real-world usage scenarios. Through face-to-face direct communication with interviewees during the interviews, the study sought to understand the gap between interviewees' expectations and their actual usage experiences of AI-assisted writing tools. The interview outline was adjusted in real-time based on the progress of the interviews to ensure that the discussions delved into the key factors influencing user satisfaction. Finally, by organising and refining the interview results, the study provides data to construct a model of the factors influencing user satisfaction with AI-assisted writing tools.

(3) Questionnaire Survey Method

The questionnaire survey method is the primary method used in this study to collect data on user satisfaction with AI-assisted academic writing tools. As one of the most commonly used methods in empirical research, questionnaire surveys have been widely applied in the field of educational technology. This study employs a quantitative research approach, designing a questionnaire based on a five-point Likert scale to quantify users' perceptions and attitudes toward various factors influencing satisfaction. The questionnaire design is based on the Technology Acceptance Model (TAM), the Information Systems Success Model (ISSM), and interview results, covering multiple dimensions such as tool usability, functionality, content quality, and user support services. By distributing the questionnaire, feedback from academic writers is collected to identify key factors influencing user satisfaction. The questionnaire design ensures that questions are concise and clear, making it easier for respondents to understand and answer, thereby enhancing the validity and reliability of the data.

(4) Partial Least Squares Structural Equation Modelling

Data analysis employs Partial Least Squares Structural Equation Modelling (PLS-SEM), an effective statistical tool for handling complex models and testing relationships between variables. This study selected PLS-SEM rather than the traditional covariance-based structural equation

modelling (CB-SEM), with the choice based on a comprehensive consideration of research objectives, data characteristics, and model complexity (Hair et al. 2021.). First, the study focuses on exploring the factors influencing user satisfaction with AI-assisted writing tools, exhibiting both 'theoretical exploratory' and 'predictive-oriented' characteristics. Second, compared to CB-SEM, which relies on data normality, large sample sizes, and strict model fit, PLS-SEM exhibits greater robustness under small sample conditions and does not require assumptions about data distribution, making it more adaptable to non-normal data or limited samples that may exist in emerging technology scenarios (Henseler et al. 2016.)

1.5 Technical approach

This study aims to explore the factors influencing user satisfaction with AI-assisted academic writing tools. Therefore, this paper first uses literature analysis and the grounded theory research paradigm to identify the important factors influencing user satisfaction with AI-assisted academic writing tools and establish a theoretical model. It then proposes research hypotheses and uses a questionnaire survey method to collect data for structural equation modelling validation and testing the validity of the proposed hypotheses, ultimately providing corresponding insights.

1.6 Innovation Points

This study focuses on the factors influencing user satisfaction with AI-assisted academic writing tools, with innovation manifested in the following two aspects:

(1) Exploring AI-assisted academic writing tools from the perspective of user satisfaction

Currently, research on AI-assisted academic writing tools primarily focuses on technical principles, tool functions, and application scenarios, with relatively limited exploration of 'user satisfaction' as a key variable. Existing studies primarily treat it as an intermediate variable, lacking systematic analysis. This study focuses on the core concept of user satisfaction, using semi-structured interviews to identify the factors influencing satisfaction.

(2) Focusing on academic writing users

Existing research generally explores the general application scenarios of AI tools, lacking targeted analysis of the academic writing field. This study takes university teachers, graduate students, and other academic writing groups as the core research subjects. By combining the experiences of

academic writing groups using AI-assisted writing, it delves into academic users' functional needs and ethical concerns regarding AI-assisted academic writing tools. Through semi-structured interviews, it summarises satisfaction factors unique to academic scenarios, providing empirical evidence for the refined improvement of AI tools in research scenarios.

(3) Constructing a user satisfaction factor model

Building on the integration of the TAM and ISSM models, this study focuses on semi-structured interviews with the target user group. Through rigorous analysis of interview texts, it identifies and incorporates key factors unique to the academic writing context, constructing a new user satisfaction influence factor model. This significantly enhances the explanatory power of the formation mechanism of user satisfaction with AI-assisted academic writing tools, providing a more comprehensive and appropriate theoretical framework for understanding the complex user attitudes in this field.

2 Concepts

2.1 AI-assisted academic writing tools

AI-assisted writing tools are intelligent software systems developed using artificial intelligence (AI) technology. They simulate human intelligent behaviour through computer simulation to assist users in completing tasks related to text creation, optimisation, and management. AI technology encompasses capabilities such as learning, reasoning, problem-solving, perception, and language understanding. It can autonomously learn and adaptively process complex data, thereby efficiently executing cognitive tasks traditionally performed by humans. (Li, et al. 2017.) (Chattu V K, 2021.)

Since the concept of AI was first proposed in the 1950s, the field has undergone multiple technological development stages, from symbolism and logical reasoning to machine learning and deep learning. Currently, mainstream AI technologies are based on big data, algorithms, and computing power as their core foundations. (Semmler & Rose, 2017.) Specifically, big data provides abundant training resources, algorithms are responsible for deep learning and optimisation of data, and computing power ensures the efficiency and stability of the technology's operation. (Lee, D., & Yoon, S. N, 2021.)

AI-assisted academic writing tools primarily utilise natural language processing (NLP), machine learning, and deep learning technologies (Radford A et al. 2018.), with core functions including text generation, language correction, style adjustment, content optimisation, and multilingual support. Text generation is based on pre-trained language models, enabling the automatic generation of article paragraphs, summaries, or even complete documents (Zhao, 2024.); language correction uses grammatical analysis and semantic understanding to correcting spelling errors, grammatical issues, and inappropriate word choices; style adjustment can modify the tone and complexity of the text according to the target audience or writing context; content optimisation provides suggestions such as paragraph restructuring and sentence simplification to enhance the logical coherence and readability of the text. (Krajka, J., & Olszak, 2024.)

In recent years, various typical AI-assisted academic writing tools have emerged on the market. For example, Grammarly focuses on language correction and is widely used in academic writing and business communication; ChatGPT, based on generative pre-trained models, supports various text generation tasks; QuillBot specialises in text rewriting and optimisation; Hemingway Editor helps users simplify their expressions and improve the readability of their articles; and Writefull is

specifically designed for academic writing, providing language optimisation suggestions based on a vast amount of academic literature. (Fitria et al. 2022.)

In academic writing scenarios, AI-assisted academic writing tools play a particularly significant role, with key features including efficient draft generation, precise language polishing, intelligent literature recommendations, and logical structure optimisation. These features help researchers quickly establish article structure, alleviate initial writing pressure; optimise language expression, enhance text accuracy and standardisation; recommend relevant literature, simplify citation and literature management; and identify and correct logical flaws in the text, strengthening the rigor and coherence of arguments. (Abdul Rahman, Zulkornain, & Hamzah, 2022; Nazari, Shabbir, & Setiawan, 2021; Zulkornain, Mat, & Rahman, 2023)

In summary, AI-assisted academic writing tools are based on artificial intelligence technology and utilise natural language processing technology to assist users in text creation and optimisation. They promote the intelligent transformation of academic creation processes and paradigms. (He, J., Baxter, S. L., Xu, J., Xu, J., Zhou, X., & Zhang, K, 2019)

2.2 User Satisfaction with AI-assisted Academic Writing Tools

Satisfaction theory originated in the business field in the mid-20th century. Cardozo (1965) first proposed that consumers' satisfaction with a product is influenced by both cost input and expected value. Oliver (1980) further defined satisfaction as 'the positive psychological feedback formed after users complete a consumption behaviour', emphasising the comparison between actual experience and expected standards. Kotler (1993) explained satisfaction from the perspective of cost-benefit ratio, pointing out that user satisfaction stems from a rational balancing of benefits gained and costs incurred. With the development of research paradigms, two major theoretical branches have emerged: the 'immediate response theory' and the 'cumulative evaluation theory.' The former focuses on emotional feedback from a single behaviour, while the latter focuses on the overall evaluation of long-term consumption experiences. (Johnson, M. D., & Fornell, C, 1991)

Additionally, Li Haoling et al. (2017) confirmed that satisfaction is essentially a dynamic value perception process involving the three-dimensional interaction of cost expectations, experience quality, and emotional feedback.

In the digital age, satisfaction theory has transcended traditional business boundaries and is widely applied across multiple fields such as e-commerce, educational assessment, public services, and information technology, serving as a key indicator for evaluating user experience. (Fornell, C. et al. 1996.) Theoretical models such as the Expectancy-Confirmation Theory (ECT) reveal the cognitive comparison mechanism of satisfaction, the Technology Acceptance Model (TAM) deconstructs user experience from the functional perception dimension, the Information Systems Success Model (ISSM) establishes a quantitative relationship between quality and satisfaction, and the SERVQUAL model enhances the precision of satisfaction measurement through the service quality gap theory. (Parasuraman, A., Zeithaml, V. A., & Berry, L. L, 1994)

Specifically for AI-assisted academic writing tools, user satisfaction primarily manifests as evaluations of the tool's functionality, performance, and overall user experience. The key influencing factors include functional practicality, ease of use, output quality, response speed, personalised support, and technical support and updates. (Raheem, B. R., Anjum, F., & Ghafar, Z. N, 2023.) For example, Grammarly has achieved high satisfaction ratings due to its precise language correction capabilities and user-friendly interface design, while ChatGPT has received widespread praise for its flexible text generation capabilities and adaptability across multiple scenarios. (Bibi, Z., & Atta, A, 2024.) Different user groups have varying satisfaction assessment criteria due to differing needs. For example, academic researchers place greater emphasis on the tool's performance in draft generation, language polishing, and literature recommendation.

3 Theoretical Foundations

3.1 Information Systems Success Model (ISSM)

Since its initial proposal in 1992, the information systems success model has undergone multiple updates and expansions. In 2003, DeLone and McLean added the dimension of service quality to the original model to better evaluate the service support components within information systems, particularly in e-commerce and other technical support systems, where improvements in service quality are critical to the overall success of the system. (DeLone, W. H., & McLean, E. R, 2003.)

The 2013 revision further expanded the model's scope, with researchers proposing multiple independent variables to reveal how external environmental factors influence the success of information systems. These independent variables include task characteristics, user characteristics, social characteristics, project characteristics, and organisational characteristics, among others, which influence various dimensions of information systems through different mechanisms. These extensions enhance the explanatory power of the ISSM model across diverse application scenarios, particularly in fields such as e-commerce, online education, artificial intelligence, and mobile applications.

The ISSM model is widely used in the research and evaluation of various information systems, particularly in e-commerce, mobile applications, and enterprise resource planning (ERP) systems, where researchers utilise the model to assess the factors contributing to system success. For example, in e-commerce, system quality and information quality directly influence user satisfaction and usage frequency, which in turn affect long-term user engagement and the platform's sustained development. Additionally, the ISSM model has been widely applied in public service systems, government information systems, and educational management systems. Information systems in these fields not only need to improve efficiency but also enhance service quality and user satisfaction to maximise social benefits. (Petter, S., DeLone, W., & McLean, E, 2013.)

The Information Systems Success Model (ISSM) provides a multi-dimensional framework for comprehensively evaluating the success of information systems through multiple dimensions such as system quality, information quality, and user satisfaction. As information technology continues to develop and application scenarios become more diverse, the ISSM model is also being continuously expanded and improved, particularly in the further exploration of service quality and

independent variables, thereby enhancing its applicability and explanatory power across different fields.

3.2 Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM) was proposed by Davis in 1989 based on the Theory of Reasoned Action and is one of the most widely used user behaviour research models in the field of information systems. This model aims to explain and predict users' acceptance of new technologies, positing that users' technology usage behaviour is influenced by their attitudes and intentions, which are primarily determined by perceived usefulness and perceived ease of use. (Davis, F. D,1989.)

Perceived usefulness refers to the extent to which users believe that new technology can improve their work efficiency or bring practical value, while perceived ease of use reflects users' subjective judgments about the difficulty of operating the technology and the cost of learning it. (Zhang,2024.) TAM posits that perceived ease of use not only directly influences users' attitudes toward use but also indirectly influences their intentions to use the technology by enhancing perceived usefulness. When users perceive a technology as easy to use, they are more likely to perceive its usefulness and be willing to continue using it. (Venkatesh, V. et al. 2003.)

As research has progressed, TAM has been expanded multiple times to accommodate user acceptance behaviour analysis in different technological environments. For example, the TAM2 model introduced social influence processes and cognitive instrumental processes on the basis of the original model to further explain how external environments influence users' acceptance of technology. (Venkatesh, V., & Davis, F. D, 2000.) The social influence process includes variables such as subjective norms and image, emphasising how the social environment shapes users' technology acceptance behaviour, while the cognitive instrumentality process focuses on users' long-term assessment of the practical value of technology. Additionally, the TAM3 model further expands the factors influencing perceived usefulness and perceived ease of use, including individual differences, system characteristics, social influence, and convenience conditions. (Venkatesh, V., & Bala, H, 2008.) These extensions enhance the explanatory power of TAM across different application scenarios, particularly in user acceptance research in fields such as e-commerce, mobile applications, online education, and artificial intelligence.

Overall, TAM provides an important theoretical framework for understanding users' acceptance and usage behaviour toward new technologies. Although its core variables are relatively simple, the

model's flexibility allows it to adapt to various technological environments and continue evolving to explain more complex technology adoption behaviours. As information technology continues to innovate, TAM remains widely applied and refined, providing theoretical support for user research in the field of information systems.

This study integrates TAM with ISSM to reveal the interactive mechanisms between users' subjective perceptions and the objective characteristics of systems. Specifically, system quality in ISSM directly influences users' perceptions of tool usability, while information quality indirectly promotes satisfaction by enhancing perceptions of tool utility.

3.3 User Perceived Value

User-perceived value, as a core concept of subjective cognition, emphasises the dynamic evaluation mechanism of individuals regarding the utility of objects. The development of this theoretical framework has followed a multi-dimensional evolutionary path: Sheth et al. (1991) pioneered a five-dimensional value framework encompassing functional, contextual, social, emotional, and cognitive dimensions, revealing the composite driving characteristics of consumer decision-making. Woodruff (1997) further deepened the dynamic comparative attributes of value assessment, pointing out that users form their final value perception through the difference between actual utility and expected utility, this dual-utility game mechanism fundamentally reflects consumers' balancing strategy between attribute benefits and risks.

As theoretical research has deepened, scholars have reached a consensus on the dynamic nature of perceived value. Gallarza and Holbrook (2011) innovatively proposed that value creation has significant experiential characteristics, forming throughout the entire consumption cycle and dynamically evolving with the context. This perspective builds upon Zeithaml's (1988) classic definition, and subsequent studies by Ulagarza (2003) and others have confirmed that consumer value perception exhibits conditional dependence and individual heterogeneity. such as Huang et al. (2019) finding significant fluctuations in value dimensions across different decision-making stages in mobile marketing scenarios. In terms of value dimension classification, the academic community has evolved from a binary model to a multi-dimensional system. The early 'utilitarian-hedonistic' dichotomy has gradually been replaced by a three-dimensional model. For example, Arslanagic, Kalajdzic et al. (2017) constructed a 'functional-emotional-social' three-dimensional framework in the professional services sector. Despite differences in dimension classification standards, most

scholars agree that value perception is fundamentally a comprehensive assessment of 'benefits-costs' by consumers, with this balancing perspective particularly prominent in e-commerce research. Zhao Yuting (2020) proposed a 'material-spiritual' dual value orientation for online consumption scenarios, which reflects the multi-layered characteristics of user value assessment.

Currently, scholars generally focus on user needs insight and value creation strategies. Although the theoretical community has not yet reached a complete consensus on the specific definition of perceived value, 'dynamism,' 'subjectivity,' and 'trade-offs' have become core consensus elements.

4 Analysis of Influencing Factors of User Satisfaction with AI-assisted Academic Writing Tools

User satisfaction with AI-assisted academic writing tools is influenced by a variety of factors. While existing research has explored the advantages of these tools in enhancing academic writing efficiency and optimising text quality, there remains a lack of systematic research on the specific factors that influence user satisfaction. Therefore, conducting exploratory qualitative research to reveal the formation mechanisms and key influencing factors of user satisfaction with AI-assisted academic writing tools holds significant theoretical and practical value.

This chapter focuses on user satisfaction with AI-assisted academic writing tools, employing semi-structured interviews to collect data and applying grounded theory to systematically identify and summarise the core factors influencing user satisfaction. Based on the analysis results of grounded coding, combined with the Technology Acceptance Model (TAM) and the Information Systems Success Model (ISSM), a model of the influencing factors of user satisfaction with AI-assisted academic writing tools is constructed, and corresponding research hypotheses are proposed to provide theoretical support for subsequent empirical analysis.

4.1 Interview Data Collection

4.1.1 Interview Outline Design

This study focuses on user satisfaction with AI-assisted academic writing tools, designing an interview outline that covers multiple key dimensions to systematically explore the core factors influencing user satisfaction. The interview outline primarily includes the following four aspects: (1) the interviewee's understanding and usage of AI-assisted academic writing tools; (2) the interviewee's actual usage experience and issues encountered during academic writing; (3) the key factors influencing the interviewee's usage satisfaction; and (4) the interviewee's expectations for future improvements to AI-assisted academic writing tools.

Before the formal interview, the researcher needs to briefly introduce the background of this study, the current development status of AI-assisted academic writing tools, and their main application scenarios in academic writing to help the interviewee better understand the interview content. In addition, the researcher will explain the scope of use of the interview data to the interviewee,

emphasising the anonymity and confidentiality of the data to enhance the interviewee's willingness to participate and freedom of expression.

During the interview, researchers will adjust their approach based on the respondent's specific answers, asking follow-up questions at appropriate times to clarify key details or delve deeper into issues to ensure the collection of detailed and accurate information. At the same time, researchers should strive to create an open and harmonious interview atmosphere, avoiding fatigue or impatience on the part of respondents due to prolonged interview duration. To this end, the interview duration is limited to 20–30 minutes to ensure the quality and efficiency of the interview.

Table 1. Interview Outline

Interview Section	Interview Questions
Motivation for Using the Tool	How did you start using AI-assisted writing tools? What are your main goals?
First Impressions	When you first used the tool, what aspects impressed you the most?
Continuous Use Habits	Do you continue to use these tools? Have you discovered any unexpected uses or had any surprising experiences?
Function Evaluation	Which features of the tool do you find most useful? Which features are the least useful or missing?
Content Quality	Evaluation How do you evaluate the quality of the content generated by the tool? Does it meet your expectations?
Usability and Technical Support	Did you encounter any difficulties while using the tool? How were the issues resolved?
Personalisation and Academic Adaptability	Does the content generated by the tool align with your personal writing style and research field requirements?
Ethics and Trust	Do you have any ethical or privacy concerns when using the tool? What are they specifically?
User Satisfaction and Improvement Suggestions	What is your overall satisfaction with the tool? Do you have any improvement suggestions?

4.1.2 Sample Selection

To ensure the scientific and rational nature of the sample in this study, the sample selection process strictly adhered to the principle of purposive sampling. This principle requires researchers to select respondents who can provide the most valuable information based on specific research objectives. Based on this principle, this study established a series of screening criteria for the interviewees to ensure that the selected sample could effectively support the research conclusions: (1) The

interviewees must have a certain level of understanding of AI-assisted academic writing tools and use them frequently in the academic writing process; (2) The gender ratio of the interviewees should be as balanced as possible; while maintaining a moderate distribution in terms of education level and age to enhance the theoretical saturation and explanatory power of the research results; (3) Respondents must come from different disciplinary backgrounds to ensure data diversity and make the research conclusions more widely applicable; (4) Respondents must be willing to participate in the interviews, have sufficient time, and agree to have the interview data used for academic analysis in this study.

After multiple rounds of screening and careful consideration, the final number of respondents was determined to be 21. These respondents are primarily aged between 20 and 40, a group that demonstrates higher levels of interest in emerging AI-assisted academic writing tools, greater actual usage, and stronger academic research capabilities and time commitment for interviews compared to other age groups.

Table 2. Basic Information about Respondents

ID	Age	Gender	Educational Level	Major
P1	28	F	Doctoral Student	Education
P2	24	F	Master's Student	Materials Science and Engineering
P3	29	F	Doctoral Student	Computer Science
P4	24	F	Master's Student	Chinese Language and Literature
P5	24	F	Master's Student	Library and Information Science
P6	28	M	Master's Student	Library and Information Science
P7	38	M	Researcher	Sociology
P8	28	F	Doctoral Student	Sociology
P9	29	F	Doctoral Student	Information Systems Science
P10	30	F	Doctoral Student	Psychology
P11	25	M	Master's Student	Data Architecture and Data Warehouse Design
P12	32	M	university lecturer	History
P13	25	F	Master's Student	Information Management
P14	39	M	Researcher	Education
P15	25	M	Master's Student	Library and Information Science
P16	24	F	Master's Student	Biotechnology
P17	29	F	Doctoral Student	Economics
P18	26	M	Master's Student	Computer Science
P19	25	F	university lecturer	Environmental Science
P20	23	F	Master's Student	Biology
P21	30	M	university lecturer	Information Systems Science

4.1.3 Data Collection

The interviews for this study were conducted between October and December 2024. To ensure the smooth collection of data, all interviews were conducted online. Before the interviews began, the researchers explained the purpose of the study to the interviewees in detail and informed them that the interviews would be recorded in their entirety.

During the interviews, to encourage participants to express themselves freely and guide them toward providing deeper insights, the researchers flexibly adjusted their interview strategies, adding questions or probing for key details based on the participants' responses, until the participants could no longer provide new information. Each interview lasted between 20 and 30 minutes, with a total cumulative duration of approximately 620 minutes. After the interviews, all audio recordings were manually transcribed into text by the researchers and organised into complete interview transcripts, totaling approximately 130,000 words.

To ensure the accuracy of the interview data, researchers sent the transcribed materials to the interviewees for verification and confirmation after transcription. For ambiguous or unclear parts, further communication and revisions were conducted with the interviewees to maximise the accuracy of their true intentions. Finally, all interview text materials were imported into NVivo for grounded coding analysis.

4.2 Grounded Theory Coding Analysis

Grounded theory typically involves four main steps: open coding, axial coding, selective coding, and testing for theoretical saturation. In implementing grounded coding, researchers need to conduct an in-depth analysis of the collected interview materials, extract and summarise core concepts (Appendix 2), and thereby arrive at more systematic and comprehensive research conclusions.

4.2.1 Open Coding

The core components of open coding include two stages: primary concept extraction and basic categorisation. During this process, researchers must eliminate subjective biases and the influence of existing cognitive frameworks, and conduct refined coding and systematic reconstruction of the collected interview data. Specifically, researchers first need to conduct an in-depth analysis of the original text materials and select original expressions closely related to the core research questions

from the vast amount of information. They then convert these core statements into primary concepts of research value by adding labels or assigning corresponding definitions. Building on this foundation, researchers progressively construct more concise and generalisable foundational categories through multi-dimensional clustering and abstraction. This study conducted concept extraction on the factors influencing user satisfaction with AI-assisted writing tools. Through the aforementioned methodological framework, a complete primary concept network and foundational category framework were ultimately constructed. The specific results are detailed in the Table 3.

Table 3. Summary of Basic Categories

Basic categories	Code
A1 System Stability	Delayed resolution of technical failures, automatic error checking
A2 Localization of Technology	Market disparities leading to content differences
A3 Degree of Personalization	Insufficient personalization, self-learning improvement, higher level of specialized support
A4 Format Standardization	Non-compliance with academic standards
A5 Legality of Content	Ensuring content legality, lack of age classification
A6 Academic Fairness	Unequal distribution of academic resources, varying levels of query proficiency
A7 Usage Costs	Legal restrictions, paid access, removal of query limitations
A8 Ease of Operation	Simple operation
A9 Operational Barriers	Cluttered interface, need for detailed operation guides, lack of emphasis on key information, lack of clear functional guidance
A10 User Feedback Mechanism	User involvement in testing, enhancement of user feedback mechanisms
A11 Professional Risks	Academic misconduct, risk warnings, over-reliance on the tool
A12 Privacy Protection	Concerns about data privacy, lack of clear privacy protection commitments and measures
A13 Authenticity	Generation of false content
A14 Logical Coherence	Inconsistent logic across queries, poor logical consistency, time required for revisions
A15 Content Value	Clear organization of generated content, poor quality of generated content, acceptable quality for simple content, strong literature review capability
A16 Functional Completeness	Format diversity, format adjustments, lack of advanced data analysis capabilities, ability to integrate with other services
A17 Performance Advantages	Reducing workload, improving efficiency, fast generation speed, plagiarism reduction
A18 Writing Assistance Advantages	Understanding unfamiliar fields, improving non-native writing quality, expanding writing ideas, language polishing
A19 Social Recommendations	Recommendations from colleagues, classmates, and friends
A20 Online Promotion	Online trends, hot search promotions

4.2.2 Axial Coding

Main axis coding serves as a pivotal link in the grounded theory research process, bridging the gap between open coding and theoretical framework development. Its primary function is to systematically integrate and analyse the core categories derived from open coding, identifying potential associations among different foundational categories. Through logical restructuring, this process distils concept units with intrinsic connections into higher-order theoretical frameworks. In this study, through multiple rounds of clustering and conceptual iteration via main axis coding, 10 primary categories with strong explanatory power were ultimately distilled, comprehensively covering the research dimensions of factors influencing satisfaction with AI-assisted academic writing tools in an academic context. The complete coding process and category evolution path are detailed in the appendix.

4.2.3 Selective Coding

The selective coding phase requires an in-depth analysis of the associative patterns between main categories, using systematic analysis and theoretical abstraction to clarify their interaction pathways. In this research phase, researchers reveal typical associative paradigms between dimensions through multiple rounds of conceptual iteration and logical deduction. This stage constructs a hierarchical relationship network among concepts, forming an explanatory theoretical model. The specific coding paths and association mappings are detailed in the appendix. The 'storyline' formed in this chapter is as follows:

In the field of AI-assisted academic writing tools, improvements in user satisfaction are the result of technical optimisations to the tools. Users may initially use the tools solely to enhance writing efficiency or meet basic needs, but as the quality of the tool system, information quality, and functional utility continue to improve, coupled with the personalised experience enabled by the tool's adaptability, users' motivations gradually shift towards pursuing more convenient, efficient, and high-quality writing experiences. During this process, users actively engage in interactions, continuously master and optimise their tool usage skills, and gradually develop their own unique writing styles and strategies with the tool's assistance. Meanwhile, the reinforcement of ethical compliance and resource fairness reduces users' perceived risks, enhances their trust and reliance on the tool, and further solidifies their recognition of the tool's value.

Additionally, the support and interactions within the community environment continue to influence users' enthusiasm and trust, encouraging them to utilise the tool more actively for creation. Ultimately, users transition from passive users to active collaborators, with significantly improved user experience and enhanced satisfaction. This transformation from initial exposure to deep engagement reflects individual user growth and mirrors the deep application and maturity of AI-assisted writing tools in academic settings. This process not only reflects the gradual deepening of individual users' recognition and trust in AI tools but also embodies the intrinsic logic and future trends of AI-assisted writing tools in the academic field.

4.3 Construction of the Influencing Factors Model of User Satisfaction with AI-assisted Academic Writing Tools

4.3.1 Selection of Model Variables

This study combines interview results, the Information Systems Success Model (ISSM), and the Technology Acceptance Model (TAM). Drawing extensively on relevant research literature and considering the unique characteristics of AI-assisted academic writing tools, the study ultimately identified system quality, tool adaptability, ethical compliance, resource fairness, community influence, information quality, functional utility, perceived risk, user involvement, user experience, perceived usefulness, and perceived ease of use as the independent variables for this study. Among these, system quality, information quality, and functional utility are the core variables for evaluating user satisfaction in the ISSM model (DeLone, W. H., & McLean, E. R, 2003.); perceived usefulness and perceived ease of use are key factors influencing user acceptance behaviour in the Technology Acceptance Model (Davis, F. D, 1989.); User experience and user engagement have been confirmed by previous studies as important antecedent variables for users' continued usage intent and satisfaction (Guo et al. 2024.) Additionally, tool adaptability, ethical compliance, resource fairness, community influence, and perceived risk are variables newly added in this study through interviews and grounded analysis, combined with the usage context of AI-assisted academic writing tools. These variables effectively reflect the unique user needs and usage environment characteristics of academic scenarios.

Furthermore, this study excluded intermediary variables such as usage attitude and behavioural intention from the Technology Acceptance Model, as these variables focus on user psychology and behavioural processes, while this study prioritises users' direct evaluations of tool usage, i.e., user

satisfaction. Additionally, variables commonly used in other fields, such as economic cost and perceived entertainment value, were not included, as these factors have relatively low relevance to the usage context of academic writing tools. Therefore, user satisfaction was ultimately selected as the dependent variable, forming a variable system more aligned with the research question, and the relevant variables were redefined and corresponding measurement designs were developed.

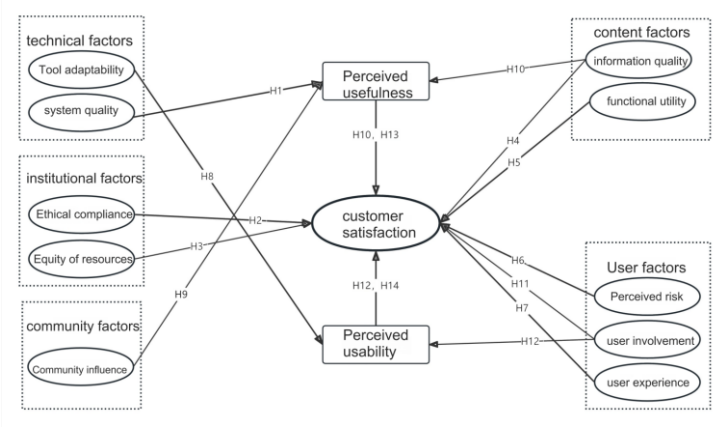

Figure 1. Satisfaction Influence Factor Model in This Study

4.3.2 Definition of Model Variables

Table 4. Model Variable Definition

Variable	Definition Overview
System Quality	Basic performance characteristics, such as tool stability, response speed, and the reliability of its technical architecture.
Tool Adaptability	The flexibility of the tool in meeting the needs of different disciplines, writing scenarios, and personalized user requirements.
Ethical Compliance	The degree to which the tool adheres to academic standards, copyright requirements, and data privacy protection protocols during use.
Resource Fairness	The equality of access to tool functions and services, as well as the reasonableness of usage costs.
Community Influence	The attitudes of academic peers, mentors, or research groups towards the use of the tool, and the demonstration effect of their behaviors.
Information Quality	The accuracy, logical rigor, and academic value of the generated content.
Functional Utility	The actual contribution of the core functions of the tool to improving research efficiency.
Perceived Risk	The level of concern users have about potential negative impacts of the tool, such as academic misconduct or data leakage risks.
User Involvement	The frequency and depth of interaction between users and the tool during use.
User Experience	A comprehensive evaluation of subjective experiences, such as the friendliness of the interface and smoothness of operation.
Perceived Usefulness	The user's perception of the tool's effectiveness in improving writing quality and reducing research time.
Perceived Ease of Use	The user's subjective judgment of the learning costs, operational complexity, and technical barriers of the tool.

4.4 Research Hypotheses

(1) System quality has a positive impact on perceived usefulness.

In this study, system quality primarily refers to the overall performance of AI-assisted academic writing tools, including platform stability, operating speed, interface design, and personalised services. System quality, as a key factor in user experience, is widely recognised as having a direct impact on perceived usefulness. For example, Venkatesh et al. (2003) noted in their study of the technology acceptance model that system usability and functionality significantly influence users' acceptance of technology, thereby affecting their perceived usefulness of the system. Additionally, Lee et al. (2003) found in their study on users' use of e-commerce platforms that system stability and response speed are key factors in enhancing users' perceived usefulness, particularly in high-demand academic writing and information retrieval processes, where platform performance directly impacts users' willingness to use the system and their efficiency.

Specifically for AI-assisted academic writing tools, when the system provides a smooth user experience, reduces latency, and improves response speed, users' experience is significantly enhanced, thereby strengthening perceived usefulness. Conversely, if the system is unstable or cumbersome to operate, user experience will be significantly diminished, reducing satisfaction and usage frequency. In this process, the role of personalised services cannot be overlooked, as they can provide customised features based on user needs and preferences, further enhancing the system's appeal and usability. Therefore, this paper proposes the following hypotheses:

H1: The system quality of AI-assisted academic writing tools has a positive impact on perceived usefulness.

(2) Ethical compliance has a positive impact on user satisfaction.

Ethical compliance refers to a platform's behaviour in accordance with legal, moral, and industry standards, particularly in terms of data privacy protection, transparency, information security, and compliance. As data privacy issues become increasingly severe, users are paying more attention to a platform's ethical compliance. When users perceive that a platform adheres to strict ethical standards and ensures privacy protection and data security when using their personal information, they typically exhibit higher levels of trust and satisfaction.

Existing research indicates that ethical compliance has a significant positive impact on user satisfaction. For example, Martin et al. (2017) noted that privacy protection and data security are key factors in enhancing user trust and satisfaction. When platforms adopt transparent and reliable measures in data protection and compliance, user satisfaction and loyalty significantly improve. Additionally, Kankanhalli et al. (2005) also emphasised that users' concerns about privacy issues in the use of information systems can impact their satisfaction. If a platform can effectively meet users' expectations for privacy protection, it can significantly enhance user satisfaction and trust.

Ethical compliance is particularly important in digital platforms, especially in situations involving sensitive data and personal privacy. Wan et al. (2017) found in their study of financial service platforms that when platforms adhere to ethical standards and can ensure information security and privacy protection, user trust and satisfaction significantly increase. This finding supports the critical role of ethical compliance in enhancing user satisfaction, particularly in terms of transparency in user data processing and protection. Therefore, based on these research findings, this paper proposes the following hypothesis:

H2: Ethical compliance has a positive impact on user satisfaction.

(3) Resource fairness has a positive impact on user satisfaction.

Resource fairness refers to whether a platform can ensure that the interests of all parties are treated fairly in the process of resource allocation and use, particularly in the distribution of information, tools, functions, and services. As users increasingly focus on fairness, especially in the use of digital platforms and AI-assisted writing tools, they place greater emphasis on whether resources are distributed fairly. When users perceive that a platform maintains fairness in resource allocation and provides equal opportunities and efficient services, they typically exhibit higher levels of satisfaction and loyalty.

Existing research indicates that resource fairness has a significant positive impact on user satisfaction. For example, Adams (1965) noted that individuals who perceive unfair resource allocation experience dissatisfaction, which in turn affects their overall satisfaction and loyalty toward the platform. Conversely, when users perceive resource allocation as fair, their trust and satisfaction with the platform significantly increase. Additionally, Ajzen et al. (2000) also demonstrated in their research that perceived fairness is a key factor influencing users' willingness to pay and satisfaction. When users perceive that the platform provides fair resource allocation, they

are more willing to pay for the platform's services, thereby enhancing the platform's market competitiveness and user satisfaction.

In the application of AI writing tools, resource fairness is particularly critical. Ren et al. (2024) noted in their research that the fairness of resource allocation in AI tools not only affects user experience but also directly correlates with user satisfaction. When platforms provide fair computing resources, timely technical support, and equal access rights, user satisfaction with the platform significantly improves, especially in large language model applications. For example, differences in AI usage policies among universities such as Fudan University may lead to an 'institutional gap' in students' access to tool support, while a Wiley survey found that 64% of researchers lack confidence in tools due to insufficient training (Naddaf M, 2025). This study integrates interview results with the Technology Acceptance Model to reveal the potential impact of resource equity on user satisfaction.

Therefore, based on these research findings, this paper proposes the following hypothesis:

H3: Resource equity has a positive impact on user satisfaction.

Information quality has a positive impact on user satisfaction.

In this study, information quality refers to attributes such as accuracy, relevance, completeness, and timeliness of content provided by AI-assisted academic writing tools. Research indicates that information quality significantly positively influences user satisfaction. According to the information systems success model proposed by DeLone and McLean (1992), information quality is one of the central factors affecting system success and user satisfaction (DeLone & McLean, 2003). When information systems provide high-quality content, users experience higher satisfaction, particularly in academic writing contexts where reliance on tools for generating quality content is crucial.

Moreover, research has shown that the relevance, accuracy, and timeliness of information significantly affect user perceptions. For example, Wang and Liao (2007), in their study on user satisfaction with e-commerce websites, indicated that improvements in information quality directly enhance user satisfaction with the system (Wang & Liao, 2007). This finding also applies to academic writing tools; when users access accurate, timely, and relevant information from the

system, their overall satisfaction with the tool improves. Based on the above literature, the following hypothesis is proposed:

H4: Information quality positively influences user satisfaction.

(5) Functional utility positively influences user satisfaction.

In this study, functional utility refers to the effectiveness and helpfulness of various functions provided by AI-assisted academic writing tools for completing user tasks. Functional utility significantly positively influences user satisfaction, especially in complex tasks involving efficient information retrieval, text generation, and editing, where tool functionalities directly impact user experience and satisfaction. If users perceive that a tool's features effectively enhance their productivity, accuracy, and quality of work, their satisfaction with the tool will significantly improve. Drawing from the Technology Acceptance Model, Venkatesh and Davis (2000) argued that functional utility is a critical driver of user acceptance and use of information technology (Venkatesh et al., 2003). When users believe that a tool's functions can better assist them in completing tasks, they are more inclined to use the tool and experience higher satisfaction.

Additionally, functional utility affects not only immediate user satisfaction but also long-term user loyalty. Studies indicate that when tool functionalities effectively meet users' needs and improve productivity, user satisfaction tends to increase, enhancing their dependence on the tool and willingness for continued usage. For instance, Wixom and Todd (2005), in their research, indicated that the functionality of information systems significantly impacts user satisfaction and subsequent use, particularly in enhancing task completion efficiency (Wixom & Todd, 2005). Thus, the proposed hypothesis is:

H5: Functional utility positively influences user satisfaction.

(6) Perceived risk negatively influences user satisfaction.

In this study, perceived risk refers to the potential negative consequences or uncertainties perceived by users when using AI-assisted academic writing tools, particularly concerning data privacy, information security, and the uncertainty of tool effectiveness. Perceived risk negatively impacts user satisfaction. When users have concerns regarding the effectiveness, accuracy, or security of tools, these negative feelings affect their satisfaction. Numerous studies have indicated that higher

perceived risk correlates with lower user satisfaction, as risk perception increases users' doubts and anxieties, thereby influencing their user experience and satisfaction (Zimmer et al., 2010).

For instance, Featherman and Pavlou (2003), in their research on e-commerce, highlighted the significant negative impact of perceived risk on user satisfaction, especially when users fear privacy breaches and data insecurity, leading to lower satisfaction with services (Featherman & Pavlou, 2003). Similarly, Beldad et al. (2010) found significant negative effects of perceived risk on user trust and satisfaction regarding online services, especially when users harbor uncertainties about the platform, significantly lowering their satisfaction (Beldad et al., 2010). Therefore, the hypothesis proposed is:

H6: Perceived risk negatively influences user satisfaction.

(7) Good user experience positively influences user satisfaction.

User experience refers to users' overall perceptions while using products or services, encompassing aspects such as interface design, ease of operation, response speed, and personalized services. As users' expectations for products and services continuously rise, the role of user experience in influencing user satisfaction has become increasingly significant. Users generally exhibit higher satisfaction when they perceive the product or service as smooth, easy-to-use, and tailored to their personal needs.

Existing studies demonstrate a significant positive impact of user experience on user satisfaction. Baker (2011) suggested that an excellent user experience is a key factor in enhancing user satisfaction with information systems. Research indicates that when users can easily accomplish tasks and enjoy convenient operations, their satisfaction and loyalty significantly improve (Baker, 2011). Moreover, Ladhari (2009), studying the hotel industry, found a close connection between service quality and users' emotional satisfaction; optimizing user experience enhances emotional satisfaction and thus overall satisfaction (Ladhari, 2009).

Across various industries, optimizing user experience significantly influences user satisfaction. Alsaggaf and Althonayan (2018), through empirical research, demonstrated that improved user experience directly influences user satisfaction and indirectly affects user behavioral intentions through emotional and cognitive responses (Alsaggaf & Althonayan, 2018). This finding indicates that users' satisfaction with their experiences fosters more positive attitudes and behaviors, thereby

enhancing overall satisfaction. Hence, based on these research findings, the following hypothesis is proposed:

H7: Good user experience positively influences user satisfaction.

(8) Tool adaptability positively influences perceived ease of use.

In this study, tool adaptability refers to the capability of AI-assisted academic writing tools to self-adjust and optimize based on users' needs, behaviors, and environmental changes. Tool adaptability directly influences perceived ease of use, especially regarding personalized functions and interface design. Davis' Technology Acceptance Model explicitly points out that the perceived usefulness of a system is closely related to users' perceptions of system adaptability and flexibility. If a tool can flexibly accommodate user needs and provide customized functionalities, users are more likely to perceive the tool as easier to use (Davis, 1989).

Additionally, research has demonstrated that tool adaptability enhances users' sense of task accomplishment and efficiency, thereby increasing perceived ease of use. For example, Venkatesh and Bala (2008) highlighted in their Technology Acceptance Model 3 research that user perceptions of tool adaptability directly influence their evaluation of the tool's effectiveness, subsequently increasing perceived ease of use (Venkatesh & Bala, 2008). These findings suggest that tool adaptability not only improves user experience but also enhances users' acceptance and intention to use the tool through increased perceived ease of use. Consequently, the following hypothesis is proposed:

H8: Tool adaptability positively influences perceived ease of use.

(9) Community influence positively influences perceived usefulness.

Community influence refers to the impact individuals or groups have on others' behaviors, attitudes, and decisions, particularly within social networks and group interactions. When selecting technologies or platforms, users often consider experiences, opinions, and recommendations from others, influencing their perceived usefulness of these technologies or platforms.

Existing research shows a significant positive impact of community influence on perceived usefulness. For example, Sareen and Jain (2014) indicated that consumers during online shopping often consider peer or community opinions, thereby enhancing perceived usefulness of shopping

platforms. Positive experiences and recommendations shared by community members lead consumers to perceive higher practical value, increasing their purchase intentions (Sareen & Jain, 2014). Moreover, Lee et al. (2011) emphasized the role of positive social influence in consumer decisions, demonstrating that social influence effectively increases consumers' perceived usefulness of online shopping platforms, particularly regarding unfamiliar or emerging technologies (Lee et al., 2011).

Eckhardt et al. (2009) further explored workplace community influence on technology adoption, finding that community recommendations and support significantly enhance individuals' perceived usefulness of information technology. When individuals sense positive influences from colleagues or workgroups, their perceptions of technology usefulness increase substantially, thereby enhancing technology adoption (Eckhardt et al., 2009). Thus, based on these research findings, the following hypothesis is proposed:

H9: Community influence positively influences perceived usefulness.

(10) Perceived usefulness mediates the relationship between information quality and user satisfaction.

Perceived usefulness mediates the relationship between information quality and user satisfaction. With the widespread use of information systems across various sectors, users increasingly focus on the quality of information and services provided by systems. High-quality information significantly enhances perceived usefulness, directly impacting user satisfaction. Thus, perceived information quality directly affects user satisfaction.

Previous research indicates that information quality significantly influences user satisfaction through perceived usefulness. Tandon et al. (2017) pointed out the clear mediation between website service quality and customer satisfaction, primarily manifested through customers' perceived usefulness of information. High-quality information improves user experience and trust, increasing customer satisfaction (Tandon et al., 2017). Furthermore, DeLone and McLean's (2003) Information Systems Success Model emphasizes that information quality drives perceived usefulness, positioning perceived usefulness as a critical mediator influencing user satisfaction (DeLone & McLean, 2003).

In service quality studies, Artika et al. (2023) found that service quality indirectly influences consumer satisfaction and loyalty through enhanced perceived usefulness. Their research indicated that high-quality information elevates users' perceptions of service utility, enhancing user satisfaction and loyalty (Artika et al., 2023). Hence, based on these research findings, the following hypothesis is proposed:

H10: Perceived usefulness mediates the relationship between information quality and user satisfaction.

(11) User involvement positively influences user satisfaction.

User involvement refers to the activities and contributions invested by users in the design, development, and improvement of products or services. As consumers increasingly emphasize customized and personalized services, user involvement has become a key factor for enhancing user satisfaction. When users actively participate in the development of products or services, they typically experience higher levels of satisfaction and tend to evaluate the products or services positively.

Existing studies have indicated that user involvement significantly and positively affects user satisfaction. For example, Hoyer et al. (2010) noted that consumer co-creation activities play a crucial role in new product development. By participating in product innovation processes, consumers not only obtain products better tailored to their needs but also enhance their brand loyalty and satisfaction (Hoyer et al., 2010). Similarly, Mahmoud et al. (2018) emphasized the role of user value creation in service innovation, finding that customer satisfaction significantly increases when consumers directly participate in service innovation processes, as their needs and expectations are better fulfilled (Mahmoud et al., 2018).

These findings suggest that active user involvement enhances users' identification with the products or services, thus elevating their overall satisfaction. Such findings hold significant implications for understanding the role of user involvement in increasing user satisfaction, especially within environments characterized by customization and innovation-driven contexts. Therefore, based on these research results, this study proposes the following hypothesis:

H11: User involvement positively influences user satisfaction.

(12) Perceived ease of use mediates the relationship between user involvement and user satisfaction.

Perceived ease of use refers to users' subjective perceptions regarding the simplicity, intuitiveness, and accessibility of a system or tool during its use. Studies show that perceived ease of use not only directly influences users' experiences and satisfaction but also serves as a crucial mediator between user involvement and satisfaction. Specifically, when users perceive a platform or tool as simple and easy to use, they are more inclined to actively participate, thereby indirectly enhancing their overall satisfaction.

Existing research supports this perspective. For example, Venkatesh and Davis (2000), in their Technology Acceptance Model research, pointed out that perceived ease of use not only directly affects users' acceptance of technology but also indirectly enhances user satisfaction by increasing participation (Venkatesh & Davis, 2000). They found that users' willingness to engage significantly increases when they perceive technology as easy to use, which in turn boosts their long-term usage and satisfaction. This demonstrates that perceived ease of use encourages frequent use of technological tools, thereby positively influencing overall user experiences and satisfaction.

DeLone and McLean (2003) further emphasized the mediating role of perceived ease of use within their Information Systems Success Model. They noted that system ease of use directly influences user involvement, and increased involvement subsequently enhances trust and experience quality, ultimately improving user satisfaction (DeLone & McLean, 2003). This highlights perceived ease of use as a bridge between user involvement and satisfaction, explaining why systems perceived as easier to use often achieve higher user satisfaction.

When users perceive a platform or tool as user-friendly, they are more willing to invest time and effort, deriving greater satisfaction and enjoyment from their involvement, thus elevating their overall satisfaction. Therefore, integrating these findings, this study proposes:

H12: Perceived ease of use significantly mediates the relationship between user involvement and user satisfaction.

(13) Perceived usefulness positively influences user satisfaction.

In this study, perceived usefulness refers to the degree to which users believe that using AI-assisted academic writing tools can enhance their work efficiency, quality, and task accomplishment.

Perceived usefulness is recognized as a critical factor influencing user satisfaction. According to the Technology Acceptance Model, Davis (1989) argued that perceived usefulness is one of the core determinants of users' acceptance and continued use of technology (Davis, 1989). If users perceive that a tool effectively enhances their productivity or task completion, they typically exhibit higher satisfaction, promoting sustained usage.

Furthermore, the impact of perceived usefulness on user satisfaction has been widely validated across various fields. For instance, Zhou et al. (2010) found in their research on mobile payment systems that perceived usefulness directly influences user satisfaction, subsequently affecting usage intentions (Zhou et al., 2010). This finding similarly applies to AI-assisted academic writing tools; when users recognize the significant role of these tools in enhancing academic writing efficiency and quality, their satisfaction generally increases, reinforcing their intent to use the tools.

Additional studies highlight the critical role of perceived usefulness across various online platforms regarding user intentions and satisfaction. For example, Wu (2022), studying social media platforms, observed a significant increase in user satisfaction and loyalty upon perceiving platform utility (Wu, 2022). Such mechanisms are similarly applicable to academic writing tools, particularly in contexts where users rely heavily on these tools to generate high-quality content. Thus, supported by this literature, this study proposes:

H13: Perceived usefulness positively influences user satisfaction.

(14) Perceived ease of use positively influences user satisfaction.

In this study, perceived ease of use refers to the extent to which users find AI-assisted academic writing tools simple to operate, free from complex procedures, and easy to learn. Perceived ease of use is regarded as a crucial factor influencing user satisfaction. According to the Technology Acceptance Model, Davis (1989) stated that perceived ease of use significantly determines user acceptance and technology usage. When users find a tool easy to use without a steep learning curve, they typically have higher satisfaction and are more inclined to continue using it (Davis, 1989).

The positive effect of perceived ease of use on user satisfaction has been validated in numerous studies. For instance, Venkatesh et al. (2003) identified perceived ease of use as a critical factor directly affecting user satisfaction and subsequent usage intentions regarding information technology (Venkatesh et al., 2003). Moreover, Zhou et al. (2010) found a significant positive

impact of perceived ease of use on user satisfaction and usage intentions in their research on mobile payment systems, suggesting that ease of use significantly boosts user satisfaction (Zhou et al., 2010). Hence, this study proposes:

H14: Perceived ease of use positively influences user satisfaction.

5 Empirical Study on Influencing Factors of User Satisfaction with AI-assisted Academic Writing Tools

Using a research approach that combines semi-structured interviews and grounded theory, alongside relevant theoretical frameworks, this study constructs a model of influencing factors on user satisfaction with AI-assisted academic writing tools and proposes corresponding research hypotheses. To further explore the reliability of the theoretical model developed and the validity of the proposed hypotheses, this chapter integrates quantitative research methods—including questionnaire design, pre-survey, formal questionnaire distribution, reliability and validity analysis, and structural equation model path analysis—to empirically test the theoretical model and research hypotheses, thereby arriving at a validated model of factors influencing user satisfaction with AI-assisted academic writing tools.

5.1 Questionnaire Design

The questionnaire in this study consists of three parts: the introduction, basic information, and measurement items for relevant variables.

The introduction section explains the purpose of this survey and requests the target respondents to complete the questionnaire, facilitating the efficient collection of valid data. Additionally, respondents are assured that their provided information will not be disclosed and that the data collected will be used solely for academic research purposes. Gratitude is also expressed to all participants involved in the survey.

The second part gathers respondents' personal information, including basic demographic data such as age and gender, to enable subsequent descriptive statistical analysis. Following this, the questionnaire examines basic usage details regarding AI-assisted academic writing tools, including whether respondents have previously used such tools and their duration and frequency of use. This section aims to identify and exclude invalid questionnaires, while broadly understanding usage patterns of AI-assisted academic writing tools, facilitating the formulation of recommendations.

The third part comprises measurement items related to the model variables used in this study, as outlined in the appendix. The thirteen measurement dimensions include system quality, tool adaptability, ethical compliance, resource fairness, user experience, user involvement, perceived risk, information quality, functional utility, community influence, perceived usefulness, perceived

ease of use, and user satisfaction. This section constitutes the main body of the questionnaire. The measurement items employ a five-point Likert scale, allowing respondents to select responses based on their personal experiences.

5.2 Pre-survey

Before formally distributing the questionnaire, a pre-survey was conducted in this study, collecting a total of 72 completed questionnaires. The primary aim of the pre-survey was to assess the reliability and validity of the questionnaire. Reliability testing refers to evaluating the reliability, stability, and consistency of the questionnaire results—that is, whether the measurement outcomes accurately reflect the genuine consistency and stability of the respondents. A higher reliability coefficient indicates that the questionnaire better represents these genuine characteristics of consistency and stability among respondents. Cronbach's alpha coefficient is one of the most commonly used reliability coefficients, evaluating the consistency of scores across various items in the questionnaire. It represents an internal consistency reliability measure.The formula is as follows:

$$\alpha=\frac{k}{k-1}\left(1-\frac{\sum_{i=1}^{k}S_i^2}{S_T^2}\right)$$

As shown in the table below, the Cronbach's alpha coefficient for the overall questionnaire scale is 0.978, which is greater than 0.7, indicating excellent internal consistency and stability. Thus, the design and structure of the questionnaire items are scientifically reasonable and suitable for further analysis.

Table 5. Cronbach's Reliability Analysis

number of items	sample size	Cronbach's alpha coefficient
39	72	0.978

Validity refers to the extent to which the measured results reflect the content intended for investigation. The closer the measurement results align with the intended content, the higher the validity; conversely, the lower the validity. Validity testing primarily involves examining the Kaiser-Meyer-Olkin (KMO) coefficient and Bartlett's test of sphericity. The KMO coefficient ranges from 0 to 1, with values closer to 1 indicating better structural validity of the questionnaire. If Bartlett's test of sphericity is significant (p-value less than 0.05), the questionnaire is considered to have satisfactory structural validity.

Table 6. KMO and Bartlett's Test

KMO		0.888
Bartlett's sphericity test	approximate chi-square	2299.378
	df	741
	P-value	0.000

Using KMO and Bartlett's tests for validity verification, the table below shows a KMO value of 0.888. A KMO value exceeding 0.8 suggests the research data is highly suitable for extracting information.

5.3 Questionnaire Distribution, Collection, and Descriptive Statistics

5.3.1 Descriptive Statistical Analysis of Samples

The frequency analysis covered various demographic and behavioral data, including gender, age, educational background, workplace, occupation, academic discipline, publication record, research duration, and usage frequency of AI-assisted academic writing tools. Regarding gender, males accounted for 52.45% and females for 47.55%, with a slight predominance of males. In age distribution, individuals aged 26-35 were the most numerous, representing 43.38%, followed by those aged 18-25, comprising 34.56%, indicating a relatively younger sample group. Educationally, those with a bachelor's degree made up the highest proportion at 60.54%, followed by those with associate degrees or below at 33.09%, and those with master's degrees or above at 6.37%, suggesting varied educational levels.

Concerning workplaces, a significant number of respondents worked at universities (47.55%) and research institutes (37.99%), whereas those from enterprises accounted for a smaller proportion, only 9.31%. Regarding specific occupations, postgraduate students constituted 12.25%, while university teachers and researchers from institutes formed the major occupational groups, at 47.55% and 37.99% respectively. In academic disciplines, science and engineering fields stood out, representing 45.83%, followed by humanities and social sciences at 24.51%, and medicine at 19.61%. Regarding publication records, publications comprised the largest group at 73.04%, indicating a considerable level of international publishing capability. Research experience showed 41.18% had 1-5 years, 39.22% over five years, and 19.61% less than one year, suggesting diverse research backgrounds. In terms of frequency of using AI-assisted academic writing tools, weekly

users constituted 50%, daily users 35.54%, and occasional users 14.46%, showing that most respondents frequently use such tools.

These data reflect the sample's essential characteristics and behavior patterns, providing foundational insights for in-depth research into the academic community's research practices and tool usage.

Table 7. Familiarity With AI-assisted Academic Writing Tools

Item	Frequency	Percentage	Cumulative Percentage
Very Familiar	233	57.11%	57.11%
Somewhat Familiar	72	17.65%	74.75%
Familiar	73	17.89%	92.65%
Slightly Familiar	30	7.35%	100.00%
Total	408	100.0%	

The survey data on respondents' familiarity with AI-assisted academic writing tools reveal a distinctive distribution pattern. Among 408 respondents, the majority, 57.11% (233 respondents), claimed to be 'very familiar' with the tools, indicating that more than half had substantial familiarity, likely due to frequent engagement with these tools in academic activities or strong interest in emerging technologies. Those who reported an 'average' or 'good' understanding represented 17.65% (72 respondents) and 17.89% (73 respondents), respectively, cumulatively accounting for 92.65%. This suggests a considerable level of awareness, though not expert proficiency. The smallest group, those with only 'some understanding,' accounted for 7.35% (30 respondents), yet importantly, none reported complete ignorance. Overall, these data illustrate high recognition and widespread adoption of AI-assisted academic writing tools among respondents.

Table 8. The Usage Of AI-assisted Writing Tools

Tool	n	Percentage
ChatGPT	361	17.84%
Wenxin Yiyan	316	15.61%
DeepSeek	264	13.04%
Tongyi Qianwen	168	8.30%
Kimi	283	13.98%
Doupao	270	13.34%
CNKI AI	176	8.70%
Grammarly	104	5.14%
Zhipu Qingyan	82	4.05%

Data regarding the usage of different AI-assisted writing tools among respondents indicate ChatGPT as the most popular choice, utilized by 361 individuals (17.84%), attributed to its advanced technology and widespread recognition. Wenxin Yiyan also performed strongly with 316 users (15.61%). Usage of DeepSeek, Kimi, and Doubow accounted for about 13% each, with relatively close user numbers. Tongyi Qianwen, CNKI AI, Grammarly, and Zhipu Qingyan had lower usage rates, ranging between 4.05% and 8.70%. Overall, the varied market shares highlight competitive dynamics and diverse user preferences in the AI writing tool sector.

Table 9. The Main Use of AI-assisted Writing Tools in Academic Settings

Tool	n	Percentage
Intelligent Topic Selection and Research Suggestions	205	12.73%
Literature Retrieval and Organization	224	13.90%
Paper Draft Generation	365	22.66%
Language Polishing and Grammar Proofreading	226	14.03%
Data Analysis and Visualization	316	19.62%
Reference Management and Citation Formatting	59	3.66%
Academic Translation and Cross-language Writing	216	13.41%

These data demonstrate respondents' perceptions of AI-assisted writing tools' primary academic applications. The largest group, 22.66% (365 respondents), identified the generation of initial paper drafts as the primary use, indicating significant acknowledgment of AI's utility in early-stage academic writing. Data analysis and visualization followed closely at 19.62% (316 respondents), reflecting demand for AI's assistance in handling complex datasets. Literature search and organization (13.90%, 224 respondents), language refinement and grammar checking (14.03%, 226 respondents), and academic translation and multilingual writing (13.41%, 216 respondents) had similar proportions, indicating considerable interest in these functionalities. Intelligent topic selection and research suggestions accounted for 12.73% (205 respondents), while reference management and formatting were least popular at only 3.66% (59 respondents). Overall, these results suggest AI's broad yet varied potential in different academic processes.

Table 10. Risks or Issues AI-assisted Writing Tools May Cause

Tool	n	Percentage
Data Privacy Leakage	216	28.46%
Academic Misconduct	123	16.21%
Insufficient Accuracy of Generated Content	268	35.31%
Over-reliance on the Tool	111	14.62%
High Usage Barriers	41	5.40%

Respondents' awareness of potential risks or issues associated with AI-assisted writing tools is captured clearly in this dataset. Concerns about content accuracy were most significant, cited by 35.31% (268 respondents), highlighting worries over the precision and reliability of AI-generated content. Data privacy leakage was another substantial concern, recognized by 28.46% (216 respondents), reflecting heightened attention to personal data security. Academic misconduct issues were cited by 16.21% (123 respondents), indicating worries about potential misuse affecting academic integrity. Concerns about excessive reliance on tools accounted for 14.62% (111 respondents), while perceptions of high entry barriers to tool usage were least prevalent, cited by just 5.40% (41 respondents). Overall, these findings underscore diverse risk perceptions regarding AI-assisted writing tools, emphasizing the importance of addressing these issues.

5.3.2 Descriptive Analysis of Each Variable

Descriptive analysis of variables, results show:

Table 11. descriptive statistics

Item	Average Value	Standard Deviation
System Quality	3.798	1.006
Tool Adaptability	3.581	1.154
Ethical Compliance	3.877	0.971
Resource Fairness	3.574	1.114
User Experience	3.775	1.033
User Involvement	3.628	1.065
Perceived Risk	2.362	1.119
Information Quality	3.801	1.04
Functional Utility	3.711	1.011
Community Influence	3.605	1.108
Perceived Usefulness	3.727	1.06
Perceived Ease of Use	3.616	1.118
User Satisfaction	3.838	0.957

As can be seen from the above, the average values of each indicator range from 2.362 to 3.877. Among them, the average value for ethical compliance is the highest at 3.877, with a standard deviation of 0.971. This indicates that users have a relatively high level of recognition for AI-assisted writing tools in terms of ethical compliance, and the data dispersion is relatively small, with evaluations from different users being quite consistent. The average value for information quality is 3.801, and the average value for user satisfaction is 3.838, both of which are also at a relatively high level, indicating that the tool performs well in terms of information provision and user satisfaction. The average scores for system quality, functional utility, and perceived usefulness are 3.798, 3.711, and 3.727, respectively, all of which are also at relatively high levels, indicating that users have a relatively high level of recognition for the tool's system, functionality, and practicality. However, the average scores for tool adaptability, resource fairness, user involvement, community influence, and perceived ease of use range from 3.574 to 3.628, which are at an intermediate level, indicating that users' evaluations of these aspects are relatively average. The average score for perceived risk was the lowest at 2.362, with a standard deviation of 1.119, indicating that users perceive relatively low risk when using the tool, but there is significant variation in evaluations among different users. Overall, users have a generally positive evaluation of the AI-assisted writing tool, but there is room for improvement in certain areas.

5.4 Questionnaire Data Quality Analysis

This study will utilise Smart PLS 4.0 software to employ structural models to assess the relationships among the measured variables. The sample data conforming to a multivariate normal distribution is a fundamental requirement for data analysis using structural equation modelling [Bentler P M. Comparative fit indexes in structural models[J]. Psychological bulletin, 1990, 107(2): 238.], with the observed indicators being the skewness coefficient and kurtosis coefficient. Specifically, when the absolute value of skewness is less than 3.0 and the absolute value of kurtosis is less than 8.0, the data satisfy the normal distribution assumption [Kline R B. Principles and practice of structural equation modeling[M]. Guilford publications, 2023.]. Based on the test results in the table, the sample data in this study meet the normal distribution requirements and can proceed to further analysis.

Table 12. Shota Inspection

Name	Peakness	Skewness	Name	Peakness	Skewness
Q14.1	0.136	-0.925	Q20.3	-0.597	0.759
Q14.2	-0.265	-0.861	Q21.1	-0.021	-0.966
Q14.3	0.099	-0.944	Q21.2	0.087	-0.939
Q15.1	-0.581	-0.715	Q21.3	-0.189	-0.863
Q15.2	-0.707	-0.651	Q22.1	-0.105	-0.843
Q15.3	-0.698	-0.708	Q22.2	-0.29	-0.754
Q16.1	0.309	-0.984	Q22.3	0.036	-0.939
Q16.2	0.093	-0.953	Q23.1	-0.622	-0.72
Q16.3	0.279	-0.997	Q23.2	-0.46	-0.693
Q17.1	-0.692	-0.602	Q23.3	-0.593	-0.707
Q17.2	-0.601	-0.686	Q24.1	-0.18	-0.857
Q17.3	-0.538	-0.724	Q24.2	-0.439	-0.776
Q18.1	-0.045	-0.91	Q24.3	-0.306	-0.779
Q18.2	-0.283	-0.841	Q25.1	-0.611	-0.689
Q18.3	-0.128	-0.868	Q25.2	-0.643	-0.735
Q191	-0.453	-0.709	Q25.3	-0.461	-0.711
Q192	-0.69	-0.629	Q26.1	0.332	-0.976
Q193	-0.449	-0.723	Q26.2	0.218	-1.013
Q20.1	-0.642	0.666	Q26.3	0.378	-0.983
Q20.2	-0.561	0.768			

Measurement models depict the relationships between constructs (i.e., latent variables) and their associated measurement variables, specifically illustrating how these measurement variables collectively describe the constructs they represent. (Hair Jr J F et al. 2010.) Measurement models can be either reflective or formative. (Hair Jr J F et al. 2021.) The evaluation of measurement models primarily focuses on assessing the reliability and validity of constructs.

5.4.1 Reliability Analysis

Reliability analysis, also known as consistency analysis, is used to evaluate the consistency or stability of the measurement results of a questionnaire or measurement tool. It is an important indicator reflecting the accuracy of the content analysis results of a questionnaire or measurement tool. The evaluation indicators for reliability include Cronbach's Alpha, rho_A, and composite reliability (CR).

The Cronbach's Alpha coefficient ranges from 0 to 1. The higher the value, the higher the internal consistency of the construct, meaning that respondents demonstrate greater consistency or stability in their responses to questionnaire items measuring the same construct. Generally, if the Cronbach's Alpha coefficient of a construct is greater than 0.7, it can be considered to have good reliability. However, relying solely on Cronbach's Alpha to measure construct reliability has several limitations, such as requiring that all items in the scale be equally influenced by the latent variable and that errors between items be unrelated. Composite reliability (CR) is primarily used to address the sensitivity of Cronbach's Alpha to the number of items, which can underestimate internal consistency, and to further characterise the degree of internal consistency. In contrast, composite reliability takes into account the factor loadings of the construct. Generally, a composite reliability (CR) of 0.7 or above indicates that the construct has good reliability. (Nunnally J C., 1975.)

In addition, rho_A is also an indicator for measuring construct reliability. Hair et al. (2015) pointed out that Cronbach's Alpha coefficient is too conservative in measuring internal consistency, while composite reliability is too liberal. while the true internal consistency of a construct typically lies between these two extremes. Therefore, Dijkstra and Henseler (2015) proposed rho_A as a compromise solution to achieve an approximate precise measurement of construct reliability. When the rho_A of a construct exceeds 0.7, it indicates that each construct has high internal consistency.

Table 13. Reliability and Validity Indicators

Item	Cronbach's alpha	Rho_a	Rho_c	AVE
Ethical Compliance	0.792	0.801	0.878	0.706
Information Quality	0.804	0.837	0.882	0.714
Functional Utility	0.775	0.775	0.869	0.689
Tool Adaptability	0.841	0.852	0.904	0.758
Perceived Ease of Use	0.826	0.833	0.896	0.742
Perceived Usefulness	0.807	0.81	0.886	0.721
Perceived Risk	0.817	0.82	0.891	0.732
User Experience	0.802	0.81	0.883	0.715
User Involvement	0.793	0.796	0.879	0.707
User Satisfaction	0.781	0.781	0.872	0.695
Community Influence	0.815	0.835	0.889	0.728
System Quality	0.792	0.805	0.878	0.706
Resource Fairness	0.827	0.83	0.897	0.743

This set of data presents the reliability and validity indices for each variable. Cronbach's alpha values range from 0.775 to 0.841, all exceeding 0.7, indicating good internal consistency for each variable. The overall reliability coefficients rho_a and rho_c are mostly around 0.8 or higher, indicating high reliability of the scale. The average variance extracted (AVE) values ranged from 0.689 to 0.758, all exceeding 0.5, indicating good convergent validity for each variable. The measurement items effectively reflect the underlying variables, and the overall scale quality is excellent.

5.4.2 Validity Analysis

Validity analysis is an indicator used to evaluate the effectiveness and accuracy of measurement tools, examining the extent to which measurement items accurately and objectively reflect the constructs being assessed. Higher consistency between measurement results and the actual characteristics of the objects indicates better construct validity. Validity analysis encompasses content validity, convergent validity, and discriminant validity.

(1) Content Validity

Content validity assesses the appropriateness of questionnaire items, including whether the items represent content that the variables should measure, whether they cover all aspects that the variables are intended to measure, and whether the proportions of items constituting the variables are appropriate. First, the measurement instruments used in this study were based on established scales both domestically and internationally. Second, experts in this research field were invited to iteratively revise and refine the measurement items according to the specific context of this study. Thus, it can be concluded that the measurement instruments used in this research exhibit high content validity.

(2) Convergent Validity

Convergent validity refers to the consistency of results obtained through repeatedly applying the same measurement method to the same object, reflecting the reliability of the measurement results. According to Fornell and Larcker's suggestions (Fornell & Larcker, 1981), convergent validity can be determined by examining the factor loadings of measurement items, composite reliability (CR), and average variance extracted (AVE). Factor loadings represent the extent to which measurement variables explain the variance of the construct. Factor loadings for measurement items should

exceed the minimum threshold of 0.6. Composite reliability reflects the consistency of all measurement items within a construct in explaining that latent variable. Composite reliability (CR) values range from 0 to 1, with higher CR values indicating greater internal consistency of the construct (Hair Jr et al., 2014). Bagozzi et al. recommend that the composite reliability (CR) value should exceed 0.7 (Bagozzi et al., 1998). The average variance extracted (AVE) represents the degree to which measurement items of a construct explain the variance of that construct.

From the cross-factor loading table (shown in appendix), it can be seen that the factor loadings of all the items for the constructs measured in this study are greater than 0.7. As shown in the table, the composite reliability (CR) values of the 13 constructs range from 0.7 to 0.95, all of which are greater than 0.7. The average variance extracted (AVE) ranges from 0.6 to 0.8, all of which are greater than 0.5. This indicates that the convergent validity of the 13 constructs in the study has passed the test, and each construct demonstrates good convergent validity.

(3) Discriminant Validity

Discriminant validity refers to the degree to which different items of a construct have a low correlation or significant differences between them. It is used to test the distinctiveness between constructs. Generally, three methods are used to test this: the cross-factor loading matrix, the Fornell-Larcker criterion, and the HTMT test.

Table 19 presents the cross-factor loading table, which shows the factor loadings of each construct's measurement items on different factors. If the factor loading of all items for a particular construct is higher on that factor than on other factors, it indicates discriminant validity. As shown in the table, the factor loadings of each construct's measurement items are higher on the respective construct than on the other constructs, suggesting that the 13 constructs have good discriminant validity. Furthermore, according to the Fornell-Larcker criterion, the correlation coefficients between constructs are compared with the square root of the average variance extracted (AVE) for each construct. If the former values are smaller than the square root of the latter, it indicates that the constructs have discriminant validity. As shown in Table 3, the square root of each construct's AVE (i.e., the bolded values along the diagonal) is greater than the correlation coefficients between the constructs, indicating that the constructs have good discriminant validity.

Table 14. Fornell-Larcker criterion

	Ethical Compliance	Information Quality	Functional Utility	Tool Adaptability	Perceived Ease of Use	Perceived Usefulness	Perceived Risk	User Experience	User Involvement	User Satisfaction	Community Influence	System Quality	Resource Fairness
Ethical Compliance	0.84												
Information Quality	0.065	0.854											
Functional Utility	0.194	0.194	0.83										
Tool Adaptability	0.354	0.178	0.323	0.871									
Perceived Ease of Use	0.192	0.169	0.298	0.246	0.861								
Perceived Usefulness	0.297	0.192	0.258	0.318	0.223	0.849							
Perceived Risk	-0.427	-0.148	-0.308	-0.377	-0.225	-0.293	0.856						
User Experience	0.322	0.137	0.281	0.409	0.275	0.324	-0.338	0.846					
User Involvement	0.172	0.168	0.301	0.19	0.253	0.245	-0.169	0.259	0.841				
User Satisfaction	0.381	0.278	0.437	0.417	0.355	0.327	-0.419	0.426	0.334	0.834			
Community Influence	0.433	0.165	0.317	0.385	0.194	0.33	-0.446	0.404	0.202	0.454	0.853		
System Quality	0.333	0.229	0.372	0.288	0.229	0.332	-0.335	0.309	0.23	0.468	0.419	0.84	
Resource Fairness	0.301	0.176	0.321	0.369	0.261	0.399	-0.335	0.39	0.294	0.453	0.408	0.447	0.862

Finally, the discriminant validity between constructs is poorer when the Heterotrait-Monotrait Ratio of Correlations (HTMT) value between two constructs approaches 1. If the HTMT value between two constructs is less than 0.85, it is considered that the constructs exhibit good discriminant validity. As shown in the table, the highest HTMT value between two constructs in this study is 0.5654, which is less than 0.85, thus satisfying the third requirement for discriminant validity testing.

Table 15. Heterotrait-monotrait Ratio (HTMT)

	Ethical Compliance	Information Quality	Functional Utility	Tool Adaptability	Perceived Ease of Use	Perceived Usefulness	Perceived Risk	User Experience	User Involvement	User Satisfaction	Community Influence	System Quality	Resource Fairness
Ethical Compliance													
Information Quality	0.078												
Functional Utility	0.248	0.239											
Tool Adaptability	0.436	0.202	0.395										
Perceived Ease of Use	0.233	0.206	0.367	0.29									
Perceived Usefulness	0.371	0.232	0.326	0.392	0.271								
Perceived Risk	0.533	0.173	0.386	0.452	0.27	0.361							
User Experience	0.409	0.162	0.352	0.498	0.336	0.403	0.413						
User Involvement	0.218	0.207	0.386	0.232	0.313	0.308	0.207	0.326					
User Satisfaction	0.482	0.344	0.56	0.509	0.438	0.412	0.523	0.535	0.423				
Community Influence	0.539	0.191	0.397	0.468	0.229	0.397	0.545	0.508	0.251	0.565			
System Quality	0.417	0.282	0.473	0.354	0.286	0.41	0.419	0.388	0.292	0.597	0.522		
Resource Fairness	0.375	0.21	0.399	0.443	0.312	0.489	0.407	0.482	0.365	0.562	0.497	0.552	

In conclusion, based on the three methods of discriminant validity testing, all 11 constructs meet the requirements. Therefore, the 11 constructs in this study exhibit good discriminant validity.

5.5 Analysis of Sample Differences

5.5.1 One-way ANOVA Analysis by Education Level

Table 16. Analysis of Variance Results for Educational Attainment Factors

	Educational Attainment (mean ± standard deviation)				
	A.Master's degree or above(n=26)	B.Bachelor's degree(n=247)	C.College degree or below(n=35)	F	p
System quality	3.91±0.91	3.82±1.02	3.74±1.01	0.480	0.619
Tool applicability	3.63±1.13	3.60±1.16	3.54±1.16	0.116	0.891
Ethical compliance	3.83±1.12	3.95±0.91	3.74±1.04	2.098	0.124
Resource fairness	3.81±0.92	3.56±1.15	3.55±1.08	0.610	0.544
User experience	3.56±1.24	3.79±1.04	3.78±0.98	0.588	0.556
User participation	3.51±1.17	3.65±1.06	3.62±1.06	0.195	0.823
Perceived risk	2.45±1.12	2.28±1.08	2.49±1.19	1.672	0.189
Information quality	3.82±1.18	3.87±0.97	3.77±1.06	0.460	0.632
Functional utility	3.67±1.04	3.71±1.03	3.72±0.98	0.036	0.965
Community impact	3.59±1.16	3.66±1.10	3.50±1.11	0.944	0.390
Perceived usefulness	3.59±1.11	3.85±0.99	3.53±1.14	4.230	0.015*
Perceived ease of use	3.78±1.07	3.58±1.15	3.65±1.06	0.491	0.612
User satisfaction	3.91±0.87	3.84±0.99	3.82±0.92	0.092	0.912

As shown in the table above, using analysis of variance to study the differences in educational attainment across 13 items—system quality, tool applicability, ethical compliance, resource fairness, user experience, user participation, perceived risk, information quality, functional utility,

community impact, perceived usefulness, perceived ease of use, and user satisfaction—reveals that there are no significant differences ($p > 0.05$) among the different educational attainment samples for these 12 items. This indicates that samples with different educational backgrounds exhibit consistency across all 13 factors—system quality, tool applicability, ethical compliance, resource fairness, user experience, user participation, perceived risk, information quality, functional utility, community impact, perceived usability, and user satisfaction—with no significant differences. Additionally, educational background samples exhibit significant differences ($p < 0.05$) in perceived usefulness, indicating that samples with different educational backgrounds show differences in this factor. A detailed analysis reveals that educational attainment exhibits significant differences at the 0.05 level for perceived usefulness ($F=4.230$, $p=0.015$). Specifically, the average score comparison results show a notable difference between the groups, with 'B. Bachelor's degree > C. Associate degree or below'. In summary, educational attainment samples exhibit significant differences in one aspect of perceived usefulness.

5.5.2 One-way ANOVA Analysis by Academic Discipline

Table 17. Results of Analysis of Variance for Subject Factors

	Discipline (mean ± standard deviation)						
	A.Science and engineering(n=187)	B.Humanities and social sciences(n=100)	C.Agronomy(n=33)	D.Medicine(n=80)	E.Others（Please specify:）(n=8)	F	p
System quality	3.70±1.09	3.87±0.92	3.87±0.92	3.88±0.96	4.21±0.53	1.121	0.346
Tool applicability	3.52±1.16	3.67±1.12	3.34±1.27	3.67±1.14	3.92±1.21	0.928	0.447
Ethical compliance	3.80±1.04	3.95±0.90	3.91±0.91	3.92±0.93	4.25±0.61	0.831	0.506
Resource fairness	3.54±1.14	3.67±1.09	3.59±1.03	3.54±1.11	3.54±1.37	0.274	0.895
User experience	3.80±1.00	3.72±1.10	3.75±1.05	3.79±1.00	3.71±1.34	0.118	0.976
User participation	3.50±1.10	3.71±1.06	4.00±0.85	3.65±1.05	3.92±1.11	1.982	0.096
Perceived risk	2.33±1.13	2.28±1.09	2.95±1.14	2.27±1.04	2.58±1.50	2.697	0.031*
Information quality	3.84±1.01	3.76±1.09	3.75±1.07	3.91±0.90	4.08±0.87	0.423	0.792
Functional utility	3.74±0.99	3.73±1.00	3.54±1.05	3.62±1.07	4.46±0.35	1.573	0.181
Community impact	3.60±1.08	3.61±1.18	3.60±1.10	3.61±1.08	3.75±1.34	0.038	0.997
Perceived usefulness	3.71±1.04	3.74±1.13	3.64±1.14	3.80±0.97	3.71±1.17	0.177	0.950
Perceived ease of use	3.60±1.13	3.77±1.01	3.38±1.23	3.51±1.18	4.17±0.59	1.523	0.195
User satisfaction	3.82±1.00	3.91±0.87	3.66±1.04	3.82±0.96	4.33±0.44	1.001	0.407

As shown in the table above, using analysis of variance to study the differences in 13 items—system quality, tool applicability, ethical compliance, resource fairness, user experience, user participation, perceived risk, information quality, functional utility, community influence, perceived usefulness, perceived ease of use, and user satisfaction—across disciplines, the table reveals that: Among the different disciplinary samples, only one item—perceived risk—showed significant differences ($p < 0.05$). This indicates that there are differences in perceived risk among samples from different disciplines. A detailed analysis reveals that discipline exhibits significant differences at the 0.05 level ($F=2.697$, $p=0.031$) for perceived risk. Specifically, the average score comparisons for groups with notable differences are as follows: C. Agriculture > A. Science and Engineering; C. Agriculture > B. Humanities and Social Sciences; C. Agriculture > D. Medicine. In summary, there is a significant difference in risk perception between different disciplinary samples for one item.

5.6 Structural Equation Model Analysis

The analysis results of the measurement model presented above indicate that the data used in this study exhibit good reliability and validity and do not suffer from severe common method bias, thereby meeting the prerequisites for conducting structural model analysis. The validation of the structural model in this section is primarily conducted from several aspects, including multicollinearity diagnosis, model explanatory power, predictive power, model fit, and path coefficients.

Multicollinearity diagnosis, abbreviated as collinearity diagnosis, refers to the situation where two or more variables in a model exhibit high correlation, which may lead to significant errors in the estimation of path coefficients. To assess the impact of multicollinearity on structural equation models, the variance inflation factor (VIF) is typically used to determine whether collinearity issues exist in the data. When VIF is less than 5, multicollinearity issues are absent. (Henseler J et al. 2009.) VIF values can be presented in the results of the PLS Algorithm program.

Table 18. Internal model VIF value

Path	VIF
Ethical Compliance → User Satisfaction	1.357
Information Quality → Perceived Usefulness	1.062
Information Quality → User Satisfaction	1.093
Functional Utility → User Satisfaction	1.315
Tool Adaptability → Perceived Ease of Use	1.038
Perceived Ease of Use → User Satisfaction	1.443
Perceived Usefulness → User Satisfaction	1.206
Perceived Risk → User Satisfaction	1.332
User Experience → User Satisfaction	1.423
User Involvement → Perceived Ease of Use	1.417
User Involvement → User Satisfaction	1.038
Community Influence → Perceived Usefulness	1.211
System Quality → Perceived Usefulness	1.221
Resource Fairness → User Satisfaction	1.253

Table 19. External model VIF values

Item	VIF	Item	VIF
Q14.1	1.549	Q20.3	1.866
Q14.2	1.822	Q21.1	1.832
Q14.3	1.717	Q21.2	1.897
Q15.1	1.95	Q21.3	1.717
Q15.2	2.013	Q22.1	1.543
Q15.3	2.015	Q22.2	1.607
Q16.1	1.607	Q22.3	1.635
Q16.2	1.755	Q23.1	1.865
Q16.3	1.675	Q23.2	1.75
Q17.1	1.863	Q23.3	1.795
Q17.2	1.837	Q24.1	1.747
Q17.3	1.95	Q24.2	1.879
Q18.1	1.712	Q24.3	1.666
Q18.2	1.756	Q25.1	1.899
Q18.3	1.698	Q25.2	1.805
Q191	1.681	Q25.3	1.932
Q192	1.623	Q26.1	1.499
Q193	1.743	Q26.2	1.671
Q20.1	1.82	Q26.3	1.766
Q20.2	1.762		

The above two tables show the VIF values for the internal and external models in this study. As can be seen from the tables, the VIF values for the internal model range from 1 to 2, while those for the

external model range from 1 to 3, all of which are less than 5. This indicates that there is no multicollinearity issue in the structural model of this study.

5.6.1 Model Fit Assessment

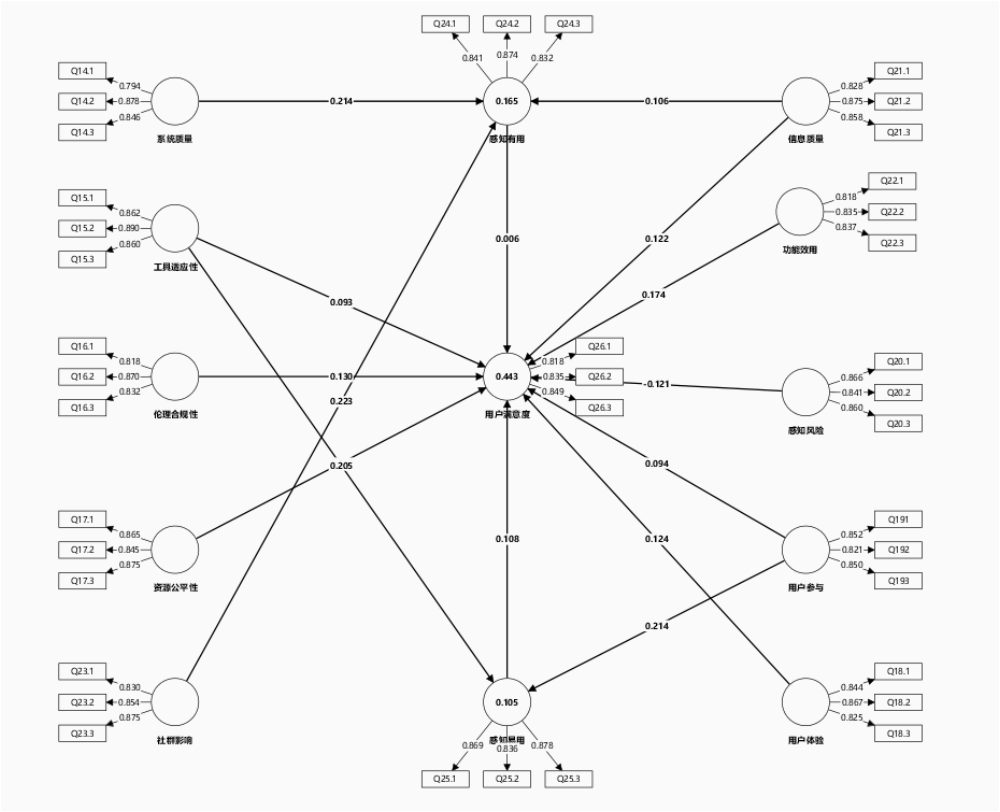

Figure2 Structural equation model diagram

(1) Model's explanatory power (R^2)

In PLS-SEM, the explanatory power of the structural model's endogenous latent variables is calculated using the PLS-SEM algorithm. The measure for explanatory power is the coefficient of determination (R^2), which ranges from 0 to 1. The closer R^2 is to 1, the better the model's explanatory power. This study used SmartPLS software to perform the PLS calculations, with results as shown in the table:

Table 20. Explanatory power of the model R-squared

	R^2	Adjusted R
Perceived ease of use	0.105	0.1
Perceived usefulness	0.165	0.159
User satisfaction	0.443	0.429

The R^2 value for Perceived Ease of Use is 0.105, with an adjusted R^2 of 0.1, indicating that the

model explains about 10% of the variance in the dependent variable. The R^2 value for Perceived Usefulness is 0.165, with an adjusted R^2 of 0.159, explaining approximately 15.9% of the variance. The R^2 value for User Satisfaction is the largest, at 0.443, with an adjusted R^2 of 0.429, meaning the model explains about 42.9% of the variance. This suggests that among these three variables, the model's explanatory power for User Satisfaction is the strongest.

(2) Model's predictive power (Q^2)

The model's predictive power is typically evaluated using predictive relevance (Q^2), which measures the predictive relevance of exogenous latent variables on endogenous latent variables. In a PLS-SEM model, the Q^2 value is computed using the Blindfolding procedure. In SmartPLS 4.0, the Q^2 values for this study's model were calculated using Blindfolding, with a distance setting of 7. The distance value typically ranges from 5 to 10, and the total sample size must not be divisible by the distance value. As the total sample size in this study was 471, which is not divisible by 7, the distance value of 7 was chosen for the Q^2 test. The higher the Q^2 value, the stronger the predictive relevance. The criterion for judging the predictive relevance of a specific endogenous latent variable is that if its Q^2 value is greater than 0, it indicates predictive relevance for that latent variable.

Table 21. Model prediction correlation Q-square

	SSO	SSE	Q^2(=1-SSE/SSO)
Ethical Compliance	1224	1224	0
Information Quality	1224	1224	0
Functional Utility	1224	1224	0
Tool Adaptability	1224	1224	0
Perceived Ease of Use	1224	1132.78	0.075
Perceived Usefulness	1224	1085.373	0.113
Perceived Risk	1224	1224	0
User Experience	1224	1224	0
User Involvement	1224	1224	0
User Satisfaction	1224	873.879	0.286
Community Influence	1224	1224	0
System Quality	1224	1224	0
Resource Fairness	1224	1224	0

(3) Model's effect size (F^2)

In SmartPLS (Partial Least Squares Structural Equation Modeling software), F^2 is used to assess

the effect size of exogenous latent variables (independent variables) on endogenous latent variables (dependent variables). The calculation of F^2 reflects the change in the R^2 (coefficient of determination, which measures the degree to which the model explains variance in the dependent variable) of the endogenous latent variables after the exogenous latent variables are included in the model. Through F^2, researchers can assess the relative importance of each exogenous latent variable on the endogenous latent variables, determining which independent variables contribute more to explaining and predicting the dependent variables. This helps researchers better understand the strength of relationships between variables and the model structure.

Table 22. F-square of the model

	Perceived Ease of Use	Perceived Usefulness	User Satisfaction
Ethical Compliance			0.022
Information Quality		0.013	0.025
Functional Utility			0.041
Tool Adaptability	0.045		0.011
Perceived Ease of Use			0.017
Perceived Usefulness			0
Perceived Risk			0.018
User Experience			0.019
User Involvement	0.049		0.013
User Satisfaction			
Community Influence		0.049	
System Quality		0.044	
Resource Fairness			0.03

In SmartPLS, F^2 is used to assess the effect size of exogenous latent variables on endogenous latent variables to determine variable importance and model structure. The data shows that the F^2 values for the exogenous latent variables on Perceived Ease of Use, Perceived Usefulness, and User Satisfaction are mostly below 0.05, indicating a small effect size. Although the effect sizes are generally small, all are positive, suggesting that the inclusion of exogenous latent variables has led to some improvement in the R^2 values of the endogenous latent variables. The data is within an interpretable range, indicating that the model can explain the relationships between variables to some extent and is thus usable.

(4) Model Fit

To assess the goodness of fit of the model, two indicators, the Goodness of Fit (GoF) and the Standard Root Mean-square Residual (SRMR), are used. The GoF value typically ranges from 0 to 1, and the higher the value, the better the model fit. The GoF value represents the overall fit of the model, and its calculation formula is as follows, $\text{Gof} = \sqrt{\overline{\text{AVE}} \times \overline{\text{R}^2}}$. However, although the GoF indicator is recognized by some scholars, it has also been criticized. Henseler and Sarstedt (2013) argue that GoF cannot be used as a standard for testing the goodness of fit of PLS models. This is because GoF does not distinguish between valid and invalid models and cannot address the issue of over-parameterization. Therefore, they strongly recommend that researchers abandon the use of this indicator. Henseler et al. (2013) introduced the well-known SRMR from CB-SEM for evaluating PLS-SEM model fit. SRMR is defined as the root mean square difference between the observed correlations and the model-implied correlations. SRMR is an absolute fit index, with 0 indicating perfect fit, below 0.08 being ideal, and below 0.11 being acceptable. According to the PLS calculation program model fit results, the SRMR for this study's model is 0.062, which is less than 0.08, further indicating that the model fit is good.

Table 23. Model Fit

	Saturated Model	Estimation Model
SRMR	0.044	0.062
d_ULS	1.512	3.018
d_G	0.716	0.76
heteroscedasticity	1808.078	1870.487
NFI	0.752	0.743

5.6.2 Path Analysis and Hypothesis Testing

In SmartPLS 4.0, the PLS algorithm is first used to obtain the path coefficients for each path, and then the significance of the path coefficients is tested using the Bootstrapping method, setting the subsample size to 5000. The significance of the path coefficients is determined using the t-statistic and p-value. If the absolute value of the t-statistic is greater than 1.96 and the p-value is less than 0.05, the path coefficient is significant, and the hypothesis is supported. The test results are shown in the table. As shown in the table:

Table 24. Direct Impact Path Analysis

Path	Path Coefficient	T-Value	P-Value	Test Result
System Quality → Perceived Usefulness	0.214	3.903	0.000	Significant
Ethical Compliance → User Satisfaction	0.13	2.55	0.011	Significant
Resource Fairness → User Satisfaction	0.156	2.84	0.005	Significant
Information Quality → User Satisfaction	0.122	2.427	0.015	Significant
Functional Utility → User Satisfaction	0.174	3.6	0.000	Significant
Perceived Risk → User Satisfaction	-0.124	2.598	0.009	Significant
User Experience → User Satisfaction	0.124	2.53	0.011	Significant
Tool Adaptability → Perceived Ease of Use	0.205	4.255	0.000	Significant
Community Influence → Perceived Usefulness	0.223	4.367	0.000	Significant
User Involvement → User Satisfaction	0.094	2.165	0.030	Significant
Perceived Usefulness → User Satisfaction	0.006	0.301	0.763	Not Significant
Perceived Ease of Use → User Satisfaction	0.108	2.308	0.021	Significant
User Involvement → Perceived Ease of Use	0.214	4.481	0.000	Significant
Information Quality → Perceived Usefulness	0.106	1.992	0.046	Significant

To test the mediation effect in the model, similarly, this study used the Bootstrapping method (5000 sample size, 95% confidence interval) in SmartPLS 4.0 to test the relevant hypotheses. The test results are shown in the table, as indicated in the table:

Table 25. Mediation Effect Path Analysis

	Path Coefficient	T-value	P-value	Test Result
Information Quality→ Perceived Usefulness → User Satisfaction	0.002	0.116	0.908	Not Significant
User Involvement → Perceived Ease of Use→ User Satisfaction	0.023	1.975	0.048	Significant

5.7 Results Discussion

Most of the hypotheses in this study were supported by the data, reflecting the multidimensional factors influencing user satisfaction with AI-assisted academic writing tools. Among these, factors such as system quality, functional utility, ethical compliance, resource fairness, information quality, user experience, user involvement, perceived ease of use, and community influence all significantly and positively influence user satisfaction. This aligns with the Information Systems Success Model (DeLone, W. H., & McLean, E. R. 1992.) and the Technology Acceptance Model (Davis, F. D, 1989.) For example, tool adaptability significantly enhances perceived ease of use, further improving user satisfaction, which aligns with the findings of Venkatesh & Davis (2000) and other scholars; ethical compliance and resource fairness significantly enhance satisfaction, possibly by reducing users' concerns about risks associated with tool use, which aligns with the research conclusions of Shin & Park (2019).

However, two pathways in this study were not supported by the data: perceived usefulness → user satisfaction, and the mediating effect of information quality → perceived usefulness → user satisfaction. This contrasts with findings from previous studies emphasising the importance of information quality and perceived usefulness for satisfaction. (Bhattacherjee, 2001; DeLone & McLean, 1992)

The reason why perceived usefulness does not significantly and directly influence user satisfaction may be related to the user's usage context. Traditional TAM models typically find that perceived usefulness directly enhances user satisfaction (Bhattacherjee, 2001; Davis, 1989), but this study does not support this conclusion. This may be because users of AI-assisted academic writing tools are more concerned with the tool's convenience and security rather than its actual effectiveness, and may even worry that over-reliance on the tool could lead to academic ethics issues. This contextual specificity has also been observed in previous studies, such as Featherman & Pavlou (2003) noted that in scenarios with higher perceived risk, users are more concerned with risk control than the utility of the tool itself, which may weaken the effectiveness of the tool.

The mediating path through which information quality indirectly influences user satisfaction via perceived usefulness also does not hold, possibly because academic users are more concerned with the practicality of AI-assisted academic writing tools and their ability to enhance writing efficiency and expand thinking, rather than the depth of AI-generated content, causing the chain of

information quality → perceived usefulness → satisfaction to break. This non-significant mediating path was also observed in Wixom & Todd (2005), who suggested that other more direct or influential variables may have weakened the effect of this path, such as perceived ease of use, risk, or ethical factors, which is similar to the actual situation in this study.

Differential analysis the results showed that there were no significant differences between different educational groups in most variables, except for perceived usefulness ($F=4.230$, $p=0.015$), where the 'bachelor's degree' group exhibited significantly higher perceived usefulness of AI writing tools than the 'associate degree or below' group. This phenomenon has been observed by previous scholars. Almaraz-López et al. (2023) noted that users with stronger professional backgrounds and writing task experience, typically associated with higher educational attainment, tend to understand AI tools' support for academic tasks from a functional perspective, thereby enhancing their subjective perception of the tool's value.

Additionally, users from different disciplinary backgrounds exhibit significant differences in their perception of risk ($F=2.697$, $p=0.031$), with agricultural science students perceiving higher risks associated with AI writing tools compared to students from science and engineering, humanities and social sciences, and medical disciplines. This finding can be explained by differences in professional culture and task characteristics. Agricultural disciplines emphasis empirical evidence and the rigorous use of professional terminology. If AI writing tools cannot accurately process professional terminology or avoid semantic errors, they may lead to issues such as inaccurate content and unclear logic, thereby increasing 'users sensitivity to 'usage risks' . Yan et al. (2023) also noted that in educational settings, the perception of risks associated with AI tool usage is linked to the structure of disciplinary tasks. The more complex and the more densely packed with professional terminology, the higher the requirements for controllability and transparency of AI-generated content, thereby influencing users' risk assessments. Additionally, Crompton (2023) emphasises that in high-risk perception contexts, users in certain disciplines are more concerned about whether AI systems possess sufficient explainability, transparency, and academic compliance. These user groups tend to adopt a more conservative attitude toward AI-generated content.

In summary, the findings of this study generally support the applicability of the Information Systems Success Model and the Technology Acceptance Model in AI-assisted academic writing contexts, but they exhibit differences from traditional research in terms of information quality and perceived usefulness. These differences may stem from academic users' special expectations

regarding content quality, their cautious attitude toward the efficacy of tools, and the unique disruptive effects of risk and ethical factors on the satisfaction formation process. This finding suggests that future research should consider the special nature of AI tool application contexts and further explore the mechanisms and boundary conditions of information quality and usefulness factors.

6 Strategies and Recommendations for Enhancing User Satisfaction

6.1 Optimizing Tool Functionality

This study found that functional utility and tool adaptability have a significant positive impact on user satisfaction. Therefore, improving the functionality of AI-assisted academic writing tools should be optimised in the following areas: first, optimising the response speed and accuracy of core functions. Research users have high demands for the core functions of the tool (such as literature retrieval, grammar checking, text generation, etc.). As shown in the Table 26, the coefficient of functional utility's impact on user satisfaction is 0.174, with a P-value < 0.05, indicating that functional utility directly influences user satisfaction. Therefore, it is essential to prioritise improving the tool's efficiency and accuracy. For example, in the literature search function, intelligent algorithms can be introduced to support cross-database rapid search and generate literature review frameworks; in grammar checking, subject-specific terminology databases can be integrated to reduce logical and wording errors in academic writing. By optimising system architecture and computational resource allocation, user waiting times can be reduced, ensuring efficient response to complex tasks and thereby enhancing the tool's practicality. Second, developing personalised functional modules is also crucial. The coefficient of influence of user engagement on user satisfaction is 0.094, and the P-value is <0.05. The significant influence of user engagement on user satisfaction indicates that personalised design can effectively enhance user satisfaction. The tool should customise functions based on user identity and research field. For example, provide clinical trial data analysis templates for medical researchers and add theoretical framework generation modules for humanities and social sciences users. Additionally, supporting user-defined functional combinations, allowing users to enable or disable specific modules based on their needs, enhances the tool's flexibility and adaptability. Finally, establishing a dynamic feedback and iteration mechanism is crucial. The positive impact of user experience on satisfaction indicates that promptly collecting and responding to user feedback is an effective way to optimise functionality. It is recommended to set up feedback channels within the tool, regularly collect user evaluations of functional usage, and optimise designs based on data. For frequently occurring user feedback issues, such as 'insufficient academic rigor in text generation,' optimisation can be achieved by incorporating domain-specific knowledge graphs. A dedicated technical support team should be established to swiftly address technical obstacles, regularly update features, and transparently communicate improvement progress to enhance user trust. In summary, the functional optimisation of AI-assisted tools should prioritise user needs while balancing efficiency,

personalisation, and continuous improvement, ultimately enhancing user satisfaction in academic writing scenarios.

6.2 Enhancing User Experience

6.2.1 Simplifying Operational Processes and Strengthening Interactive Design

Based on previous research, the coefficient of influence of perceived usability on user satisfaction is 0.108, with a P-value < 0.05. Given the significant impact of perceived usability on satisfaction, it is necessary to redesign the core operational pathways of the tool: integrate high-frequency functions such as literature search, text generation, and grammar correction into a unified control panel, providing one-click quick access; interface design should align with academic users' visual habits, using a clean colour scheme and clear icons, to avoid information overload, and a dynamic new user guidance module to lower the learning curve. Additionally, interactivity should be enhanced, such as embedding real-time collaboration features to support multi-user online annotation and document sharing, meeting the collaborative needs of research teams; emotional design should be employed to increase user retention, such as triggering positive feedback prompts upon completing writing tasks or inserting encouraging messages during text generation to alleviate academic stress and enhance emotional connection.

6.2.2 Establishing a Data Security Protection System and Transparency Mechanism

The coefficient of the impact of perceived risk on user satisfaction is -0.124. Given the significant negative impact of perceived risk on satisfaction, it is necessary to use end-to-end encryption technology to store user data, allow users to independently set the scope of data sharing, and strengthen account security through hierarchical permission management and biometric technology. Differential privacy technology should be introduced simultaneously, using data anonymisation for algorithm optimisation to balance privacy protection and tool performance. A privacy policy summary should be provided in a prominent location on the interface, with visual charts showing data flow, and a 'one-click clear history' function to support local and cloud-based record deletion. For high-risk operations, a secondary confirmation pop-up and 'do not share' option should be added to avoid anxiety caused by forced authorisation. Additionally, ethical compliance certification should be promoted, with regular transparency reports disclosing the scope of data usage and outcomes of security incident handling. Annual audits by third-party institutions should be introduced to enhance credibility. Considering the unique nature of academic scenarios, an

'academic confidentiality mode' could be developed to default to disabling data collection functionality, thereby reducing ethical risks from the source.

6.2.3 Developing a Dynamic Mechanism for Cultivating User Trust

The coefficient of influence of tool adaptability on perceived usability is 0.205, and the P-value is <0.05. Therefore, based on the positive effect of tool adaptability, it is necessary to flexibly design functional adaptations to meet diverse needs: provide a 'minimalist mode' for privacy-sensitive users, and customise a 'collaboration security protocol' for team users to clarify member data permissions; establish trust metrics through regular privacy satisfaction surveys, and feed the results back into product iterations. Additionally, ethical standards must be deeply embedded into the design process, such as implementing explicit consent rules during data collection and excluding copyright-disputed content during algorithm training. Through a three-dimensional closed-loop system combining technical safeguards, institutional protections, and user empowerment, perceived risks can be systematically reduced, ultimately achieving synergistic optimisation of operational efficiency, emotional resonance, and security control.

6.2.4 Addressing Heterogeneous Demands of Different User Groups

According to the results of the analysis of variance conducted on educational attainment and subject variables, users of AI-assisted writing tools exhibit certain heterogeneous needs in terms of their background characteristics. Specifically, significant differences were observed only in the 'perceived usefulness' dimension (F=4.230, P=0.015), with university undergraduate users reporting significantly higher perceived usefulness than those with associate degrees or lower. This suggests that users with higher educational attainment are more likely to recognise the practical benefits of AI-assisted tools in enhancing writing efficiency and quality, potentially due to their more frequent engagement in research writing activities and familiarity with academic writing conventions. Therefore, it is recommended that tool developers provide more functional guidance and usage demonstrations for users with lower educational attainment during product promotion and user training, offering specific application examples rather than abstract descriptions. In page design, avoid excessive technical terminology, highlight key functional buttons, and provide usage prompts or a help assistant to assist users in quickly familiarising themselves with the tool and getting started, thereby enhancing their recognition of the tool's value and its practical application effectiveness.

Additionally, users from different disciplinary backgrounds exhibit significant differences in the 'perceived risk' dimension ($F=2.697$, $p=0.031$), with agricultural science users perceiving significantly higher risks than users from science and engineering, humanities and social sciences, and medical fields. This difference may stem from the agricultural science field's heightened sensitivity to potential issues such as the misuse of professional terminology, content accuracy, and ethical compliance in AI text generation. Based on this, it is recommended that AI writing tools increase investment in supporting discipline-specific customisation, such as providing agricultural science users with more extensive terminology databases, professional writing templates, and content review functions to reduce their perceived risk and enhance trust. Additionally, developers can collaborate with universities or research institutions to build specialised AI training databases tailored to the unique terminology and knowledge systems of agricultural science, and have these databases manually reviewed by subject matter experts to ensure the accuracy of professional expressions in generated text and reduce the risk of content errors. Finally, introducing a content traceability feature for AI-generated content allows users to trace the origin and generation process of each AI-assisted text, thereby enhancing user trust in the tool's generated content and reducing their perception of potential risks.

In summary, educational background and disciplinary expertise significantly influence user perception, indicating that the design and service of AI-assisted writing tools should place greater emphasis on the differentiated characteristics of user groups, achieving precise alignment of functionalities and support strategies to enhance overall user satisfaction and usage effectiveness.

6.3 Enhancing Social and Academic Recognition

6.3.1 Strengthening Academic Recognition of the Tools

Enhancing the social impact and academic recognition of AI-assisted academic writing tools is one of the key factors in further improving user satisfaction. With the rapid development of AI technology, the academic community's acceptance and recognition of these tools is gradually increasing, but there is still a need to continuously promote their widespread application and recognition within the academic community.

6.3.2 Focusing on Academic Ethics and Fairness

AI-assisted writing tools should prioritize academic ethics and regulatory compliance, ensuring that the content they provide aligns with scholarly standards and helps prevent plagiarism and academic misconduct.

At the institutional level, it is necessary to establish an academic ethics assurance system by integrating anti-plagiarism databases and academic guideline frameworks. Functions such as format verification and duplication rate alerts should be embedded into the pre-submission review processes of core academic journals to ensure that the content generated by these tools adheres to academic integrity standards.

At the technical level, invisible identifiers should be embedded in AI-generated content, and users should be required to disclose the AI model version used, the input prompts, and the proportion of the AI's contribution.

At the user education level, individuals must pass scenario-based assessments before using the tool, demonstrating that they understand the compliant use of AI-generated content.

Furthermore, to ensure equitable access to AI writing tools, it is essential to address resource barriers through three strategies: technological inclusion, capacity building, and collaborative governance.

For technological inclusion, a tiered service model should be established: a free basic version offering core features, a public academic version providing compute subsidies to low-income regions, and an enterprise-customized version whose commercial revenues support public interest initiatives.

In terms of capacity building, localized interfaces for minority languages and context-specific prompt libraries should be developed, while accessibility features should be optimized in accordance with established standards.

From a governance perspective, it is recommended to establish a multi-stakeholder fairness audit committee to periodically release transparency reports, ensuring accountability and equitable development.

6.3.3 Establishing User Communities and Interactive Platforms

Establishing user-involved communities and interactive platforms is also an effective strategy for enhancing the social impact of AI-assisted writing tools. By creating an open academic community that allows users to share their experiences, feedback, and suggestions, a mechanism for co-creating user value can be developed through academic interaction platforms. These platforms can host prompt engineering workshops led by domain experts, transform high-quality user-contributed prompts into discipline-specific writing templates, and integrate influence-tracking systems to evaluate improvements in knowledge dissemination efficiency. This not only aids tool developers in continuously refining their products but also strengthens users' sense of identification and loyalty toward the tool.

Active user participation and word-of-mouth promotion will significantly enhance the tool's recognition within the academic community and its broader societal influence. In conclusion, improving the social impact and academic credibility of AI-assisted academic writing tools—through close collaboration with the academic community, enhancing academic rigor, establishing robust ethical standards, and expanding user communities—will help build user trust and satisfaction, promoting the widespread adoption and long-term development of such tools in scholarly research.

7 Conclusions and Prospects

7.1 Research Conclusions

This study focuses on the practical application of AI-assisted academic writing tools and integrates the Technology Acceptance Model with the Information Systems Success Theory to construct a theoretical framework for user satisfaction. A total of 14 research hypotheses were proposed and empirically tested. Based on structural equation modeling analysis of 408 valid questionnaire responses, the study yields three key conclusions:

First, functional utility, tool adaptability, user experience, resource fairness, and information quality exert significant positive effects on user satisfaction, while perceived risk shows a significant negative effect. The study also reveals two indirect effect pathways: tool adaptability influences satisfaction through perceived ease of use, and user involvement affects satisfaction via perceived ease of use. However, the mediating role of perceived usefulness in the relationship between information quality and satisfaction was not empirically supported.

Second, the integrated model demonstrates strong explanatory power, confirming the synergistic value of tool performance optimization and user experience design. The model's fit indices provide a theoretical reference for the development of AI tools in academic contexts.

Third, based on the empirical findings, management strategies are proposed across three dimensions: functional iteration, user experience enhancement, and trust building. Specifically, it is recommended to improve the precision of literature retrieval and text generation to enhance functional utility; reduce perceived risk through end-to-end encryption technologies and transparency reports; and optimize operational workflows and interface design to elevate user experience.

This study not only extends the application of Technology Acceptance Theory within the domain of intelligent academic tools but also provides empirical evidence to support product optimization. Future research could explore the heterogeneity of user needs in cross-cultural contexts or adopt longitudinal approaches to investigate the dynamic evolution of user satisfaction.

7.2 Research Limitations and Future Prospects

This study, based on the Technology Acceptance Model and the Information Systems Success Theory, systematically investigates the influencing factors of user satisfaction with AI-assisted academic writing tools and completes theoretical validation. Due to limitations in research conditions and academic scope, the current study has room for improvement in the following aspects: First, the sample structure presents distinct group characteristics, as data collection mainly relied on online channels, resulting in a sample concentrated among university faculty, students, and research institution personnel aged 20–35. Although this group constitutes the core user base of current AI-assisted academic writing tools, it does not include senior scholars or corporate researchers, which may affect the general applicability of the research findings.

Second, the construction of the theoretical framework places more emphasis on technical functional attributes and individual perception dimensions, without fully integrating social contextual factors such as academic community norms and disciplinary cultural differences. This limits the model’s explanatory power in complex usage scenarios. In addition, the real-time Q&A mechanism set during the research process may have led to systematic bias in the measurement data due to users' differing understandings of abstract concepts such as ethical compliance and resource fairness.

To address these limitations, future exploration can be deepened along four dimensions: In terms of sample design, it is recommended to adopt stratified sampling methods to cover a more diverse user group, focusing on the moderating effects of regional cultural characteristics on the formation mechanism of satisfaction. In terms of theoretical construction, it is necessary to integrate theories of social support and organizational innovation adoption to systematically analyze the interaction mechanisms between institutional factors such as team collaboration models and research ethics policies and individual behaviors. In terms of dynamic tracking, a longitudinal research paradigm can be applied to reveal the co-evolution patterns of perceived ease of use and user satisfaction during tool iteration, particularly the long-term impact of ethical controversy events on user trust. In terms of methodological innovation, it is urgent to introduce cognitive neuroscience experiments and human-computer interaction evaluation techniques to capture implicit cognitive load and emotional responses during user interactions through multimodal data.

Although this study has preliminarily constructed an analytical framework for user satisfaction with AI-assisted academic tools, the expansion of its academic value and application boundaries still relies on continued deepening through interdisciplinary research.

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Appendices

Appendix 1 Questionnaire

Introduction

Dear Participant,

Thank you for participating in this survey. This study aims to explore the key factors affecting users' satisfaction with AI - assisted academic writing tools, providing a scientific basis for optimizing tool design and enhancing user experience. The survey is anonymous, and all data will be strictly confidential and used solely for academic research. Please answer based on your actual usage experience. It will take about 10 - 15 minutes. Your response is crucial to this study. Thank you for your support!

Part 1: Basic Information

(Select according to your actual situation)

1. What's your gender? [Single - choice question] *

○A. Male

○B. Female

2. What's your age? [Single - choice question] *

○A. 18 - 25

○B. 26 - 35

○C. 36 - 45

○D. 46 or above

3. What's your educational level? [Single - choice question] *

○A. Master's degree or above

○B. Bachelor's degree

○C. Associate degree or below

4. What's your workplace? [Single - choice question] *

○A. Research institute

○B. University

○C. Enterprise

○D. Other (please specify:) _____*

5. What's your specific occupation? [Single - choice question] *

○A. Graduate student

○B. University teacher

○C. Research institute researcher

○D. Other (please specify:) _____*

6. What's your academic discipline? [Single - choice question] *

○A. Science and engineering

○B. Humanities and social science

○C. Agriculture

○D. Medicine

○E. Other (please specify:) _____*

7. What's your current academic paper publication status? [Single - choice question] *

○A. Both Chinese and English

○B. Only Chinese

○C. Only English

○D. Never published

8. How long have you been engaged in research work? [Single - choice question] *

○A. Within one year

○B. One to five years

○C. Over five years

9. How often do you use AI - assisted academic writing tools? [Single - choice question] *

○A. Daily

○B. Weekly

○C. Occasionally

○D. Never (if selected, the survey ends)

Part 2: Current Use and Understanding of Tools

10. How familiar are you with AI - assisted academic writing tools? [Single - choice question] *

○A. Very familiar

○B. Generally familiar

○C. Familiar

○D. Somewhat familiar

○E. Not familiar at all

11. Which AI - assisted writing tools do you currently use? [Multiple - choice question] *

☐A. ChatGPT

☐B. Erni Bot

☐C. DeepSeek

☐D. Qwen

☐E. Moonshot AI

☐F. Doubao

☐G. CNKI AI

☐H. Grammarly

☐I. Zhipu Qingyan

☐J. Other (please specify:) _____*

12. What do you think are the main uses of AI - assisted writing tools in academic scenarios? [Multiple - choice question] *

☐A. Intelligent topic selection and research suggestions

☐B. Literature retrieval and organization

☐C. Initial draft generation of papers

☐D. Language polishing and grammar correction

☐E. Data analysis and visualization

☐F. Reference management and format generation

☐G. Academic translation and cross - language writing

☐H. Other (please specify:) _____*

13. What risks or problems do you think AI - assisted writing tools may cause? [Multiple - choice question] *

☐A. Data privacy leakage

☐B. Academic misconduct

☐C. Inaccurate generated content

☐D. Over - reliance on tools

☐E. High tool usage threshold

☐F. Other (please specify:) _____*

Part 3: Evaluation of Influencing Factors

Based on your usage experience, select the most appropriate option (1 = Strongly disagree, 5 = Strongly agree):

14. System Quality

The tool's operation process is smooth without obvious lag or delay. [Single - choice question] *

○1 ○2 ○3 ○4 ○5

The tool is available on multiple platforms with consistent experience. [Single - choice question] *

○1 ○2 ○3 ○4 ○5

The tool demonstrates efficient computing during data processing and generation. [Single - choice question] *

○1 ○2 ○3 ○4 ○5

15. Tool Adaptability

The tool can meet my different subject - specific needs. [Single - choice question] *

○1 ○2 ○3 ○4 ○5

The tool's functions align with my writing habits. [Single - choice question] *

○1 ○2 ○3 ○4 ○5

The tool can adapt to various academic scenarios. [Single - choice question] *

○1 ○2 ○3 ○4 ○5

16. Ethical Compliance

The tool's generated content follows academic standards. [Single - choice question] *

○1 ○2 ○3 ○4 ○5

The tool specifies the source and copyright information of generated content. [Single - choice question] *

○1 ○2 ○3 ○4 ○5

The tool promises data privacy protection. [Single - choice question] *

○1 ○2 ○3 ○4 ○5

17. Resource Equity

The tool's pricing model is reasonable and within my economic capacity. [Single - choice question] *

○1 ○2 ○3 ○4 ○5

I have equal opportunities to access and use various tools as others. [Single - choice question] *

○1 ○2 ○3 ○4 ○5

The tool's resource allocation is fair without high usage barriers. [Single - choice question] *

○1 ○2 ○3 ○4 ○5

18. User Experience

The tool offers clear guides or tutorials for quick mastery. [Single - choice question] *

○1 ○2 ○3 ○4 ○5

The tool's error prompts and help information are clear for quick problem - solving. [Single - choice question] *

○1 ○2 ○3 ○4 ○5

Using the tool is efficient and pleasurable. [Single - choice question] *

○1 ○2 ○3 ○4 ○5

19. User Involvement

I often participate in the tool's testing and feedback. [Single - choice question] *

○1 ○2 ○3 ○4 ○5

I think the tool developer takes my improvement suggestions seriously. [Single - choice question] *

○1 ○2 ○3 ○4 ○5

I'm willing to provide usage feedback to the developer. [Single - choice question] *

○1 ○2 ○3 ○4 ○5

20. Perceived Risk

I'm worried about data privacy leakage when using the tool. [Single - choice question] *

○1 ○2 ○3 ○4 ○5

The tool's generated content may pose academic misconduct risks. [Single - choice question] *

○1 ○2 ○3 ○4 ○5

I'm concerned that over - reliance on the tool may weaken my writing ability. [Single - choice question] *

○1 ○2 ○3 ○4 ○5

21. Information Quality

The tool's generated content is true and reliable. [Single - choice question] *

○1 ○2 ○3 ○4 ○5

The tool's information is substantially helpful to my research. [Single - choice question] *

○1 ○2 ○3 ○4 ○5

The tool's generated content is logically clear and requires little modification. [Single - choice question] *

○1 ○2 ○3 ○4 ○5

22. Functional Utility

The tool has diverse functions to meet various academic writing needs. [Single - choice question] *

○1 ○2 ○3 ○4 ○5

The tool's functions are innovative, addressing traditional writing pain points. [Single - choice question] *

○1 ○2 ○3 ○4 ○5

The tool's functions help me better handle complex research data and information. [Single - choice question] *

○1 ○2 ○3 ○4 ○5

23. Social Influence

Friends' recommendations are important for my tool usage. [Single - choice question] *

○1 ○2 ○3 ○4 ○5

Social media reviews affect my tool choice. [Single - choice question] *

○1 ○2 ○3 ○4 ○5

My academic circle generally recognizes the tool's value. [Single - choice question] *

○1 ○2 ○3 ○4 ○5

24. Perceived Usefulness

The tool helps me complete academic writing tasks more efficiently. [Single - choice question] *

○1 ○2 ○3 ○4 ○5

The tool improves the quality of my academic writing tasks. [Single - choice question] *

○1 ○2 ○3 ○4 ○5

The tool reduces repetitive writing labor. [Single - choice question] *

○1 ○2 ○3 ○4 ○5

25. Perceived Ease of Use

The tool's operation process is well - designed and intuitive. [Single - choice question] *

○1 ○2 ○3 ○4 ○5

The tool's functions are well - laid - out for quick access. [Single - choice question] *

○1 ○2 ○3 ○4 ○5

I can master the tool without extra training. [Single - choice question] *

○1 ○2 ○3 ○4 ○5

26. User Satisfaction

Overall, I'm satisfied with the tool's usage experience. [Single - choice question] *

○1 ○2 ○3 ○4 ○5

I would recommend the tool to other academic researchers. [Single - choice question] *

○1 ○2 ○3 ○4 ○5

I plan to continue using the tool in the future. [Single - choice question] *

○1 ○2 ○3 ○4 ○5

Part 4: Open - ended Questions (Optional)

24. What suggestions do you have for improving AI - assisted academic writing tools? [Fill - in - the - blank question]

Appendix 2 Conceptual coding example

Initialisation concepts	Examples of primitive statements
a1 Non-compliance with academic standards	When citing historical sources and literature, it is essential to strictly adhere to specific academic citation formats and accurately indicate the source and other detailed information. However, tools often generate citation content in a simple listing format, lacking the required precision and standardization. (P2)
a2 Insufficient personalization	If the tool could learn these personal preferences, it would generate content more tailored to my habits, functioning as a customized writing assistant. (P15)
a3 Understanding unfamiliar fields	When exploring an unfamiliar field, tools can quickly provide summaries of knowledge, saving a lot of time in acquiring basic information. (P6)
a4 Reducing workload	The tool helps me quickly generate preliminary content, alleviating my writing burden and allowing me more time to focus on core research questions and in-depth data analysis. (P11)
a5 Lack of coherence	When I ask multiple questions on the same topic, the tool may generate responses in different conversations that lack logical consistency, which reduces my trust in its answers. (P4)
a6 Removal of query limitations	I hope the usage limitations for paid services, such as the limited number of queries for GPT-4 within a certain time frame, can be removed. (P6)
a7 Integration with other services	I would like it to integrate with other mainstream academic tools, such as literature management software, data analysis tools, and programming platforms. (P3)
a8 Addition of user feedback mechanisms	I strongly hope that the development team can provide more user feedback mechanisms, such as regular surveys or inviting users to test new features. (P8)
a9 Academic misconduct	Improper use of the tool may lead to academic misconduct, such as over-reliance on tool-generated content without deep thinking and analysis or directly plagiarizing the tool's output as one's own research findings. (P7)
a10 Unequal distribution of academic resources	There is an unequal distribution of tools, with some researchers having access to more advanced and powerful tools, while others may not, which could lead to imbalanced academic resource allocation and affect academic fairness. (P3)
a11 Content differences due to market disparities	The paper repository is primarily based on foreign academic websites. There are significant differences in language habits between English and Chinese writing, which may cause content discrepancies. (P6)
a12 Delay in addressing technical issues	I ask some continuous questions, but if the tool crashes, the previous data may be lost and cannot be recovered, which wastes time. (P19)
a13 Expanding writing ideas	I use the tool to help expand article topics; it quickly provides several article themes, specific writing directions, arguments, and detailed points for further discussion. (P4)

Initialisation concepts	Examples of primitive statements
a14 Querying skills	A significant barrier is the lack of understanding of how to properly use the tool's query function and how to accurately input requirements to obtain ideal results. (P10)
a15 Varying querying proficiency	The quality of individual research writing is influenced by each user's proficiency in using AI tools. (P11)
a16 Improving efficiency	AI tools help me quickly generate frameworks for experimental design and initial data analysis ideas, greatly improving my work efficiency. (P12)
a17 Improving non-native writing quality	When preparing English manuscripts, I rely more on such tools to ensure correct grammar and native-like expression, making the language more fluent. (P17)
a18 Ease of operation	The operation is straightforward, similar to a search engine, where inputting keywords results in output without requiring extensive time for learning. (P11)
a19 Data privacy concerns	I am concerned that the tool records my academic achievements in historical data. If others inquire about related topics, it might leak my work to them, affecting the originality of my research. (P20)
a20 Strong literature review capability	I ask the tool to analyze the limitations of a particular literature and suggest future research directions. The answers provided are often quite surprising and insightful. (P18)
a21 Higher level of specialized support	Regarding content expertise, I hope the tool can incorporate more authoritative and specialized knowledge bases, such as explanations of specialized terminology and classic theoretical models from different disciplines. (P7)
a22 Recommendation from friends	I first learned about the tool through recommendations from lab colleagues, who mentioned that ChatGPT is very practical for optimizing English expressions and generating structural frameworks. (P13)
a23 Format diversity	Initially, I only used the AI for text editing and idea generation, but later I also used it for tasks like image recognition and file summarization. (P21)
a24 Format adjustments	Some features seem powerful, such as generating versions in multiple languages or handling complex layout designs, but I rarely use these features in practice. (P3)
a25 Legal restrictions	There are network restrictions, such as the limited number of users in certain regions like China, resulting in fewer feedback contributions from these areas. (P15)
a26 Clarity of generated content	The generated content is logically structured, clearly presenting the connections and integration ideas between different cases, far exceeding my initial expectations. (P10)
a27 Poor content quality	The answers provided by the tool have obvious AI traits and often lack depth. (P12)
a28 Acceptable for simple content	I provide key points, and although the generated content may be somewhat generalized, the overall structure and framework are still satisfactory. (P14)
a29 Generation of false content	The tool may generate fictitious references or results that do not align with current contexts or situations, which can mislead users. (P4)

Initialisation concepts	Examples of primitive statements
a30 Fast generation speed	After inputting keywords and requirements, the tool generates results quickly. (P2)
a31 User involvement in testing	Participating in testing allows me to learn about new features that will be launched and see if these features meet my needs and are user-friendly. (P21)
a32 Interface clutter	When there are many historical conversations, finding specific topics may become cumbersome and time-consuming. (P6)
a33 Ensuring content legality	Many prompts can bypass the tool's basic safety protocols, leading to the generation of potentially illegal content. (P3)
a34 Lack of clear function guidance	The interface is too simple, which means that many users fail to utilize even 30% of the tool's capabilities due to a lack of guidance. (P14)
a35 Lack of age-level restrictions	Most tools are designed for all age groups, but when exploring more sensitive content, they may apply unnecessary content filters. (P18)
a36 Lack of clear privacy protection promises and measures	The tool could disclose how it uses users' data, maintaining transparency from the development side to ensure privacy protection. (P19)
a37 Lack of advanced data analysis functions	If the tool could include advanced data analysis functions, such as generating visual charts or conducting correlation analyses, it would save significant time spent looking for other data analysis software. (P9)
a38 Online promotion	AI tools are promoted across various social media platforms, and I have seen applications that made me wonder if they could be applied to my academic writing. (P21)
a39 Automatic error checking	If there are frequent or repetitive errors, I would like the tool to have a stronger error-checking function to help improve content accuracy. (P1)
a40 Self-learning and improvement	If the tool could learn and optimize its results based on my writing habits or historical data, I would be more inclined to use it. (P5)
a41 Language polishing	After finishing my writing, I would have the tool polish my sentences to improve grammar and make the text flow more smoothly. (P5)
a42 Over-reliance on the tool	However, if I habitually rely on the tool over the long term, my ability to think critically and explore issues deeply may weaken. (P7)
a43 Poor logic	The tool needs to improve the logical coherence when generating academic content. (P16)
a44 Lack of emphasis on key information	When recommending literature, it would be helpful if the tool presented both the document title and useful sections, as this would highlight the most important information. (P18)
a45 Reducing repetition	The tool can be effective in reducing the repetition rate of a paper, thus contributing to lowering the similarity index. (P17)
a46 Paid features	Currently, the high-intelligence version is only available for use with payment, which limits accessibility. (P2)
a47 Requires time for revision	AI-generated language has a certain 'machine-like' feel, so I often need to spend time revising the language to avoid redundancy and awkward phrasing. (P4)

Initialisation concepts	Examples of primitive statements
a48 Detailed operation guides needed	Sometimes when encountering issues or wanting to learn advanced functionalities, it is time-consuming to figure things out by myself. Detailed tutorials would be very helpful. (P12)
a49 Risk warnings	Sometimes I am not fully aware of the potential risks of certain features; it would be helpful if the system could provide timely warnings to avoid these risks. (P19)

Appendix 3 Summary of Basic Categories

Basic categories	Code
A1 System Stability	Delayed resolution of technical failures, automatic error checking
A2 Localization of Technology	Market disparities leading to content differences
A3 Degree of Personalization	Insufficient personalization, self-learning improvement, higher level of specialized support
A4 Format Standardization	Non-compliance with academic standards
A5 Legality of Content	Ensuring content legality, lack of age classification
A6 Academic Fairness	Unequal distribution of academic resources, varying levels of query proficiency
A7 Usage Costs	Legal restrictions, paid access, removal of query limitations
A8 Ease of Operation	Simple operation
A9 Operational Barriers	Cluttered interface, need for detailed operation guides, lack of emphasis on key information, lack of clear functional guidance
A10 User Feedback Mechanism	User involvement in testing, enhancement of user feedback mechanisms
A11 Professional Risks	Academic misconduct, risk warnings, over-reliance on the tool
A12 Privacy Protection	Concerns about data privacy, lack of clear privacy protection commitments and measures
A13 Authenticity	Generation of false content
A14 Logical Coherence	Inconsistent logic across queries, poor logical consistency, time required for revisions
A15 Content Value	Clear organization of generated content, poor quality of generated content, acceptable quality for simple content, strong literature review capability

Basic categories	Code
A16 Functional Completeness	Format diversity, format adjustments, lack of advanced data analysis capabilities, ability to integrate with other services
A17 Performance Advantages	Reducing workload, improving efficiency, fast generation speed, plagiarism reduction
A18 Writing Assistance Advantages	Understanding unfamiliar fields, improving non-native writing quality, expanding writing ideas, language polishing
A19 Social Recommendations	Recommendations from colleagues, classmates, and friends
A20 Online Promotion	Online trends, hot search promotions

Appendix 4 Main axis encoding

Dimension	Main Category	Basic Category	Category Connotation
Technological Factors	B1 System Quality	A1 System Stability	Stability of tool operation and failure recovery capabilities
		A2 Localization of Technology	Ability of the tool to optimize for local needs
	B2 Tool Adaptability	A3 Degree of Personalization	Tool's ability to support personalized demands and specialized scenarios
Institutional Factors	B3 Ethical Compliance	A4 Format Standardization	The tool's content generation aligns with academic norms and legal requirements
		A5 Legality of Content	Content legality and age classification management
	B4 Resource Fairness	A6 Academic Fairness	Fairness in the distribution of tool resources
		A7 Usage Costs	Barriers to use and economic costs
User Factors	B5 User Experience	A8 Ease of Operation	User evaluation of the tool's operational convenience
		A9 Operational Barriers	User perception of learning and operational difficulty with the tool
	B6 User Involvement	A10 User Feedback Mechanism	Mechanisms that involve users in the tool's improvement process
	B7 Perceived Risks	A11 Professional Risks	User concerns regarding academic misconduct and over-reliance on the tool
		A12 Privacy Protection	Data privacy and security protection measures
Content Factors	B8 Information Quality	A13 Authenticity	Authenticity of generated content
		A14 Logical Coherence	Logical consistency of the generated content
		A15 Content Value	Practical value of the generated content

Dimension	Main Category	Basic Category	Category Connotation
		A16 Functional Completeness	Completeness of content formats and functionalities
	B9 Functional Utility	A17 Performance Advantages	Core functions that enhance tool efficiency
		A18 Writing Assistance Advantages	Tool's assistance capability in specific scenarios
Community Factors	B10 Community Influence	A19 Social Recommendations	Influence of social relationships on tool usage
		A20 Online Promotion	Role of media and online promotion in tool advocacy

Appendix 5 Selective Coding

Dimension	Relationship Structure	Relationship Type	Relationship Connotation
Technological Factors	System Quality → User Satisfaction	Direct Positive Relationship	System stability and localization adaptation enhance user trust in the tool's reliability, directly increasing satisfaction.
	Tool Adaptability → Perceived Ease of Use	Direct Positive Relationship	Personalization support and specialized functions enhance user recognition of the tool's practicality.
Content Factors	Information Quality → User Satisfaction	Direct Positive Relationship	The authenticity and logical consistency of generated content directly affect user judgment of the tool's value.
	Functional Utility → User Satisfaction	Direct Positive Relationship	Tool efficiency improvements (e.g., plagiarism reduction, language polishing) directly enhance user satisfaction.
	Information Quality → Perceived Usefulness → User Satisfaction	Mediation Effect	High-quality content indirectly promotes satisfaction by enhancing user perception of the tool's usefulness.
User Factors	Perceived Usefulness → User Satisfaction	Direct Positive Relationship	When users believe the tool improves writing efficiency, satisfaction significantly increases.
	Perceived Ease of Use → User Satisfaction	Direct Positive Relationship	Simple operation and user-friendly interface reduce learning costs and indirectly increase satisfaction.

Dimension	Relationship Structure	Relationship Type	Relationship Connotation
	User Involvement → User Satisfaction	Direct Positive Relationship	User involvement in tool improvements (e.g., feedback, testing) directly enhances satisfaction.
	User Experience → User Satisfaction	Direct Positive Relationship	Easy-to-use operation and user-friendly interface directly enhance user satisfaction.
	Perceived Risks → User Satisfaction	Direct Negative Relationship	Risks such as privacy leakage and academic misconduct directly undermine user trust and satisfaction.
	User Involvement → Perceived Ease of Use → User Satisfaction	Mediation Effect	User involvement indirectly enhances satisfaction by optimizing the tool's ease of use.
Institutional Factors	Ethical Compliance → User Satisfaction	Direct Positive Relationship	When the tool complies with academic norms and legal requirements, users are more willing to use it long-term.
	Resource Fairness → User Satisfaction	Direct Positive Relationship	Removing payment restrictions and ensuring equitable resource distribution reduces barriers to use, thus increasing satisfaction.

Appendix 6 Measuring Scale

Variable Name	Design Questions	References
System Quality	The tool operates smoothly without noticeable lag or delay.	Delone, W. H., & McLean, E. R. (2003). Bhattacherjee, A. (2001).
	The tool supports multi-platform usage with a consistent experience.	
	The tool demonstrates efficient computational power during data processing and generation.	
Tool Adaptability	The tool provides personalized support based on my different academic needs.	Interview Materials
	The tool's functional design aligns with my writing habits.	
	The tool can adapt to the demands of different academic scenarios.	
Ethical Compliance	The content generated by the tool complies with academic standards.	Interview Materials,

Variable Name	Design Questions	References
	The tool clearly marks the source and copyright information for generated content.	Martin,K.,Borah,A.,& Palmatier,R.W.(2017)
	The tool provides a commitment to data privacy protection.	
Resource Fairness	The pricing model of the tool is reasonable and within my financial capacity.	Interview Materials, Ren,Q.,Jiang,Z.,Cao, J.,Li,S.,Li,C.,Liu,Y.,... &Chen,Y.(2024).
	I have equal opportunities to access and use various tools compared to others.	
	The tool's resource distribution is fair, with no noticeable usage barriers.	
User Experience	The tool provides clear usage guides or tutorials to help me get started quickly.	Alsaggaf,M.A.,&Altho nayan,A.(2018)，Ladhari,R.(2009)
	The tool's error messages and help information are clear and resolve issues promptly.	
	The process of using the tool feels efficient and enjoyable.	
User Involvement	I frequently participate in testing and providing feedback for the tool.	Mahmoud,M.A.,Hinso n,R.E.,&Anim,P.A.(20 18)
	I believe the tool's developers seriously consider my suggestions for improvement.	
	I am willing to provide feedback to the developers about my tool usage experience.	
Perceived Risk	I am concerned that using the tool may lead to data privacy breaches.	Interview Materials
	The content generated by the tool may carry academic misconduct risks.	
	I am worried that over-relying on the tool may weaken my writing skills.	
Information Quality	The content generated by the tool is reliable and authentic.	Wang,Y.S.,&Liao,Y. W.(2007)
	The information provided by the tool is substantively helpful for my research.	
	The content generated by the tool is logically clear, requiring minimal modification.	
Functional Utility	The tool offers a variety of functions that meet diverse academic writing needs.	Interview Materials
	The tool's functionality is innovative and addresses the pain points of traditional writing.	
	The tool's features help me better handle complex research data and information.	
Community Influence	Recommendations from friends have a significant impact on my decision to use the tool.	Interview Materials
	Evaluations on social media influence my choice of tools.	
	The academic community I belong to generally recognizes the value of the tool.	
Perceived Usefulness	The tool helps me complete academic writing tasks more efficiently.	Interview Materials

Variable Name	Design Questions	References
	The tool helps me improve the quality of academic writing tasks.	
	The features provided by the tool help reduce repetitive tasks in the writing process.	
Perceived Ease of Use	The tool's operation process is well-designed and aligns with my intuition.	Cheah,J.S.,Isa,S.M.,&Yang,S.(2021)
	The tool's feature layout is logical, making it easy to find the necessary functions.	
	I can use the tool proficiently without additional training.	
User Satisfaction	Overall, I am satisfied with my experience using the tool.	Woodruff,R.B.,Cadotte,E.R.,&Jenkins,R.L.(1983)
	I would recommend the tool to other academic researchers.	
	I plan to continue using the tool in the future.	

Appendix 7 Summary of basic sample information

Name	Option	Frequency	Percentage (%)
1. Your Gender	Male	214	52.45
	Female	194	47.55
2. Your Age	18-25 years	141	34.56
	26-35 years	177	43.38
	36-45 years	70	17.16
	46 years and above	20	4.9
3. Your Education Level	Master's or above	26	6.37
	Bachelor's degree	247	60.54
	College or below	135	33.09
4. Your Workplace	Research Institute	155	37.99
	University	194	47.55
	Enterprise	38	9.31
	Other (Please specify:)		
	Graduate student	21	5.15
	Other (Please specify:)	50	12.25
5. Your Specific Occupation	University Professor	194	47.55
	Researcher at a Research Institute	155	37.99
	Other (Please specify:)	5	0.01
6. Your Research Field	Science and Engineering	187	45.83
	Humanities and Social Sciences	100	24.51
	Agriculture	33	8.09
	Medicine	80	19.61
	Other (Please specify:)	8	1.96

Name	Option	Frequency	Percentage (%)
7. Your Paper Publication Status	Both Chinese and English	298	73.04
	Only Chinese	62	15.2
	Only English	39	9.56
	Not Published Yet	9	2.21
8. Duration of Your Research Career	Less than one year	80	19.61
	1 to 5 years	168	41.18
	More than 5 years	160	39.22
9. Frequency of Using AI-assisted Academic Writing Tools	Daily	145	35.54
	Weekly	204	50
	Occasionally	59	14.46

Appendix 8 cross-factor load

	Ethical Compliance	Information Quality	Functional Utility	Tool Adaptability	Perceived Ease of Use	Perceived Usefulness	Perceived Risk	User Experience	User Involvement	User Satisfaction	Community Influence	System Quality	Resource Fairness
Q14.1	0.254	0.182	0.282	0.233	0.198	0.241	-0.288	0.253	0.169	0.371	0.336	0.794	0.359
Q14.2	0.31	0.175	0.324	0.241	0.185	0.31	-0.275	0.249	0.185	0.364	0.34	0.878	0.384
Q14.3	0.27	0.184	0.328	0.252	0.198	0.279	-0.285	0.281	0.224	0.451	0.383	0.846	0.382
Q15.1	0.314	0.172	0.259	0.862	0.213	0.294	-0.294	0.354	0.172	0.344	0.314	0.266	0.324
Q15.2	0.301	0.181	0.329	0.89	0.236	0.234	-0.356	0.366	0.179	0.409	0.352	0.243	0.324
Q15.3	0.312	0.1	0.245	0.86	0.189	0.313	-0.331	0.349	0.143	0.328	0.339	0.244	0.315
Q16.1	0.818	0.048	0.127	0.312	0.106	0.265	-0.383	0.271	0.14	0.297	0.352	0.262	0.284
Q16.2	0.87	0.042	0.166	0.29	0.207	0.276	-0.35	0.253	0.149	0.355	0.387	0.293	0.228
Q16.3	0.832	0.056	0.196	0.293	0.162	0.206	-0.349	0.292	0.145	0.304	0.351	0.282	0.252
Q17.1	0.265	0.121	0.333	0.281	0.217	0.345	-0.289	0.309	0.268	0.402	0.331	0.423	0.865
Q17.2	0.268	0.161	0.233	0.338	0.172	0.332	-0.286	0.377	0.282	0.36	0.369	0.376	0.845
Q17.3	0.246	0.177	0.26	0.337	0.28	0.355	-0.292	0.328	0.214	0.407	0.357	0.356	0.875
Q18.1	0.268	0.136	0.216	0.404	0.205	0.261	-0.262	0.844	0.199	0.358	0.317	0.224	0.365
Q18.2	0.251	0.101	0.283	0.323	0.261	0.303	-0.333	0.868	0.22	0.397	0.323	0.299	0.309
Q18.3	0.305	0.129	0.206	0.312	0.229	0.254	-0.256	0.825	0.242	0.321	0.395	0.258	0.318
Q191	0.149	0.128	0.234	0.148	0.218	0.188	-0.198	0.218	0.852	0.304	0.153	0.162	0.244
Q192	0.187	0.113	0.272	0.179	0.214	0.204	-0.119	0.195	0.821	0.251	0.181	0.23	0.256
Q193	0.101	0.192	0.257	0.155	0.207	0.227	-0.106	0.24	0.85	0.283	0.177	0.193	0.243
Q20.1	-0.359	-0.133	-0.293	-0.33	-0.202	-0.252	0.866	-0.313	-0.147	-0.38	-0.396	-0.282	-0.285

	Ethical Compliance	Information Quality	Functional Utility	Tool Adaptability	Perceived Ease of Use	Perceived Usefulness	Perceived Risk	User Experience	User Involvement	User Satisfaction	Community Influence	System Quality	Resource Fairness
Q20.2	-0.366	-0.104	-0.234	-0.315	-0.176	-0.208	0.841	-0.306	-0.109	-0.339	-0.344	-0.285	-0.274
Q20.3	-0.373	-0.131	-0.26	-0.321	-0.198	-0.292	0.86	-0.247	-0.177	-0.354	-0.402	-0.295	-0.301
Q21.1	0.006	0.8	0.116	0.063	0.116	0.128	-0.052	0.036	0.128	0.114	0.038	0.149	0.116
Q21.2	0.028	0.863	0.155	0.185	0.12	0.18	-0.173	0.155	0.147	0.17	0.152	0.176	0.156
Q21.3	0.093	0.87	0.188	0.172	0.165	0.181	-0.121	0.143	0.157	0.213	0.18	0.207	0.167
Q22.1	0.142	0.162	0.818	0.268	0.218	0.196	-0.253	0.198	0.276	0.356	0.248	0.298	0.259
Q22.2	0.153	0.126	0.835	0.298	0.293	0.213	-0.259	0.264	0.256	0.369	0.287	0.316	0.252
Q22.3	0.189	0.177	0.837	0.237	0.229	0.234	-0.255	0.236	0.219	0.363	0.254	0.311	0.287
Q23.1	0.367	0.137	0.264	0.354	0.144	0.22	-0.372	0.364	0.155	0.361	0.83	0.356	0.337
Q23.2	0.393	0.126	0.251	0.337	0.124	0.29	-0.389	0.374	0.21	0.406	0.854	0.33	0.371
Q23.3	0.353	0.145	0.294	0.306	0.22	0.318	-0.381	0.307	0.151	0.391	0.875	0.387	0.337
Q24.1	0.257	0.185	0.2	0.274	0.199	0.842	-0.286	0.276	0.217	0.269	0.267	0.259	0.323
Q24.2	0.248	0.185	0.228	0.24	0.184	0.874	-0.247	0.227	0.196	0.267	0.313	0.328	0.336
Q24.3	0.253	0.131	0.229	0.299	0.186	0.831	-0.215	0.327	0.212	0.299	0.257	0.253	0.359
Q25.1	0.163	0.102	0.268	0.229	0.869	0.206	-0.212	0.214	0.236	0.302	0.168	0.179	0.235
Q25.2	0.156	0.16	0.199	0.177	0.836	0.161	-0.152	0.228	0.211	0.267	0.135	0.209	0.203
Q25.3	0.175	0.158	0.293	0.225	0.878	0.204	-0.212	0.267	0.207	0.343	0.194	0.207	0.234
Q26.1	0.298	0.161	0.395	0.378	0.349	0.295	-0.334	0.354	0.253	0.818	0.389	0.405	0.41
Q26.2	0.325	0.163	0.395	0.355	0.215	0.274	-0.363	0.363	0.283	0.835	0.413	0.399	0.355
Q26.3	0.33	0.186	0.299	0.306	0.322	0.248	-0.35	0.349	0.3	0.848	0.331	0.365	0.367

Data Management Plan

Thesis Title: Impact Factors of User Satisfaction With AI-Assisted Academic Writing Tools

Domain	Category	Protocols
1. Data Description	**1.1 Survey Data**	• Format: CSV (Qualtrics export) • Size: ≤200 participants; ≤2MB
	1.2 Interview Data	• Format: MP3 recordings + DOCX transcripts • Size: 15-20 participants; ≤500MB
2. Ethics & Compliance	**2.1 Anonymization**	• Surveys: Auto-remove IPs/emails • Interviews: Replace names → [P01]; blur affiliations
	2.2 Legal	• GDPR-compliant storage
3. Storage & Backup	**3.1 Active Storage**	• Institutional encrypted drive • Access: Researcher + Supervisor only
	3.2 Backup	• Daily encrypted backups
	3.3 Archiving	• Public: Aggregated data → Zenodo/Figshare (DOI) • Raw interviews: 2-year embargo → secure deletion

4. Processing	**4.1 Quantitative**	• Tools: SmartPLS • Documentation: Variable codebook
	4.2 Qualitative	• Tools: Thematic analysis (NVivo) • Output: Theme framework
5. Sharing	**5.1 Public**	• Survey summaries • Interview excerpts (anonymized)
	5.2 Restricted	• Raw surveys → Request via institutional email + NDA
	5.3 Confidential	• Original recordings • Signed consent forms (secure deletion post-thesis)
6. Roles	**Researcher**	Data collection, anonymization, metadata
	Supervisor	Ethics compliance verification

AI Use Statement

AI was used only for proofreading. Correcting spelling/grammar errors, improving sentence fluency, no AI-generated content, analysis, or data processing was involved.