

Research Article

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Artificial Intelligence in Academic Writing and Research: Adoption and Effectiveness

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Abstract: This study inspects the effect of artificial intelligence (AI) tools on Ph.D. scholars at Babasaheb Bhimrao Ambedkar University. The research assesses the types of AI tools used, the purpose of using AI tools, and the challenges faced in using AI tools. A structured questionnaire was used for data collection. The study results indicate a high adoption rate of AI tools, with 91.2% of respondents using technologies such as plagiarism detection software, large language models, paraphrasing tools, and academic research databases with AI features. These tools were predominantly effective for literature reviews and research writing, improving precision, proficiency, and creativity. This study presents distinctive understandings of the transformative role of AI in academic research, precisely within the setting of doctoral education. By concentrating on the experiences of Ph.D. students, it highlights both the potential and challenges of AI incorporation, paying attention to the role of technology-driven invention in higher education and bring into line with sustainable development objectives for knowledge dissemination.

Keywords: AI tools, quality education, knowledge acquisition, creative thinking, ethical frameworks, academic writing

1 Introduction

Academic writing plays a crucial role in constructing arguments, recording methodologies, engaging in scholarly discourse, advancing knowledge, earning respect, securing funding, and achieving promotions. It is a fundamental component of a successful graduate program, especially at the doctoral level. Scholars are expected to produce their theses and academic publications in a scholarly style. However, many lack specialized training in academic writing, which hampers their writing ability. Consequently, numerous scholars encounter significant challenges in scholarly writing.

Artificial intelligence (AI) is a computing system capable of performing human-like tasks such as learning, adapting, synthesizing, self-correcting, and utilizing data for complex processing activities (Popenici & Kerr, 2017). AI has emerged as a transformative force in scholarly research, providing powerful tools that enhance efficiency, accuracy, and innovation (Khalifa & Albadawy, 2024). Researchers widely employ AI applications like machine learning, natural language processing (NLP), and data analytics across various fields to automate data collection, improve literature reviews, and assist with writing and editing. AI-driven writing assistants support grammar, structure, citation management, and compliance with disciplinary standards. AI tools improve academic writing efficiency by enabling writers to concentrate on essential and innovative research

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elements (Golan & Azoulay, 2023). These tools save time and help researchers uncover new insights by analysing large datasets that would otherwise be too complex to process manually. While academic writing presents specific challenges, AI tools significantly facilitate this process, boosting research productivity and enhancing overall work efficiency.

AI tools used in academia span several categories based on their function and application. Writing assistants, such as ChatGPT, Jasper, and Grammarly, aid in drafting, editing, paraphrasing, and improving grammar and coherence in academic writing (Pryma, Pelivan, Teletska, Tsobenko, & Zagrebelna, 2025; Sontake, 2025). Plagiarism detection tools like Turnitin and iThenticate compare submissions against extensive databases to identify potential instances of copied content, ensuring academic integrity (Sontake, 2025). Data analysis tools, including IBM SPSS and IBM Watson, support researchers in statistical processing and machine learning applications (Jiang, Liu, Baig, & Li, 2024; Sontake, 2025). Generative AI models, such as DALL-E, Midjourney, and Stable Diffusion, convert text prompts into visuals, playing a growing role in science communication and conceptual illustration (Joynt et al., 2024). In addition, literature discovery and research design tools like Semantic Scholar, Elicit, Iris.ai, and ResearchRabbit utilize AI to streamline literature searches, identify research gaps, and visualize citation networks (Oklahoma State University Libraries, 2025; Pinzolits, 2024; Texas Tech University Libraries, 2025). These tools, though varied in purpose, collectively enhance efficiency, accuracy, and creativity in academic research and writing.

This study aims to address the following key research questions:

- (1) What are the prevalent AI tools used by Ph.D. students at BBAU?
- (2) For what purposes are AI tools most commonly employed in research?
- (3) How do Ph.D. students comprehend the usefulness of AI tools in enriching research?
- (4) What obstacles restrict the utilisation of AI tools in research?
- (5) How do AI tools determine students' creativity, problem-solving, and knowledge acquisition?

Study Objectives

- To examine the AI tools utilized by Ph.D. students at BBAU.
- To understand the intent of using AI tools in research.
- To examine Ph.D. students' discernment of AI tools use in enriching research.
- To understand challenges in using AI tools in research.
- To inspect the perceived advantages of AI tools in research.

2 Literature Review

2.1 Theoretical Framework on Technology Adoption

Several theoretical frameworks are used to understand technology adoption. Among all the frameworks, the technology acceptance model (TAM), innovation diffusion theory (IDT), and the unified theory of acceptance and use of technology (UTAUT) are notable frameworks. TAM is a theoretical framework that explains the techniques to encourage user acceptance and use of new technology (Davis, 1989). It is widely used to handle the difficulty faced by organizations in promoting the acceptance of new technology (Liu, Dedehayir, & Katzy, 2015). Two dimensions of TAM consist of perceived usefulness and perceived ease of use (Davis, 1989). Zhang, Hu, and Zhou (2025) study extended TAM and found that perceived utility strongly influences adoption, and ethical concerns considerably moderate this relationship, particularly in public universities. Likewise, Al-Bukhrani, Alrefaee, and Tawfik (2025) employed the theory of reasoned action to examine the adoption of AI writing tools and found that attitudes and subjective norms are main predictors of intention, whereas perceived barriers did not significantly deter adoption, a notable deviation from TAM and UTAUT supposition.

Rogers (1962) introduced IDT, IDT is widely employed to understand the influence of innovation diffusion. This framework emphasizes the diffusion of the innovation process occurring over a social system through specific

channels over a period of time. The five characteristics of IDT consist of “advantage,” “complexity,” “trialability,” “compatibility,” and “observability”. IDT explains that the adoption of novel technology is influenced by the features of the innovation, the channels of communication, the social framework, and the features of the adopters (Mbatha, 2024). Gutiérrez-Leefmans, Picazo-Vela, and Kareem (2025) study identified relative advantage, observability, and compatibility as strong predictors of adoption among centennial users, whereas complexity was less influential than in earlier IDT-based studies. Likewise, Almaiah et al. (2022) noted that trialability and observability were necessary for effective AI integration in institutional online learning environments.

The UTAUT is a framework intended to understand user acceptance and the use of new technologies (Williams, Rana, & Dwivedi, 2015). Four factors, i.e. performance expectancy (PE), social influence (SI), effort expectancy (EE), and facilitating conditions (FC) (Venkatesh, Morris, Davis, & Davis, 2003), made up the UTAUT model. Additionally, it integrates four individual variables, i.e. gender, age, experience, and voluntariness of use, which attempt to forecast the association between the primary factor, behavioural intention, and usage behaviour (Venkatesh et al., 2003). In the UTAUT framework, PE, SI, EE, and FC influence intention to use technology. Liu et al. (2015) exhibited that performance and EE determine university educators’ eagerness to engage with tools like ChatGPT. While Mbatha (2024) stressed trainability and complexity as core DOI factors affecting Chatbot technology use in education.

2.2 Overview of AI Tool Usage in Research

AI has swiftly become a transformative force in various sectors with considerable influence on academic research (Golan & Azoulay, 2023). The implementation of AI tools in education and research improves productivity and efficiency. AI tools reduce the time spent on data processing and improve the quality of output through grammar checks, structural support, and citation management (Zhao, 2023). AI applications in academic writing include assisting in content creation, such as writing assistants, plagiarism detection, and automated peer reviews (Golan & Azoulay, 2023). In the field of medicine, AI has made profound aids in diagnostics and patient treatment predictions (Davenport & Kalakota, 2019), in financial institutions, AI helps in detecting fraud and forecasting trends (Li, Sigov, Ratkin, Ivanov, & Li, 2023), and in retail marketing, AI enhances customer service (Lu, Cheng, Tzou, & Chen, 2023). In the field of education, AI helps in personalizing learning experiences and improving administrative tasks, providing customized tutoring interference centred on student needs (Zawacki-Richter, Marín, Bond, & Gouverneur, 2019).

The application of AI is transforming research in multiple arenas like biology, mathematics, physics, chemistry, and the humanities. In the field of biology, AI improves molecular dynamics simulations, strengthening discernment of the SARS-CoV-2 virus and its spike protein (Casalino et al., 2020). In the field of mathematics, AI locates patterns and anomalies, resulting in new theorems and enhanced forecasting in fields like knot theory and astrophysics (Davies et al., 2021). In the field of humanities, AI application supports data analysis and creative processes, like examining emotional tones in texts (Taherdoost & Madanchian, 2023), creating themes from topic modelling (Mustak, Salminen, Plé, & Wirtz, 2021), and helping in digital archiving (Teel, 2024). AI tools like Google Translate alleviate cross-cultural research by translating historical documents and studying language development (Moneus & Sahari, 2024).

2.3 Types of AI Tools in Academic Research

AI tools are widely used in academic research; the most widely used AI tools are Grammarly, ChatGPT, Elicit, Perplexity, and Consensus (Granjeiro et al., 2025). AI tools like ChatGPT have gained significant attention as they offer assistance in generating ideas, answering questions, and improving language fluency (Pham, 2025). Grammarly is a commonly used AI-powered proofreading tool that assists in improving academic writing by correcting grammar, punctuation, and sentence clarity. Likewise, Elicit, Consensus, and Perplexity provide

support for literature reviews and information synthesis (Granjeiro et al., 2025). In spite of all the benefits, AI tools have certain limitations. It has concerns with the content accuracy, over-standardization of writing style, and the possible erosion of authorship accountability prevailing (Granjeiro et al., 2025). Moreover, published literature indicates that generative AI tools, while helpful for fostering productivity and creativity, necessitate deliberate pedagogical frameworks to guarantee responsible usage and to cultivate ethical and digital literacy skills among students (Saúde, Barros, & Almeida, 2024).

Moreover, the adoption of AI writing assistants in non-Western and low-resource contexts poses more challenges. For example, research from Tanzanian universities indicates that the lack of assistance for local languages such as Swahili, affordability issues, and ethical uncertainty are major obstacles to adoption (Kondoro, 2025). The outcomes indicate the need for culturally adaptive and linguistically inclusive AI tools that can serve diverse student populations effectively. Nevertheless, AI tools are rescaling academic workflows, making research approachable and effective. Nevertheless, AI tools integration must be aided by ethical standards, proper direction, and an awareness of their contextual limit.

2.4 Plagiarism Detection Tools

In the age of AI, it is imperative to maintain academic integrity. Plagiarism detection tools function using algorithms based on machine learning, NLP, and semantic analysis to equate the similarities between written content and published content (Amirzhanov, Turan, & Makhmutova, 2025). Out of many tools available, Turnitin is the most widely used tool because of its robust database. Turnitin examines student papers with millions of submissions in its database (Von Isenburg, Oermann, & Howard, 2019). Published literature indicates that Turnitin AI achieves an accuracy rate between 92 and 100%, signifying its efficacy in detecting both human and AI-generated texts (Canyakan, 2025).

Copyscape is another tool widely used for detecting plagiarism across corporate websites. Investigators use it to reveal instances of “content theft” (Foltýnek et al., 2020). GPTZero, Copyleaks, and OpenAI Classifier are other tools that use advanced AI-based classifiers to identify AI-authored content. For instance, GPTZero was developed to avoid AI-assisted academic dishonesty by identifying generative form in student submissions, whereas Copyleaks is used in educational platforms to detect plagiarized content (Sajid, Sanaullah, Fuzail, Malik, & Shuhidan, 2025).

Despite all the positive paybacks, plagiarism detection tools also have challenges, such as false positives, which can take place, especially in clinical and scientific circumstances, causing unnecessary academic penalties. In the field of medical education, false positives from Turnitin cause worry about fairness in AI-assisted plagiarism detection (Daungsupawong & Wiwanitkit, 2025). Published literature indicates that while anti-plagiarism systems are efficient, their acceptance by faculty is uneven, mostly obstructed by an absence of training and impedance to change (Kolhar and Alameen, 2021). With AI-generated content and paraphrased plagiarism, the intricacy of plagiarism detection has extended. Published literature indicates that there is a need to adopt hybrid techniques that combine semantic text analysis, deep learning models, and stylometric examination to capture subtler forms of intellectual theft (Amirzhanov et al., 2025; Sajid et al., 2025). Moreover, cross-language and code plagiarism detection continues to rise; thus, customized detection algorithms are required (Amirzhanov et al., 2025).

2.5 Purposes of Use of AI Tools by Students

AI tools are widely used by university students for various purposes such as writing support, language correction, and self-directed learning. Published literature indicated that AI tools like ChatGPT are used for idea generation, while Grammarly is used for grammar correction, QuillBot is used for summarization, paraphrasing, grammar checking, plagiarism checking, etc. (Tokdemir Demirel, 2024). AI tools improve writing

clarity and coherence and also assist students in improving vocabulary. Sussha, Viberg, and Koren (2024) conducted a study to examine students' feelings about co-writing essays with ChatGPT. Students flagged using AI for idea creation, content design, and language editing. Nonetheless, students indicate that they require critical thinking, fact-checking, and ethical consciousness when using AI tools.

Li, Sadiq, Qambar, and Zheng (2025) undertook a quasi-experimental study and found that using ChatGPT in research considerably improved students' research skills, self-directed motivation, and self-directed learning behaviours. Students using ChatGPT to complete the assigned task outperformed those in control groups, signalling that AI tools can promote active participation and deeper learning. Likewise, Yousef, Deeb, and Alhashlamon (2025) found that 87% of Palestinian medical students used AI tools often, with ChatGPT being used by 76%. These students used AI for drafting literature, analyzing data, researching performance, and enhancing research. Nevertheless, the students report that proper training is required in using AI tools.

Bista and Bista (2025) examine doctoral students' use of ChatGPT, Google Gemini, and Microsoft Copilot and found that AI tools are used to refine academic texts, manage cognitive load, and enhance writing. At the same time, students were concerned about the accuracy and the requirement of maintaining academic integrity. Dai, Lai, Lim, and Liu (2023) study found that postgraduate research students in Australia employed ChatGPT to improve critical thinking and independence in research. These outcomes indicate that students use AI tools to perform academic tasks, enhance learning outcomes, and gain autonomy. Nonetheless, proper training, ethical awareness, and institutional counsel are required to assure effective and responsible use.

2.6 Perceived Benefits of AI Tools in Academic Research

The implementation of AI tools in academic research has brought several benefits for students, including improvement in productivity, learning efficiency, and language expression. Almassaad, Alajlan, and Alebaikan (2024) examine the use of Generative AI (GenAI) tools like ChatGPT and Gemini among students in Saudi Arabia and found that AI tools help in saving time, ease of access, and instant feedback, thereby supporting efficient academic performance. Similarly, Arbab, Dhuhli, Krishnan, and Crisostomo (2024) examine AI tools usage in Oman and found that students perceived AI tools as instrumental in improving writing skills, analytical thinking, and critical reasoning. At the same time, they stressed using AI tools judiciously for idea generation and structure planning rather than complete task automation. It is also widely appreciated that AI tools have the ability to personalize learning, streamline research tasks, and enhance understanding of complex subjects, but are about over-dependency on AI tools (Kostas, Paraschou, Spanos, Tzortzoglou, & Sofos, 2025).

Al-Bukhrani et al. (2025) indicate that AI writing tools considerably promote productivity, especially in drafting manuscripts and minimizing language obstacles for non-native English speakers. Chiu (2025) stressed that awareness of AI tools is imperative in shaping perceptions of AI usefulness. These studies' findings recommend that AI tools offer substantial academic value by enhancing writing fluency, promoting personalized learning, assisting research inclusion, and improving motivation and participation at the same time, calling for attentive integration, training, and supervision to guarantee responsible use.

2.7 Challenges in Student Adoption of AI Tools

In spite of the many potentials that AI offers in the academic environment. There are many challenges hindering the wide adoption among students. Students are concerned about how AI tools collect and possibly misuse personal data, raising fears of privacy breach and infringement of confidentiality (Klimova, Pikhart, & Kacetl, 2023). AI systems lack the contextual awareness required for classroom interactions, resulting in student distrust and avoidance toward AI-facilitated teaching and learning (Han, Coghlan, Buchanan, & McKay, 2025). Moreover, there is a technological shortfall, like uneven service quality and the necessity for pedagogical adaptation (Salhab, 2025).

Institutional support is another factor that significantly influences AI adoption. Absence of training on AI tools, absence of digital orientation, and inadequate infrastructure are factors that influence AI adoption among students (Jackman, Marshall, & Carrington, 2024). Some students use AI tools to complete tasks, such as checking grammar and idea generation. While others avoid owing to fear of academic dishonesty (Smerdon, 2024), bias, privacy issues, lack of explainability, transparency, and accountability (Chiu, 2025). This understanding complicates the adoption of AI tools. Published findings indicate that though encouraging attitudes and social principles promote adoption, perceived barriers like lack of lucidity on ethical use and inadequate training hinder AI adoption (Al-Bukhrani et al., 2025). Kostas et al. (2025) also identified ethical concerns, reliability, and decreasing creativity as major student worries. Almassaad et al. (2024) noted subscription fees, misinformation, and reduced peer interaction as practical and social barriers. The findings underline the importance of AI literacy orientation and clear guidelines to guide ethical AI use.

2.8 Copyright Implications of AI-Generated Academic Content

Use of AI-generated content has caused considerable legal and ethical issues, particularly with copyright and authorship. With the advancement in AI tools, determining the ownership is becoming a challenging task. The traditional principles of authorship indicate that authorship requires human contribution. Now, AI tools such as GPT-3 and GPT-4 can produce literary works, along with academic texts, raising the question of whether such content generated using AI tools qualifies for copyright protection. Publication guidelines, national legislation, and conventions such as the Berne Convention proposed that copyright must be with human authorship (Gaffar and Albarashdi, 2025). This indicates that content generated using AI tools lacks legal protection. In the case of the European Union, the Copyright Directive does not expressly cover AI authorship, leaving it to national courts to analyse authorship and ownership. In the European Union, it proposed frameworks that permit individuals to own AI-generated content; however, no distinct stand has been taken in this case (Zhuk, 2024). The United States specifies the “human authorship” doctrine rigorously and denies copyright to machine-generated outputs.

Kretschmer, Margoni, and Oruç (2024) draw on how AI development is reliant on large-scale text and data mining (TDM) from copyrighted sources, especially for training large language models (LLMs). EU law allows TDM under limited exemptions, but only when lawful access is guaranteed in the absence of consent from the copyright holders; it can break copyright laws. Chu, Song, and Yang (2024) suggest a means to minimize the replication of copyrighted materials in outputs through a mathematical framework; however, they admit that perfect compliance remains impalpable. Considering the policy perspective, unregulated AI use risks undermining the creative and academic sectors (Glenster, Hampton, Neff, & Lacy, 2025). In the field of music, Enochson (2025) exemplifies this in the instance of AI-generated songs imitating human artists. Such instances underline the urgency for academic and legal institutions to shed light on how AI-generated academic content should be regulated under copyright law. The copyright position of AI-generated academic content appears to be evolving.

2.9 Research Gap and Contribution of the Study

While previous studies have explored the use of AI tools in higher education and their implications for writing, productivity, and ethical concerns, much of this literature has focused on general student populations, educators, or Western institutional contexts. Limited research has specifically investigated how doctoral students, particularly within Indian universities, adopt, utilize, and perceive the effectiveness of diverse AI tools in their academic research. Moreover, few studies have systematically examined the intersection of AI usage with research creativity, knowledge acquisition, and inventive thinking. This study addresses this gap by focusing on Ph.D. students at Babasaheb Bhimrao Ambedkar University (BBAU), offering empirical insights into the

types of AI tools used, their perceived benefits and challenges, and the influence of these tools on higher-order research capacities. By doing so, it contributes context-specific evidence to the growing discourse on AI integration in doctoral education and informs policy and practice on ethical, effective, and equitable AI adoption in academic research.

3 Methodology

3.1 Research Design

This study adopts a quantitative research design to investigate the adoption and impact of AI tools on Ph.D. students' research practices at BBAU. A structured survey-based approach was utilized to collect data on AI tool usage, effectiveness, barriers, and the influence of AI on research productivity, creativity, and knowledge acquisition.

3.2 Sampling

The target population includes all Ph.D. students enrolled in various research disciplines at BBAU. A sample was drawn based on departmental representation and availability. The total number of questionnaires distributed was 629, and 261 completed responses were received, resulting in a response rate of 41.5%. According to Krejcie and Morgan (1970), the minimum sample size for a population of 629 is 242, confirming that our sample is statistically adequate for analysis.

3.3 Instrumentation

The research instrument consisted of a structured questionnaire divided into four sections:

- (1) Demographic Information: Captured the respondent's gender and age.
- (2) AI Tool Usage: Assessed whether students utilize AI tools and their usage frequency.
- (3) Primary Purposes for Using AI Tools: Explored the main purposes for employing AI tools in their research.
- (4) Challenges and Limitations: Identified barriers hindering the effective adoption of AI tools.

Before the main data collection, a pilot study was conducted to test the questionnaire's clarity and effectiveness. Feedback from the pilot study led to refinements in the instrument to ensure comprehensibility and relevance.

The study variables, such as gender, age, AI tools used in research, frequency of AI tool usage, purpose of using AI, and barriers to using AI tools, are measured in a checklist. While AI Tool Effectiveness and Knowledge Acquisition are measured on a 5-point Likert scale, challenges or limitations in using AI tools for creative tasks are measured in checklists.

3.4 Data Collection

Data were collected through an online survey distributed via institutional mailing lists. Ethical considerations, including informed consent and respondent anonymity, were strictly maintained. Data collection occurred from September 10 to September 20, 2024.

3.5 Data Analysis

Statistical analyses were conducted using SPSS. To assess the reliability and validity of the data, factor analysis was performed. The Kaiser–Meyer–Olkin (KMO) measure and Bartlett’s test of Sphericity confirmed sampling adequacy ($KMO > 0.9$) and significant correlation among variables ($p < 0.05$). Three primary dimensions of AI tool usage were examined: Effectiveness, Efficiency, and their influence on Knowledge Creation and Inventive Thinking. Cronbach’s alpha values for each factor exceeded 0.8, indicating high internal consistency.

Descriptive and inferential statistical techniques were employed to analyse the data. Independent sample *t*-tests and ANOVA were conducted to evaluate differences in perceptions based on demographic variables such as gender, age, year of Ph.D., and frequency of AI tool usage.

3.6 Data Visualization and Presentation Tools

To effectively present and interpret the quantitative survey results, visual representations of key findings were generated. The data collected from 261 Ph.D. students was first cleaned and organized using Microsoft Excel. For graphical representation, Python programming (version 3.10) was used, specifically for creating bar charts and horizontal bar graphs. Each figure was designed to highlight demographic distributions, AI tool usage patterns, perceived benefits, challenges, and limitations. Distinct colour schemes, percentage labels, and respondent counts were included to enhance clarity and visual appeal.

4 Results

4.1 Demographic Information

Figure 1 presents the demographic profile of the 261 Ph.D. student respondents. In terms of gender distribution, the sample was nearly balanced, with 51% identifying as male ($n = 133$) and 49% as female ($n = 128$). The majority of participants (61.3%) were aged 27 and above, while 31.4% were between 25 and 26 years, and only 7.3% were in the 23–24 age range. Regarding the year of Ph.D. enrolment, nearly half of the respondents (48.3%) were in their first year, followed by 23.8% in the third year. The remaining participants were in their second year (11.5%), fourth year (10.3%), or fifth year and beyond (6.1%). Concerning the frequency of AI tool usage in research, a notable portion (41.4%) reported using AI tools occasionally, while 28% used them daily and 24.9% weekly. Only 5.7% reported monthly use. These figures reflect a high level of engagement with AI tools among early-career researchers, particularly those in the initial phases of their doctoral journey.

Figure 2 illustrates the overall adoption of AI tools among the surveyed Ph.D. students. An overwhelming majority (91.2%, $n = 238$) reported using AI tools in their research activities, while only 8.8% ($n = 23$) indicated that they did not use such tools. This high adoption rate underscores the growing reliance on AI technologies in academic research and suggests that these tools have become integral to the research workflows of doctoral scholars at BBAU.

4.2 Types of AI Tools Utilized in Research

The data from Figure 3 illustrate the range and frequency of AI tools adopted by Ph.D. students at BBAU in their research workflows. The most widely used tools are those that support academic writing and ensure content originality. Plagiarism detection tools (62.1%) top the list, indicating that students prioritize academic integrity and compliance with originality standards. This is followed closely by LLMs like ChatGPT and GPT-4

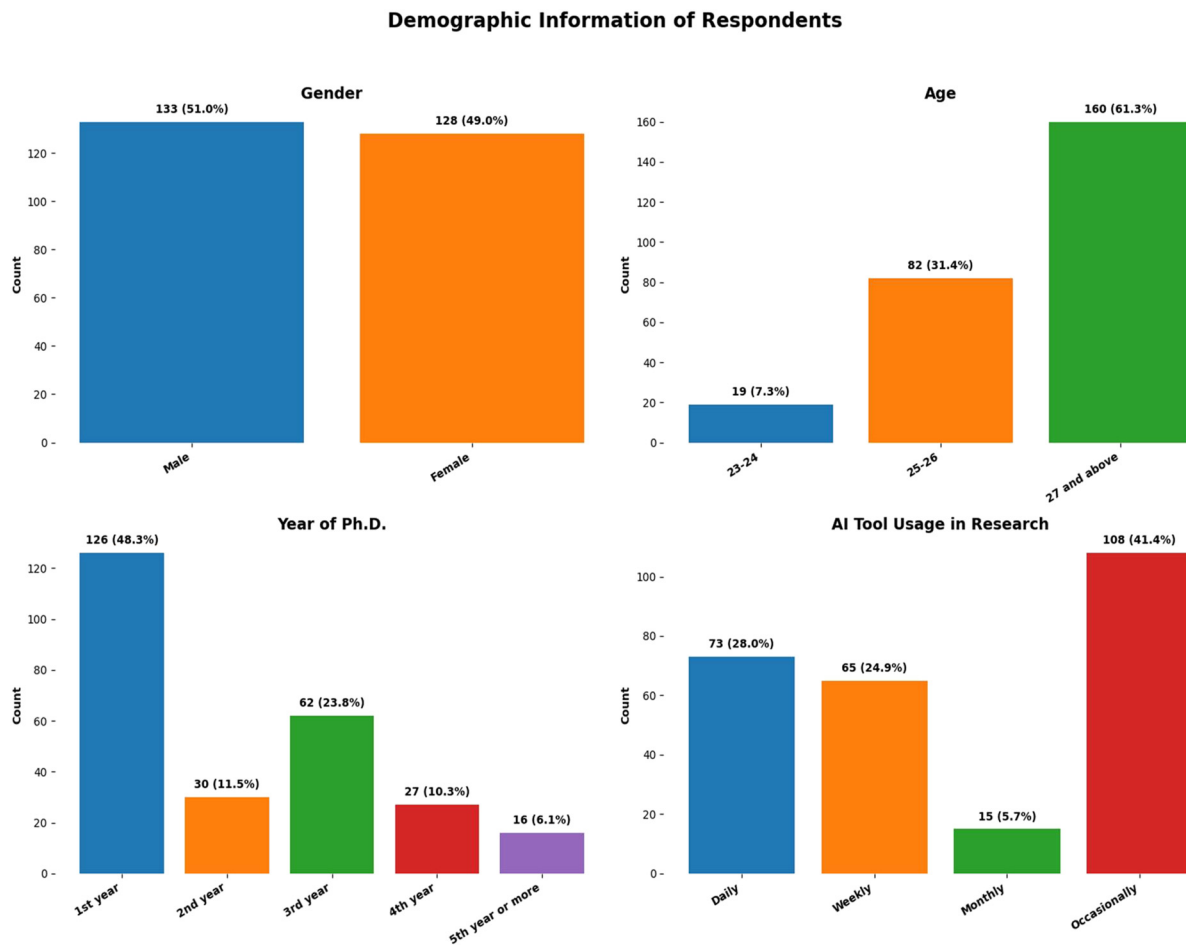


Figure 1: Demographic information.

(59.4%), and paraphrasing tools (56.3%), which suggests that students are leveraging generative AI to improve the clarity, structure, and novelty of their writing.

Tools that assist in grammar and style correction, such as Grammarly and ProWritingAid, are used by 54.4% of students, reinforcing the focus on enhancing the linguistic quality of academic texts. A significant portion (43.7%) also uses AI-enhanced research databases like Semantic Scholar and Google Scholar, indicating the growing reliance on AI for more efficient literature discovery and review processes.

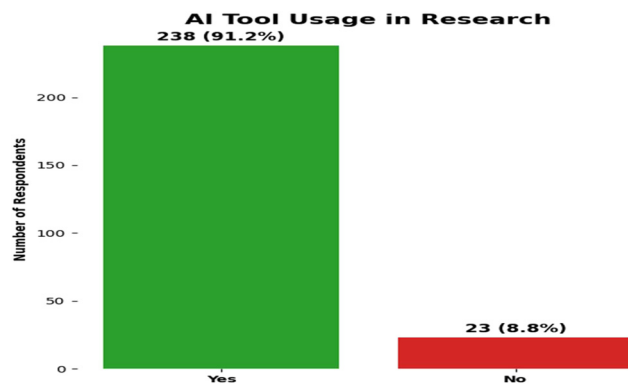


Figure 2: AI tool usage in research.

Mid-tier adoption is observed for tools that support summarization (41%), virtual assistance (31%), and automated translation (29.1%), reflecting their utility in content comprehension, multitasking, and language support, particularly for non-native English speakers. However, more technical and specialized AI tools, such as those for predictive analytics (18.8%), data analysis frameworks (18%), and image/speech recognition (15.7% and 13%, respectively), show relatively lower usage, likely due to limited relevance for students in non-STEM disciplines or lack of training.

Only a small percentage of students reported using code generation tools (11.9%), machine learning frameworks (8.4%), NLP tools (6.9%), and sentiment analysis systems (3.1%), suggesting that more advanced or discipline-specific AI tools are still on the periphery of doctoral research in this context. Notably, 8.8% of respondents indicated no use of AI tools in their research.

The results demonstrate that the most frequently used AI tools among Ph.D. scholars are those that directly support writing, reviewing, and ensuring the originality of academic content. More technical AI applications show lower adoption, pointing to a potential gap in training or applicability across disciplines. These patterns underscore the need for broader exposure and skill development to enable more comprehensive use of AI in research.

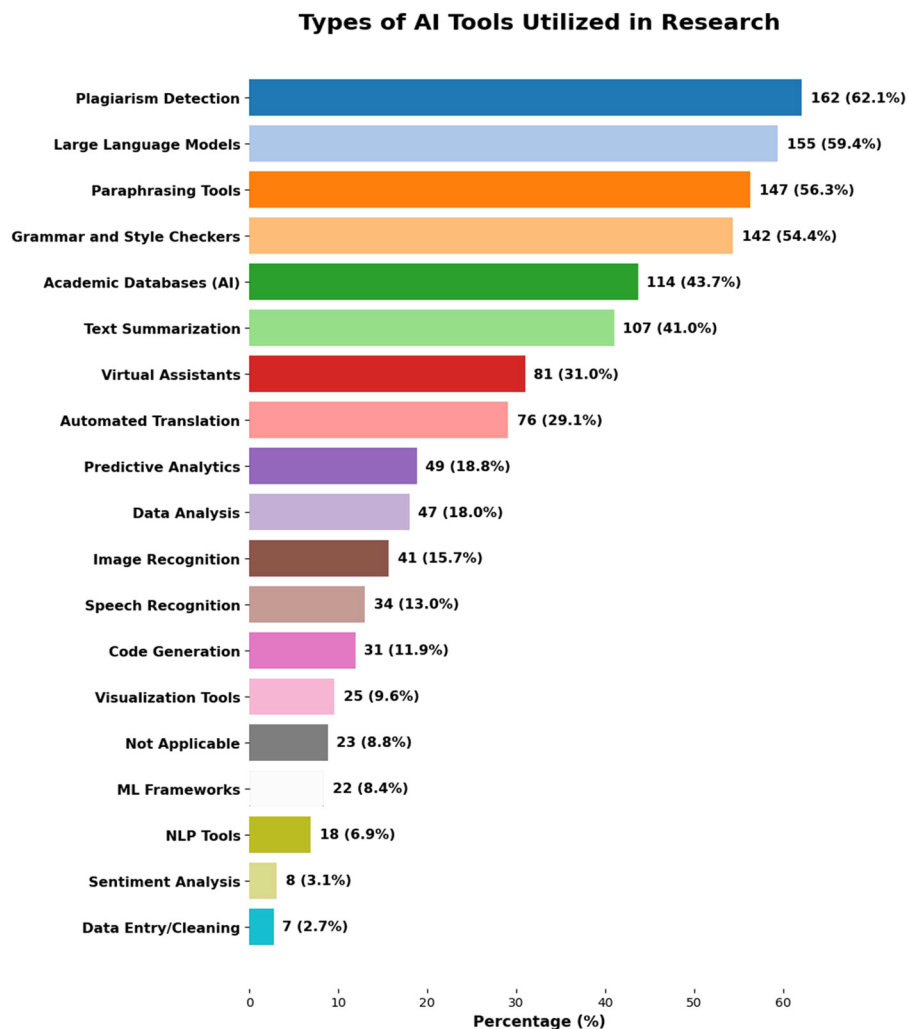


Figure 3: Types of AI tools utilized in research.

4.3 Primary Purposes for Using AI Tools in Research

Figure 4 presents a detailed breakdown of the specific research tasks for which Ph.D. students at BBAU utilize AI tools. The most prominent purpose is research paper writing and editing, reported by 59.8% of respondents. This reflects students' reliance on AI tools like Grammarly and language models to enhance grammar, coherence, and overall academic writing quality, an observation consistent with prior studies (Almassaad et al., 2024; Tokdemir Demirel, 2024).

Closely following is the literature review and synthesis (58.6%), suggesting that AI-powered platforms such as Semantic Scholar and Elicit are instrumental in helping students search, filter, and summarize relevant academic sources. These tools likely reduce the cognitive and time burden typically associated with comprehensive literature reviews (Granjeiro et al., 2025).

A substantial portion of students also reported using AI tools for data analysis and visualization (38.3%) and statistical analysis (34.1%), indicating that a significant number are incorporating tools like Tableau, SPSS, or R in handling research data. This shows a positive trend toward data-driven research, though the figures also imply that many students may still lack training or confidence in using AI for quantitative analysis.

One-fourth of the adoption was seen for tasks such as knowledge extraction and discovery (26.1%), hypothesis generation and testing (17.6%), and data collection and management (16.1%). These uses indicate the subsequent integration of AI into more advanced and exploratory research phases, where tools assist with text mining, predictive modelling, and data scraping.

Lower usage was reported for specialized tasks such as survey design and analysis (15.3%), experimental design (12.6%), and ethics and compliance monitoring (12.3%). This may be due to limited awareness of such AI

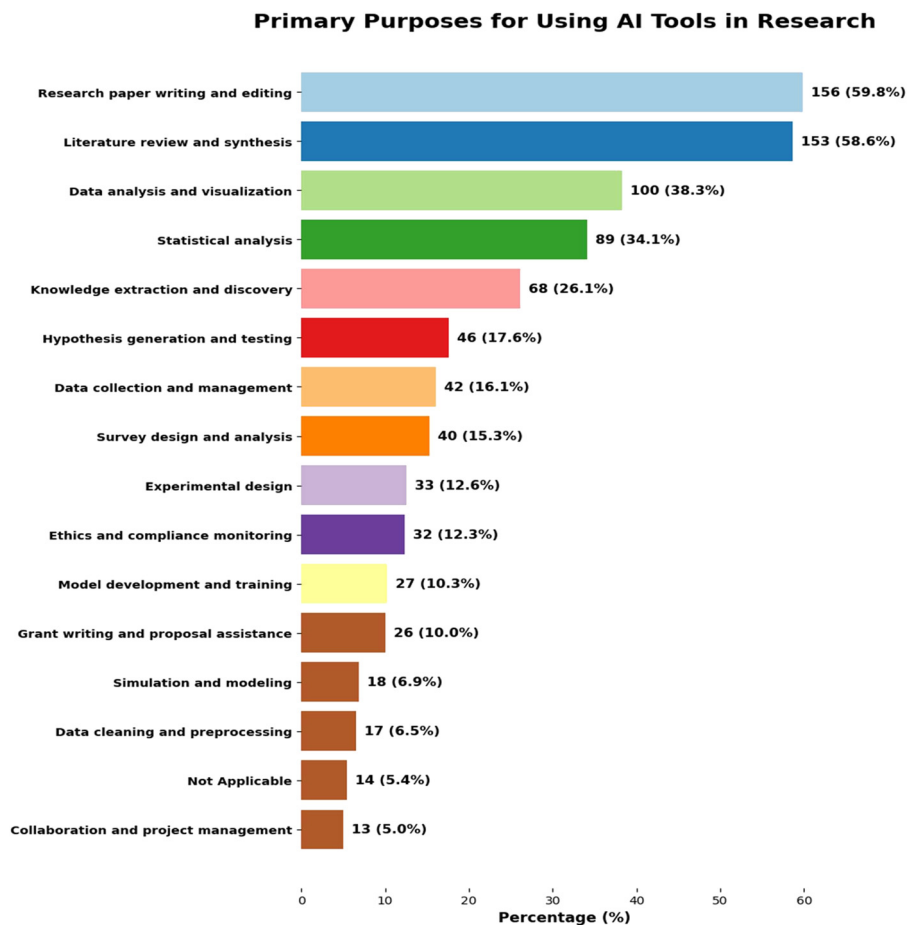


Figure 4: Primary purposes for using AI tools in research.

capabilities or their lesser relevance to many students' research domains. Similarly, tasks involving model development and training (10.3%), simulation and modelling (6.9%), and data cleaning and reprocessing (6.5%) received lower mentions, which could reflect their predominance in technical fields like computer science or engineering.

Only 5% of students reported using AI for collaboration and project management, and 5.4% indicated no current application, suggesting untapped potential for broader AI integration into research workflows beyond writing and analysis.

The data illustrate that AI tools are predominantly used to support core academic tasks such as writing and literature synthesis, with moderate use in data handling and limited use in design, modelling, and project management. These findings point to a need for targeted training to expand AI's use in more complex and strategic aspects of research across disciplines.

4.4 Challenges Hindering AI Tool Adoption in Research

Figure 5 outlines the key barriers perceived by Ph.D. students at BBAU that hinder the effective adoption and use of AI tools in academic research. Among many challenges, the lack of access to AI tools (54%) has the highest issue, indicating that many students face obstacles related to subscription-based software, institutional licensing gaps, and limited tool availability. Followed by lack of knowledge or skills (50.6%), underlining a significant training gap. This finding is in line with the published literature (Chiu, 2025; Jackman et al., 2024), which indicates the role of digital literacy in AI adoption.

Concerns about the reliability and accuracy of AI tools (47.5%) are another prominent issue. Students are concerned about the accuracy of the content generated by AI tools. The findings reflect trust issues as indicated by Han et al. (2025) and Al-Bukhrani et al. (2025). Cost is another barrier, rated by 45.2% of respondents. The cost of licensing fees of premium tools like Turnitin, Grammarly Premium, and advanced AI-based analytics software is costly, particularly with lower-income, data privacy, and security concerns (44.1%). Exposing the challenges around how personal and sensitive research data is handled by AI platforms, especially cloud-

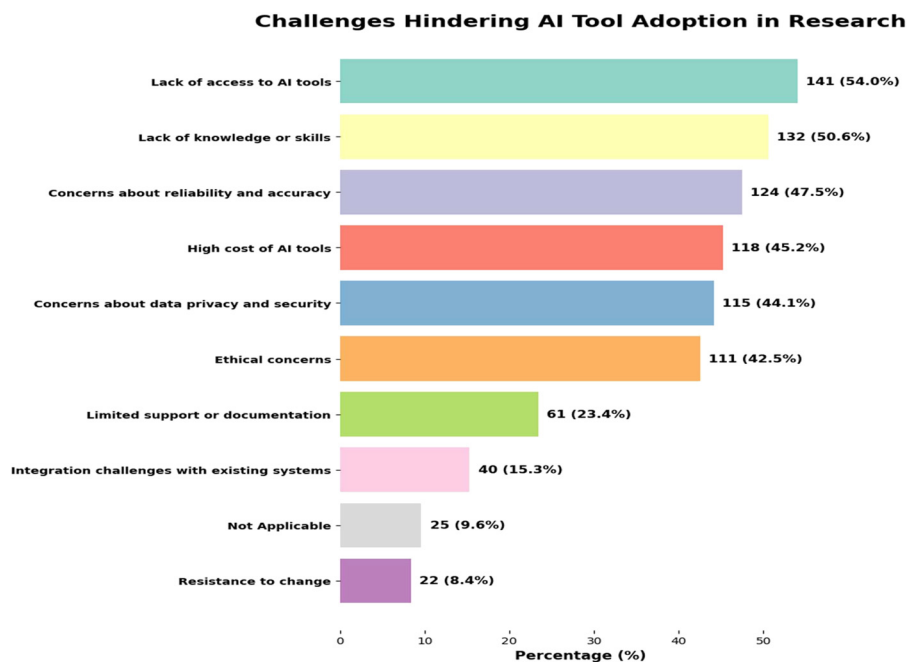


Figure 5: Challenges hindering AI tool adoption in research.

Table 1: KMO and Bartlett's test

KMO measure of sampling adequacy		0.916
Bartlett's Test of Sphericity	Approx. Chi-square	1558.963
	df	45
	Sig.	0.000

based services. Ethical concerns are rated by 42.5% of students, signifying concern about attribution and originality. The findings support legal and academic discussion on authorship, plagiarism, and transparency in AI-assisted writing (Gaffar & Albarashdi, 2025; Glenster et al., 2025).

Limited support or documentation (23.4%) and integration challenges (15.3%) are less frequently reported but still notable. These findings indicate that students lack guidance. Only 8.4% of respondents rated resistance to change, signifying reluctance and attachment to traditional methods. These outcomes indicate that while students use AI in research, they also face challenges such as access, cost, skills, training, and ethical or trust-related issues.

4.5 Factor Analysis of AI Tools Used in Research

Table 1 shows the KMO and Bartlett's test, assessing sampling adequacy and sphericity. The KMO measure is 0.916, indicating the sample is suitable for factor analysis. Bartlett's Test of Sphericity yields a chi-square value of 1558.963, confirming adequate correlations among variables for factor analysis.

Table 2 details the factor analysis of AI tools used in research. It identifies two factors: effectiveness and efficiency. The effectiveness factor, with an eigenvalue of 5.829, accounts for 58.295% of the variance and has a high Cronbach's alpha of 0.889, indicating strong internal consistency. Key items loading on this factor include "AI tools have significantly enhanced the accuracy of my research findings" (0.871) and "AI tools have helped me uncover new insights and perspectives I might have otherwise missed" (0.791). The efficiency factor has an eigenvalue of 0.997, explaining 9.970% of the variance, with a Cronbach's alpha of 0.864, reflecting its reliability. Significant loadings in this category include "AI tools have made my research more innovative and original" (0.835) and "AI tools have helped me stay up-to-date with my field's latest developments" (0.820). The analysis underscores AI tools used in research and enhances effectiveness and efficiency.

Table 3 presents the independent sample *t*-test results of gender with AI tools used in research. The findings indicate that "effectiveness" ($t = 0.159$, $p = 0.874$) and "efficiency" ($t = 0.565$, $p = 0.912$) do not have a significant difference. Indicating that gender difference does not have a difference in using AI tools for research.

Table 4 illustrates the differences in means regarding the utilization of AI tools in research. The analysis indicates that "effectiveness" shows a statistically significant difference in relation to the duration of Ph.D. studies ($F = 3.428$, $p = 0.009$). In contrast, "effectiveness" does not demonstrate significant differences when correlated with age ($F = 0.515$, $p = 0.598$) or the frequency of AI tool usage in research ($F = 1.932$, $p = 0.125$). Likewise, "efficiency" does not reveal significant differences concerning age ($F = 0.894$, $p = 0.410$), the duration of Ph.D. studies ($F = 0.275$, $p = 0.280$), or the frequency of AI tool usage in research ($F = 1.983$, $p = 0.117$). The findings indicate that there is a variation in the utilization of AI tools for research effectiveness among research scholars, which correlates with the number of years they have been enrolled.

4.6 Factor Analysis of AI Tools in Knowledge Creation

Table 5 shows the KMO and Bartlett's test results, assessing sampling adequacy and sphericity. The KMO measure is 0.944, indicating the sample is suitable for factor analysis. Bartlett's Test of Sphericity yields a chi-square value of 1918.649, confirming adequate correlations among variables for factor analysis.

Table 2: Factor analysis of AI tools used in research

Factors	Factor loading	Eigen values	% Of variance	Cronbach's alpha
Effectiveness		5.829	58.295	0.889
AI tools have significantly enhanced the accuracy of my research findings	0.871			
AI tools have helped me uncover new insights and perspectives I might have otherwise missed	0.791			
AI tools have improved the efficiency of my data analysis and visualization	0.783			
AI tools have made it easier for me to identify and correct errors in my research	0.698			
AI tools have helped me to strengthen the theoretical foundation of my research	0.633			
Efficiency		0.997	9.970	0.864
AI tools have made my research more innovative and original	0.835			
AI tools have helped me stay up-to-date with my field's latest developments	0.820			
AI tools have helped me to collaborate more effectively with other researchers	0.726			
I am highly satisfied with the effectiveness of AI tools in supporting my research	0.679			
AI tools have improved the quality of my writing and communication	0.573			

Table 3: Differences in AI tools used in research based on gender

AI tools used in research	Male	Female	t-value	p-value
Effectiveness	3.6256	3.6109	0.159	0.874
Efficiency	3.4571	3.4469	0.565	0.912

Table 4: ANOVA on AI tools used in research

Variable	Indicator	Mean	F-value	p-value
Effectiveness				
Age	23–24	3.6105	0.515	0.598
	25–26	3.5512		
	27 and above	3.6537		
Year of Ph.D.	1st year	3.6730	3.428	0.009
	2nd year	3.5933		
	3rd year	3.7161		
	4th year	3.5333		
	5th year or more	3.0000		
Frequency of AI tool usage in research	Daily	3.7863	1.932	0.125
	Weekly	3.6031		
	Monthly	3.4667		
	Occasionally	3.5352		
Efficiency				
Age	23–24	3.4632	0.894	0.410
	25–26	3.3610		
	27 and above	3.4975		
Year of Ph.D.	1st year	3.6730	1.275	0.280
	2nd year	3.5933		
	3rd year	3.7161		
	4th year	3.5333		
	5th year or more	3.0000		
Frequency of AI tool usage in research	Daily	3.6164	1.983	0.117
	Weekly	3.4246		
	Monthly	3.5333		
	Occasionally	3.3463		

Table 5: KMO and Bartlett's test

KMO measure of sampling adequacy		0.944
Bartlett's test of sphericity	Approx. chi-square	1918.649
	df	45
	Sig.	0.000

Table 6 details the factor analysis of AI Tools on knowledge creation. It identifies two factors: creativity and innovation. The creativity factor, with an eigenvalue of 6.616, accounts for 66.160% of the variance and has a high Cronbach's alpha of 0.915, indicating strong internal consistency. Key items loading on this factor include "AI tools help to understand complex concepts or theories more easily" (0.843). The innovation factor has an eigenvalue of 0.681, explaining 6.809% of the variance, with a Cronbach's alpha of 0.878, reflecting its reliability. Significant loadings in this category include "AI tools motivate to engage in lifelong learning and continue to develop knowledge and skills" (0.8885). The analysis underscores AI Tools in knowledge creation and enhances creativity and innovation during research.

Table 6: Factor analysis of AI tools in knowledge creation

Factors	Factor loading	Eigen values	% of variance	Cronbach's alpha
Creativity		6.616	66.160	0.915
AI tools help to understand complex concepts or theories more easily	0.843			
AI tools help to connect different ideas or concepts in research	0.788			
AI tools help to synthesize information from various sources more effectively	0.733			
AI tools help to apply knowledge to solve complex problems more effectively	0.701			
AI tools stimulate critical thinking skills and help to evaluate information more critically	0.688			
AI tools help to explore a wider range of research topics or perspectives	0.567			
Innovation		0.681	6.809	0.878
AI tools motivate to engage in lifelong learning and continue to develop knowledge and skills	0.888			
AI tools help to retain information better and recall it more easily	0.760			
AI tools help to delve deeper into specific research areas	0.683			
AI tools help to conduct research more efficiently by providing quick access to relevant information	0.603			

Table 7: Differences in AI tools in knowledge creation based on gender

AI tools on knowledge creation	Male	Female	<i>t</i> -value	<i>p</i> -value
Creativity	3.5038	3.5573	−0.566	0.572
Innovation	3.4906	3.5078	−0.179	0.858

Table 8: ANOVA on AI tools in knowledge creation

Variable	Indicator	Mean	F-value	p-value
Creativity				
Age	23–24	3.4825	0.729	0.483
	25–26	3.4533		
	27 and above	3.5750		
Year of Ph.D.	1st year	3.5820	2.418	0.049
	2nd year	3.6111		
	3rd year	3.5914		
	4th year	3.3457		
	5th year or more	3.0417		
Frequency of AI tool usage in research	Daily	3.6849	1.583	0.194
	Weekly	3.5205		
	Monthly	3.5000		
	Occasionally	3.4352		
Innovation				
Age	23–24	3.4737	0.049	0.952
	25–26	3.4817		
	27 and above	3.5109		
Year of Ph.D.	1st year	3.5675	2.034	0.090
	2nd year	3.4417		
	3rd year	3.5524		
	4th year	3.4074		
	5th year or more	3.0156		
Frequency of AI tool usage in research	Daily	3.6747	2.044	0.108
	Weekly	3.5000		
	Monthly	3.4500		
	Occasionally	3.3866		

Table 7 displays the results of the independent sample *t*-test examining the relationship between gender and the use of AI tools in knowledge creation. The findings reveal that there is no significant difference in “creativity” ($t = -0.566$, $p = 0.572$) and “innovation” ($t = -0.179$, $p = 0.858$). This suggests that gender does not influence the utilization of AI tools used in knowledge creation.

Table 8 illustrates the results concerning the differences in means related to the utilization of AI tools in the process of knowledge creation. The analysis indicates that “creativity” exhibits a statistically significant difference in relation to the duration of Ph.D. studies ($F = 2.418$, $p = 0.049$). In contrast, “creativity” does not show significant differences when correlated with age ($F = 0.729$, $p = 0.483$) or the frequency of AI tool usage in

Table 9: KMO and Bartlett’s test

KMO measure of sampling adequacy		0.949
Bartlett’s test of Sphericity	Approx. Chi-Square	2272.820
	df	45
	Sig.	0.000

Table 10: Factor analysis of AI tools in inventive thinking

Factors	Factor loading	Eigen values	% of variance	Cronbach's alpha
Creative thinking		7.095	70.949	0.930
AI tools have encouraged me to take more risks and experiment with new approaches	0.870			
AI tools have improved my ability to think critically and evaluate different options	0.784			
AI tools have had a positive impact on my creative thinking and problem-solving abilities	0.726			
AI tools have helped me to become more innovative in my research	0.720			
AI tools have helped me to approach problems from different perspectives	0.621			
AI tools have helped me to identify new patterns or connections that I might have otherwise missed	0.590			
Novelty		.551	5.508	0.910
AI tools have stimulated my imagination and encouraged me to think creatively	0.841			
AI tools have helped me to develop a more open and flexible mindset	0.836			
AI tools have made it easier for me to generate novel and original ideas	0.763			
AI tools have inspired me to think outside the box and explore unconventional solutions	0.594			

Table 11: Differences in AI Tools in inventive thinking based on gender

AI Tools on inventive thinking	Male	Female	<i>t</i> -value	<i>p</i> -value
Creative thinking	3.4524	3.4661	−0.140	0.889
Novelty	3.4135	3.3730	0.401	0.689

research ($F = 1.583$, $p = 0.194$). Likewise, “innovation” does not demonstrate significant differences with respect to age ($F = 0.049$, $p = 0.952$), the duration of Ph.D. studies ($F = 2.034$, $p = 0.090$), or the frequency of AI tool usage in research ($F = 2.044$, $p = 0.108$). The findings indicate that there is a variation in the utilization of AI tools for creativity among research scholars, which correlates with the number of years they have been enrolled.

4.7 Factor Analysis of AI Tools in Inventive Thinking

Table 9 shows the KMO and Bartlett’s test results, assessing sampling adequacy and sphericity. The KMO measure is 0.949, indicating the sample is suitable for factor analysis. Bartlett’s test of sphericity yields a chi-square value of 2272.820, confirming adequate correlations among variables for factor analysis.

Table 10 details the factor analysis of AI Tools on inventive thinking. It identifies two factors: creative thinking and novelty. The creative thinking factor, with an eigenvalue of 7.095, accounts for 70.949% of the variance and has a high Cronbach’s alpha of 0.930, indicating strong internal consistency. Key items loading on this factor include “AI tools have encouraged me to take more risks and experiment with new approaches” (0.870). The novelty factor

Table 12: ANOVA on AI tools in inventive thinking

Variable	Indicator	Mean	F-value	p-value
Creative thinking				
Age	23–24	3.3070	0.389	0.678
	25–26	3.4837		
	27 and above	3.4646		
Year of Ph.D.	1st year	3.5556	0.4161	0.003
	2nd year	3.4111		
	3rd year	3.5672		
	4th year	3.1728		
	5th year or more	2.8542		
Frequency of AI tool usage in research	Daily	3.5502	0.454	0.714
	Weekly	3.4385		
	Monthly	3.4000		
	Occasionally	3.4182		
Novelty				
Age	23–24	3.3421	0.174	0.840
	25–26	3.3598		
	27 and above	3.4172		
Year of Ph.D.	1st year	3.4187	1.897	0.111
	2nd year	3.4583		
	3rd year	3.4960		
	4th year	3.2500		
	5th year or more	2.9219		
Frequency of AI tool usage in research	Daily	3.4418	0.621	0.602
	Weekly	3.3308		
	Monthly	3.6167		
	Occasionally	3.3681		

has an eigenvalue of 0.551, explaining 5.508% of the variance, with a Cronbach's alpha of 0.910, reflecting its reliability. Significant loadings in this category include “AI tools have stimulated my imagination and encouraged me to think creatively” (0.841). Overall, the analysis underscores AI Tools in inventive thinking and enhances creative thinking and novelty during research.

Table 11 presents the outcomes of the independent sample *t*-test that investigates the correlation between gender and the application of AI tools in creative thinking. The results indicate that there is no statistically significant difference in “creative thinking” ($t = -0.140$, $p = 0.889$) and “novelty” ($t = 0.401$, $p = 0.689$). This implies that gender does not affect the use of AI tools in the context of inventive thinking.

Table 12 illustrates the results concerning the differences in means related to the utilization of AI tools in the process of inventive thinking. The analysis indicates that “creative thinking” exhibits a statistically significant difference in relation to the duration of Ph.D. studies ($F = 0.4161$, $p = 0.003$). In contrast, “creative thinking” does not show significant differences when correlated with age ($F = 0.389$, $p = 0.678$) or the frequency of AI tool usage in research ($F = 0.454$, $p = 0.714$). Likewise, “novelty” does not demonstrate significant differences with respect to age ($F = 0.174$, $p = 0.840$), the duration of Ph.D. studies ($F = 1.897$, $p = 0.111$), or the frequency of AI tool usage in research ($F = 0.621$, $p = 0.602$). The findings indicate that there is a variation in the utilization of AI tools for creative thinking among research scholars, which correlates with the number of years they have been enrolled.

4.8 Challenges and Limitations in Using AI Tools for Creative Tasks

Figure 6 presents critical insights into the specific challenges Ph.D. students at BBAU face when using AI tools for creative research tasks such as idea generation, academic writing, and conceptual development. The

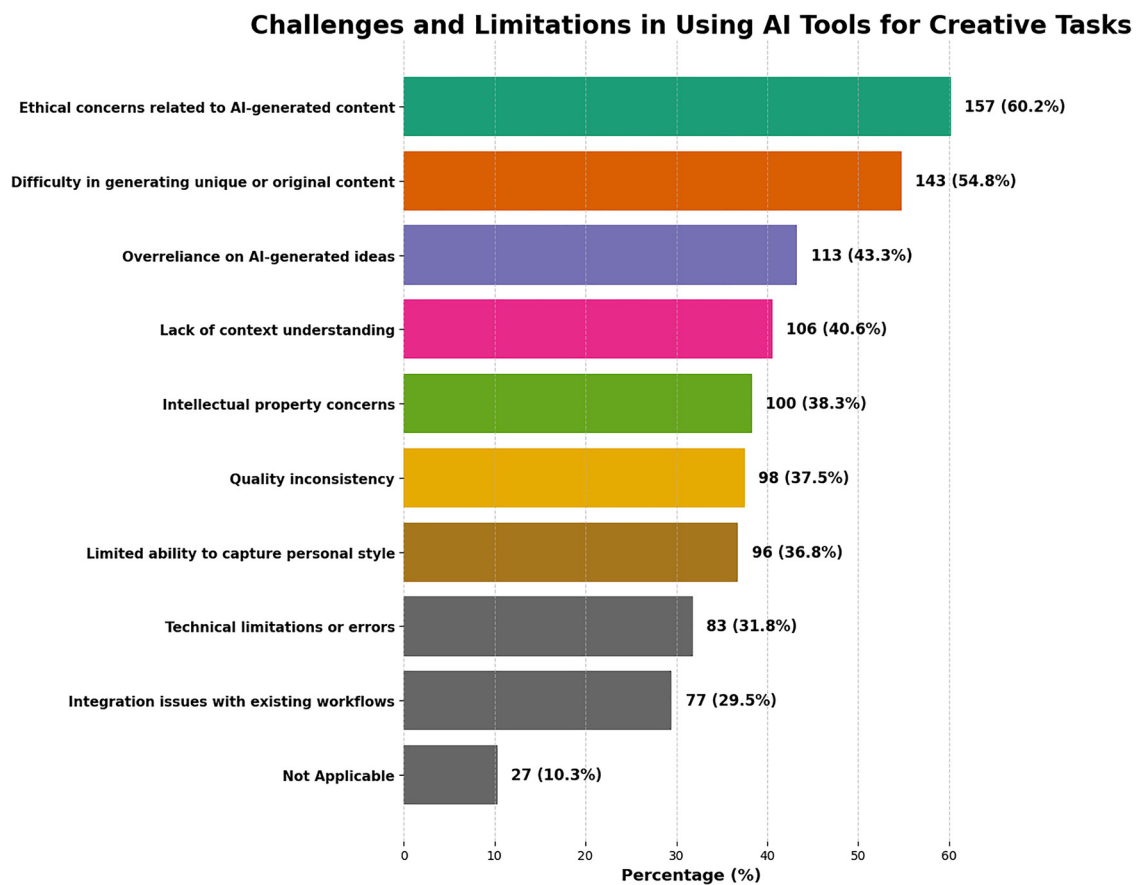


Figure 6: Challenges and limitations in using AI tools for creative tasks.

notable concern is ethical uncertainty (60.2%). This consists of concern about authorship attribution, plagiarism, and the misrepresentation of AI-generated content as original work. The findings support warnings of Glenster et al. (2025) and Gaffar and Albarashdi (2025) on originality and integrity. Difficulty in generating unique or original content using AI tools is reported by 54.8% of students, indicating that AI outputs often lack novelty or creativity (Kostas et al., 2025).

The issue of overreliance on AI-generated ideas is rated by 43.3%. This issue underscores the potential for reducing personal creativity and diminishing the development of independent research skills and academic identity (Pham, 2025; Sussha et al., 2024). Lack of contextual understanding (40.6%) is another significant limitation. The findings can affect the depth and relevance of AI-assisted writing in humanities and social science research, where context sensitivity is important. Intellectual property concerns (38.3%) are another issue signifying uncertainty over ownership of AI-generated text. The findings support the debates on the copyright status of non-human-authored content (Kretschmer et al., 2024; Zhuk, 2024).

Quality inconsistency (37.5%) and the limited ability to capture personal writing style (36.8%) are other challenges indicating students' dissatisfaction with the coherence, tone, and alignment of AI outputs. Technical errors (31.8%) and workflow integration issues (29.5%) suggest that AI tools may produce factually inaccurate results. Only 10.3% of students rated that these challenges were not applicable to them. AI tools are widely used for enhancing research creativity; at the same time, there are challenges such as ethical ambiguities, originality concerns, limited contextual awareness, and stylistic rigidity. These challenges and limitations indicate the significance of orientation, academic guidelines, and user awareness to guarantee that AI supports, rather than substitutes, human creativity in scholarly research.

5 Discussion

This study examines the adoption of AI in academic writing and research among Ph.D. students at BBAU.

5.1 AI Tool Adoption and Usage Purposes

The study outcomes indicated a high rate of AI tool adoption, with 91.2% of students reporting usage in research, indicating a growing integration of AI in education (Golan and Azoulay, 2023; Khalifa and Albadawy, 2024). Plagiarism detection software (62.1%), LLMs (59.4%), and paraphrasing tools (56.3%) were among the most commonly used tools, indicating a strong sense of maintaining academic integrity, refining language, and enhancing clarity in scholarly writing. The main objectives for using AI tools consist of research content writing and editing (59.8%), literature review and synthesis (58.6%), and data analysis and visualization (38.3%). These outcomes are aligned with the published literature (Li et al., 2025; Tokdemir Demirel, 2024; Yousef et al., 2025), which signifies the role of AI in reducing cognitive load, improving time efficiency, and facilitating data-driven insights.

5.2 Perceived Effectiveness and Efficiency

Factor analysis on AI tools used in research generates two factors, i.e. effectiveness and efficiency of research work. Students consent that these tools improved the accuracy of findings, enabled identification of novel insights, streamlined error detection, and strengthened theoretical underpinnings. The findings support Al-Bukhrani et al. (2025) and Chiu (2025) results, indicating that AI tools improve writing quality and boost research productivity, especially for non-native English speakers and early-career scholars. Fascinatingly, effectiveness evaluation differs significantly by year of Ph.D. study but not by gender or age. Third-year students exhibited higher perceived gains, probably owing to research engagement and maturity. The outcome supports earlier findings of Dai et al. (2023) and Bista and Bista (2025), who found that the research stage regulates the depth and outcome of AI tool engagement.

5.3 AI's Role in Knowledge Acquisition, Creativity, and Innovation

Factor analyses on AI Tools in knowledge creation identified creativity and innovation. The findings indicate strong associations between AI usage and students' capability to comprehend complex theories, connect ideas across disciplines, and process diverse information sources. These findings support that AI tools are not only support mechanisms but catalysts for intellectual engagement and deeper learning (Almassaad et al., 2024; Granjeiro et al., 2025). AI tools enhance creativity, critical evaluation, and generate new ideas. AI tools like ChatGPT and Elicit promote originality and innovation (Gayed, Carlon, Oriola, & Cross, 2022; Pham, 2025). At the same time, perceived creativity and innovation differ drastically based on the students' year of study. First- and third-year scholars indicate higher gains compared to final-year students, probably because of openness to experimentation and evolving research design needs (Liu et al., 2015; Mbatha, 2024).

5.4 Barriers and Ethical Considerations

The application of AI tools in research brings many benefits, but at the same time, there are several obstacles that hamper AI adoption. The main barriers that hamper AI adoption include lack of access (54%), limited digital literacy (50.6%), concerns about reliability (47.5%), cost (45.2%), and ethical concerns (42.5%). The findings support earlier findings, which identified that institutional support, training, and ethical clarity are essential enablers of effective AI use (Jackman et al., 2024; Klimova et al., 2023; Smerdon, 2024). Barriers concerning creative tasks were also notable, such as ethical dilemmas (60.2%), difficulty generating original content (54.8%), and concerns over intellectual property (38.3%), indicating apprehensiveness about authorship, plagiarism, and diminished ownership. The findings support previous findings that called for reforms in copyright law and institutional guidance to delineate boundaries between human-authored and AI-generated work (Gaffar and Albarashdi, 2025; Glenster et al., 2025). Fascinatingly, student opposition to using AI tools was owing to a lack of policy, guidance, and training, supporting Al-Bukhrani et al. (2025) findings, who proposed that favourable attitudes and social norms were not enough to ensure adoption in the absence of structural support and ethical standards.

5.5 Theoretical Implications

The outcomes from this study offer a significant understanding of technology adoption. The TAM (Davis, 1989), factors, i.e. perceived usefulness and ease of use, are evident in this study by the variables such as ethical perception, data privacy, and content accuracy (Zhang et al., 2025). Likewise, the IDT's (Rogers, 1962) factors of compatibility and trainability were applicable among early researchers' observations with various AI tools. At the same time, the UTAUT factors, PE, and facilitating term seemed relevant but incomplete in apprehending students' AI incidents. External factor impacts like institutional AI guidelines, subscription mode, and pedagogical instruction surfaced as a censorious cause (Gutiérrez-Leefmans et al., 2025).

6 Conclusion

This study investigates the adoption and effectiveness of AI in academic writing and research among Ph.D. students at BBAU. The outcome underscores that AI tools are extensively used for research purposes. Scholars used ChatGPT, Grammarly, Turnitin, and Elicit for writing, literature review, improving language and checking plagiarism. The findings confirmed that AI tools help in the generation of ideas among mid-level Ph.D. scholars.

In spite of many advantages that AI tools offer, there are many issues that need to be addressed, such as the absence of orientation, ethical guidelines, content originality, and authorship. These challenges indicate the need for institutional training, guidelines to encourage equitable access, ethical use, and AI literacy. Without which, scholars over-rely on AI tools and reduce creativity, and ultimately violate academic integrity.

The findings from this study are from a single Indian university; thus, their generalizability must be approached cautiously. The outcome for self-reported data and quantitative analysis may not capture the depth of individual experience. A mixed-methods and qualitative study is recommended to comprehend in-depth experiences. Moreover, comparative studies among universities and longitudinal studies can also be conducted to examine long-term impacts on academic performance, writing quality, and research innovation.

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Conflict of interest: The authors state no conflict of interest.

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