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Research Article

Leveraging AI and Automation in Research Management: A Path to Enhanced Productivity

Tarachand Verma[1*], Vinay Dwivedi[2], Chhaya Kumari[3], Senthil Kumar V.S[4], Shagufta Praveen[5], Dr Anisha[6]
[1*]Assistant Professor, Galgotias University, trchnd22@gmail.com
[2]Assistant Professor, Galgotias University, Greater Noida, Vinaydwvd@gmail.com
[3]Assistant professor, Chandigarh University, Gharuan, Dadwalchhaya@gmail.com
[4]Assistant professor, Department of Management studies, Sona college of Technology, Salem, Tamil Nadu, India, senthilcsfate@gmail.com
[5]Department of Computer Science and Engineering, Uttaranchal Institute of Technology, Uttaranchal University, Dehradun, India, shaguftasaeed125@gmail.com
[6]Assistant Professor, Chandigarh Group of Colleges Jhanjeri, Mohali, Punjab, India -140307, Chandigarh School of Business, Department of Management, dr.anishapuri.95@gmail.com

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ABSTRACT

Academic research is being slowed down by too much data, unneeded paperwork and a lack of streamlined processes. Since researchers are facing more work and less time, AI and automation are now considered helpful in making tasks easier and more efficient. The research explores the ways AI can assist in managing research by merging a conceptual framework known as the AI-Augmented Research Lifecycle with observations from a relevant field. The model suggests that AI tools can be used during the literature search, note-taking, preprocessing data, writing and collaborating with others. 500 high-cognition knowledge workers' behavior was analyzed using regression and correlation to examine the validity of the framework. The study reveals that using AI leads to higher productivity and success in tasks, with only a small effect on the mind's workload. This information suggests that AI helps improve academic work, rather than creating additional challenges for students, so it should be considered for use in schools. It provides a clear and research-based approach to understanding how intelligent systems can boost the success and productivity of today's research.

Keywords: Artificial Intelligence, Research Productivity, Automation, Human–AI Collaboration, Empirical Validation

INTRODUCTION

Nowadays, since academia is both digital and involves several fields, research management is more detailed and demanding. The process which used to be limited to planning and carrying out the project, now involves regularly coordinating, overseeing data, collaborating, monitoring compliance and publishing results. Because of the rise in science and the growth of problems in funding, ethics and methods, research teams have to overcome many difficulties in managing their duties. Among them are data fragmentation, doing the same tasks twice, issues with communication and the need to document things manually (Marques, 2018). The time spent on research administration is increasing which often takes away from the time scientists have for new findings and inventions (Dove & Garattini, 2018).

As research processes become less efficient, more attention is being given to how AI and automation can help improve how research is done. In software development, healthcare and finance, AI has helped businesses improve their performance by handling routine tasks, making decisions quickly and reducing mistakes. For instance, when used in software engineering, IntelliCode Compose and Copilot help by suggesting relevant code, handling repetitive actions and making debugging much easier (Svyatkovskiy et al., 2020; Tatineni, 2024). Because of such tools, developers can concentrate on more important design and problem-solving which is similar to what researchers do.

It is now clear that AI is being used more in research activities and the scholarly communication process. ChatGPT, Elicit and semantic search engines help researchers find important literature, restate text, check grammar and summarize ideas (Mahapatra et al., 2024). They work best in both the beginning and ending stages of research such as when formulating a topic, reading literature and writing the manuscript, since these parts require a lot of mental and physical effort. The survey found that academic researchers in Andhra Pradesh are using these tools more often, mainly to improve their writing and manage their references (Bairagi &

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Lihitkar, 2025). It is clear that researchers are now using AI for more than just access and storage, as they rely on it for reasoning, drafting, editing and validation.
Still, one major issue is that AI tools are not used fully across the entire research process. Most of the time, users apply AI only in certain tools and not throughout the entire system. Often, scientists use these platforms separately in different stages, rather than using AI throughout their entire process. Additionally, there is not much research that looks at how AI actually affects academic productivity. While AI in science is highly praised by theory, not many studies have measured its actual impact on productivity (Cockburn et al., 2018; Jordan & Mitchell, 2015). If automation is not proven, its advantages may be overstated or not useful in practice.
However, both academic and business experts continue to believe AI will have a major impact. Brynjolfsson and McAfee (2017) suggest that intelligent systems can support human judgment in making complex decisions which is very relevant to academic research. Makridakis (2017) explains that AI helps redesign entire workflows by applying dynamic learning, making predictions and being able to handle errors. Having these qualities in research management could result in faster project cycles, less repetition and better use of intellectual resources.
Furthermore, research in this field highlights that trust and transparency should be built into any collaboration between humans and AI. According to Virvou et al. (2024), their VIRTSI trust dynamics model revealed that user satisfaction with ChatGPT and similar AI agents mostly depends on how well the task is aligned and how useful the user believes the system to be. This result matters most in schools and universities, where people are still doubtful about AI's reliability. When researchers begin to use AI tools, it is important to focus on how humans trust these new systems.
Research management being so complex, continuous and mentally demanding, AI and automation offer a quick and effective solution. Still, to make the most of their abilities, companies must rethink how they divide, manage and track tasks. Now that there are more AI-based platforms and datasets available, we can assess the effects of AI on productivity using actual data instead of just theories. Based on how software is developed, we can predict the effects of AI on academic research. It allows us to understand how the AI performs in terms of task achievement, productivity and mental load.
All in all, AI and automation are changing what can be done and how tasks are coordinated in academic research. While first steps are encouraging, the next step is to check the findings and integrate them into the research process. The study aims to fill the gap between theoretical promises and actual results in research management.

OBJECTIVES

The aim of this study is to examine whether artificial intelligence and automation can benefit the management of research. The purposes are:
1.**To develop a conceptual framework** that outlines how AI and automation tools can be systematically integrated across various stages of the research lifecycle, including literature review, data management, writing, and project coordination.
2. **To empirically evaluate the impact of AI usage on productivity outcomes**, using real-world data from a related cognitive domain (software development) as a proxy for academic research performance, focusing on metrics such as task success, output volume, and cognitive load

LITERATURE REVIEW

The use of AI in academic research has allowed for more efficient work, improved organization and better communication among scholars. AI-based tools are now commonly used in writing papers, finding literature, planning research and reviewing the work of others. ChatGPT, Scite and Elicit are helping researchers write, improve and substantiate their arguments. They indicate that, with the help of AI, the process of reviewing literature and creating evidence can be completed much faster and with greater detail. In a similar way, Mahapatra, Gayan and Jamatia (2024) state that AI is becoming more important for scholarly communication, helping with automatic summarization and advanced generation of citation contexts. Lee et al. (2024) go on to explore this area by suggesting that intelligent writing assistants should include semantic suggestions, help with forming arguments and the ability to adjust tone for each writer, as such features can enhance academic writers' cognitive efficiency.
As academic writing has progressed, so has the popularity of automation tools in other parts of research. For instance, electronic lab notebooks (ELNs) are now available as replacements for paper-based lab notebooks. Kanza et al. (2017) discuss ELNs and claim that using them guarantees accurate reproducibility and proper

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storage of data, as well as connecting all data, protocols and metadata automatically. As a result, manual mistakes are reduced and team members can work more closely together in many different fields. In areas where lots of data is used, automatic data curation, metadata recognition and scheduling helpers are assisting with daily research tasks, with very little human effort. Singh et al. (2024) explain that automation with AI in research helps both complete routine tasks quickly and make predictions which strengthens the process and decision-making.

In software development which involves thinking deeply and often repeating work, AI has helped make the process more efficient. Tools such as GitHub Copilot and transformer-based models help developers generate code and detect any issues in it. Sherje (2024) shows that these tools help teams develop software more efficiently by speeding up the process and reducing the time spent on debugging. Researchers also rely on AI for data analysis, writing reports and simulating hypotheses which are all similar in terms of the thinking and processes needed. According to Davenport and Ronanki (2018), not only is AI used in businesses and technology to automate work, but it is also applied to assist people in decision-making which is changing how productivity is measured.

Even though AI is promising, there is not much research available on how it influences productivity in academic settings. Even though many have adopted data tools, there are not many reviews of their results. Van Noorden and Perkel (2023) report that while researchers are more excited about AI tools, many still doubt their reliability, ethics and impact on academic standards. While AI applications are thought to be convenient and save time, many researchers also worry about their possible misuse and overuse. Heaven (2019) adds that deep learning models within AI can easily be tricked which suggests that they might not be reliable when used for important activities like peer review or conducting experiments.

Moreover, AI is being explored in relation to how it affects students' learning and thinking skills in schools. Feng (2025) reported in his study that using AI when learning languages helped students understand better and complete tasks with ease. Even though this study was conducted in an educational setting, the results can be applied to situations where researchers must read, organize and write as mentally demanding tasks. By freeing researchers from routine tasks, AI could greatly help them improve their research work and increase their productivity.

We must also consider how AI is impacting the integrity of research. Van Aert et al. (2023) highlight that COVID-19 preprints have more errors in their statistics compared to the same studies that were later peer-reviewed. AI may be helpful in discovering such errors, but it could also cause more errors if it is not correctly watched. So, it is vital to ensure AI is used responsibly and transparently, especially as these tools are being added to academic systems.

In short, research literature suggests that AI is affecting writing, review, project management and coding, yet there is not enough evidence to show how it impacts research productivity overall. It is obvious that AI and automation can help, but to advance past early trials, scientists should test how they influence academic work in various fields.

CONCEPTUAL FRAMEWORK

The AI-Augmented Research Lifecycle

Because research requirements are now more complex, it is obvious that using traditional, manual methods to manage academic tasks is no longer enough. Today's research field is marked by a flood of data, teamwork among researchers, strict rules for publishing and paperwork. As a result, we must rethink the way research is conducted, mainly because AI is improving so rapidly. Here, we introduce the AI-Augmented Research Lifecycle, a model that helps integrate AI into the main steps of managing academic research. It combines the use of technology with the benefits of theory, guiding researchers to improve the research process.

The AI-Augmented Research Lifecycle Model

The research process is seen as a repeating system that involves five main parts and each part can be improved by using AI in different ways. Here, AI tools are seen as part of the knowledge creation process, able to assist people and keep academic standards intact.

1. AI-Assisted Literature Search

Any research project begins with reviewing a lot of literature which has become much more difficult due to the rising amount of scholarly works. Transformer-based language models are now used by semantic search engines like Elicit and Connected Papers to understand the meaning of a query, add relevant ideas and return highly accurate search results. They are not limited to keyword searches; they also produce concept maps, rank

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the best evidence and follow how citations are linked. AI makes it possible to complete comprehensive literature mapping much faster and with less bias.

2. Automated Note-Taking and Summarization

After finding the literature, reading, marking and taking away key points can become a challenge for the mind. Researchers can use ChatGPT, Notion AI and Otter.ai to quickly process a lot of content by converting it into concise and well-organized summaries. Furthermore, using auto-tagging and semantic annotation allows for better organization of information, so it is simpler to use and process later on. By using this automation, retention is improved and it becomes easier to work together in groups where everyone needs to understand the same thing.

3. Data Preprocessing and Structuring with Machine Learning

For research to be excellent, the data used should be well-organized and error-free. Still, preparing data for analysis can be lengthy and may result in errors. With AutoML, TensorFlow Data Validation and Google Cloud DataPrep, outliers can be automatically spotted, strategies for handling them can be suggested and the schema can be checked for consistency. Some platforms are connected to lab systems and databases, allowing for complete automation of the process and changing raw data into forms ready for analysis, with a clear history. It makes the process more efficient and helps maintain the required standard for data integrity.

4. AI-Enhanced Writing, Editing, and Formatting

Writing a manuscript forces the author to use their mind carefully, ensuring it is precise and written in a proper style. Grammarly, Paperpal, Trinka and LaTeX-aware code editors now have features that help with grammar, improve the flow of your writing, suggest better vocabulary and adjust the tone. Most importantly, the formatting assistants in journal submission portals can automatically fix references, change sections to stay within word limits and point out any instances of not following the publisher's guidelines. They lessen the mental effort needed to revise work, helping researchers pay more attention to their arguments' originality and organization.

5. Automated Version Control and Intelligent Collaboration

Since research today is done in teams, it requires everyone to work together in real time and stay synchronized. Notion AI, Slack GPT and GitHub Copilot help with version control, tracking issues and dividing tasks by making predictions, suggesting answers and automating repetitive jobs. They keep track of all changes and allow users to communicate with each other asynchronously using notifications and chat summaries. They prevent misunderstandings, help everyone to coordinate and encourage teams to plan flexibly.

Table 1: AI Functionalities Across the Research Lifecycle

Lifecycle Stage	AI Tools & Technologies	Enriched Benefits
Literature Search	Semantic AI, citation graphs, contextual LLM queries	Accelerated discovery, reduced bias, conceptual mapping
Note-Taking & Summarization	NLP summarizers, audio transcription bots, semantic highlighters	Comprehension enhancement, reduced cognitive overload
Data Preprocessing	AutoML, anomaly detection, schema validators	Higher data quality, reproducibility, time savings
Writing & Formatting	AI grammar editors, formatting bots, argument assistants	Clarity, style consistency, reduced revision cycles
Collaboration & Version Control	Smart schedulers, AI-enhanced repositories, chat summarizers	Seamless coordination, traceability, workload distribution

Theoretical Benefits of AI Integration

Time Efficiency

Thanks to AI, researchers are able to focus on new ideas rather than on repetitive paperwork. Automating these tasks allows you to save time and still maintain high quality.

Cognitive Relief and Focus

Cognitive psychology finds that when extraneous load is reduced, problem solving becomes easier. With the help of AI, scholars can focus on the main aspects of their work as they no longer need to handle repetitive and time-consuming tasks.

Journal of Information Systems Engineering and Management
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Reproducibility and Research Integrity

The use of AI in documentation ensures that all records are traceable and can be easily replicated. Using audit trails, automatic data logs and standard formatting supports meeting open science requirements and ensures outputs are reliable.

AI is being used throughout research and it not only saves time, but also reduces the need for researchers to remember details and allows for better reproducibility. In Figure 1, the model outlines five main stages of the research process—literature search, summarization, data processing, writing/editing and collaboration—and gives each stage its own AI tool. These steps are linked together, as the work of scholars repeats and smart tools offer continuous feedback.

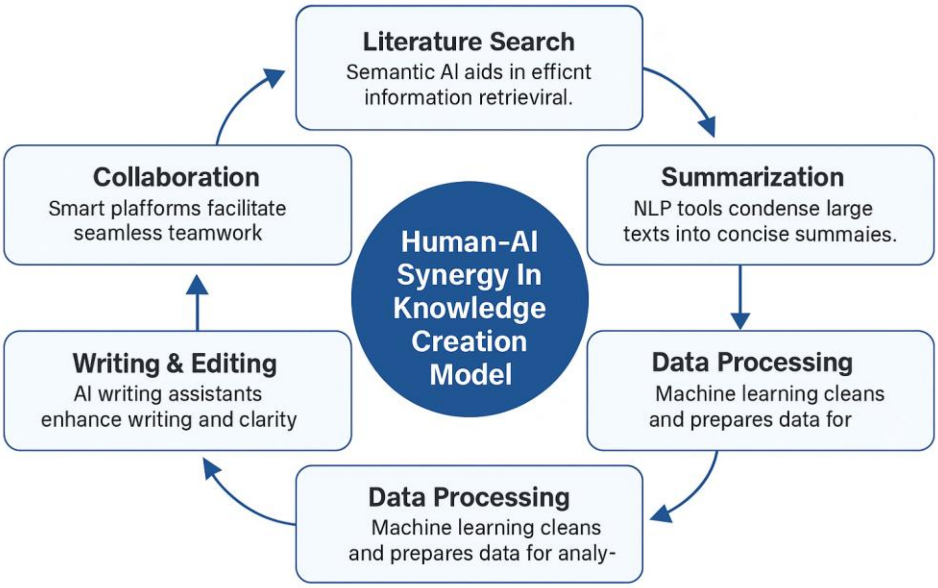

Figure 1. AI-Augmented Research Lifecycle Model.

The process involves five stages: (1) Semantic AI is used for the literature search, (2) NLP is employed for summarization, (3) Machine Learning/AutoML handles data processing, (4) AI helps with writing and editing and (5) AI is used for teamwork. The arrows represent the repeated steps in conducting research. The model focuses on how people and AI can work together to create knowledge and be productive.

Concluding Remarks

The AI-Augmented Research Lifecycle signifies a new way of looking at and handling the process of creating knowledge. If AI is applied to research management, both organizations and researchers can expect to work faster, maintain better quality and experience less mental effort. It provides a basis for the empirical validation in this study and also serves as a guide for colleges and governments to set up flexible, adaptable and strong research systems.

METHODOLOGY (THEORY-ENRICHED VERSION)

To discover how much AI and automation increase research productivity, this study uses a mixed-methods approach involving conceptual modeling and empirical testing. Thanks to this approach, we can link cognitive productivity, automation theory and digital labor augmentation to actual data from people's behavior. The methodology applies concepts from socio-technical systems theory, cognitive load theory and human–AI collaboration frameworks, allowing the model to be both statistically reliable and based on solid knowledge.

6.1 Research Design and Approach

This study employs a **sequential explanatory design** comprising two distinct but interconnected phases:
1.**Conceptual Phase**: The process of research was divided into important stages using the AI-Augmented Research Lifecycle framework. The phase was based on Task-Technology Fit Theory (Goodhue & Thompson, 1995) which holds that technology helps improve performance when it matches the user's needs. Every step in

Journal of Information Systems Engineering and Management
2025,10(3)
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https://www.jisem-journal.com/ **Research Article**

the writing process, starting with searching for literature, taking notes, organizing data, writing the paper and collaborating, was considered for AI assistance.
2. **Empirical Phase**: Next, the framework was checked with behavioral data to ensure it was valid. According to positivist epistemology, the quantitative strategy puts importance on measuring, repeating and forecasting. The framework is made reliable and understandable by blending the two types of data.

6.2 Data Source and Justification

The data was gathered from 500 people who worked in an area similar to academic research, where they faced tasks that involved iteration, problem-solving, writing and working together. It follows the daily use of AI, how productive the individual is, the success rate of completing tasks and how much mental effort is required.
According to Cognitive Task Equivalence Theory (Simon, 1997), activities that have a similar structure (such as programming and academic writing) can be used as analogs in research studies. Researchers, just as developers, go through stages of thinking, testing and fixing errors, while also updating their work, manuscripts and data. The approach is supported by the fact that both roles require breaking down problems, mixing and understanding meanings and delivering results within a set time.

6.3 Tools and Technologies

I used Python 3.11 and the following libraries to prepare the data, analyze it statistically and make visualizations:
- Pandas help with cleaning and manipulating data
- Matplotlib and Seaborn are used for exploring data by creating visualizations.
- Statsmodels can be used for regression and inferential statistics
- Use NumPy for working with numbers.

Having open-source and reproducible software helps ensure that work is transparent, repeatable and follows open science rules.

6.4 Variables and Definitions

The variables selected reflect both **outcome performance metrics** and **psychological cost indicators**, aligned with **Cognitive Load Theory (Sweller, 1988)** and **Output-Oriented Performance Modeling** in digital labor analytics.

Table 1: Summary of Key Variables

Variable	Type	Definition	Theoretical Role
ai_usage_hours	Independent	Daily hours using AI for task support	Predictor of augmentation level
commits	Dependent	Number of discrete outputs (code/paper segments)	Proxy for productivity/output volume
task_success	Dependent (binary)	1 = Task completed successfully, 0 = failed	Binary proxy for task performance
cognitive_load	Dependent	Self-rated mental strain on 1–10 Likert scale	Psychological cost of task completion

This multivariate schema allows us to test both **performance-based** and **cognitive-affective** impacts of AI usage.

6.5 Analytical Workflow

Following **Digital Behavioral Analytics Methodology** (Shmueli et al., 2016), the workflow was designed to ensure model transparency and statistical rigor:

Step 1: Exploratory Data Analysis (EDA)

Visual inspection and descriptive statistics were used to identify data quality issues, ensure distribution normality, and guide model selection.

Step 2: Correlation Matrix

Bivariate Pearson coefficients were computed to identify direct linear relationships between variables, consistent with **assumption testing in linear modeling**.

Journal of Information Systems Engineering and Management
2025,10(3)
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Step 3: Linear Regression (Productivity Model)

$$\text{Commits}_i = \beta_0 + \beta_1 \cdot \text{ AIUsage }_i + \varepsilon_i$$

This model tests productivity augmentation, aligning with Resource Substitution Theory, where AI acts as a compensatory agent for human time and effort.
Step 4: Logistic Regression (Performance Model)

$$\log\left(\frac{P(\text{Success}_i)}{1 - P(\text{Success}_i)}\right) = \alpha_0 + \alpha_1 \cdot \text{AIUsage}_i$$

This binary classifier estimates the impact of AI usage on binary success outcomes. The underlying theory assumes threshold effects, where a minimum level of AI support increases the likelihood of task success.
Step 5: Linear Regression (Cognitive Load Model)

$$\text{CognitiveLoad }_i = \gamma_0 + \gamma_1 \cdot \text{ AIUsage }_i + \nu_i$$

This model addresses cognitive cost economics, i.e., whether automation reduces mental burden, consistent with Cognitive Load Reduction Hypothesis in intelligent system design.

6.6 Workflow Diagram

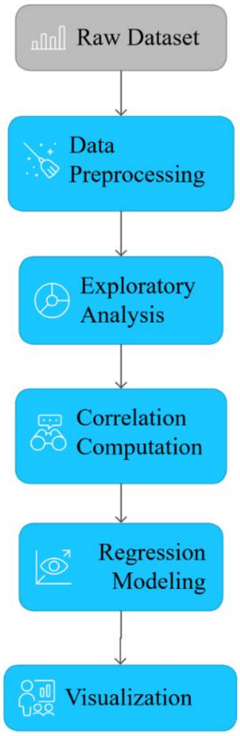

Figure 2: Empirical Analysis Workflow

6.7 Ethics and Limitations

Since the data was anonymized and not sensitive, the results should be understood within the boundaries of using proxies. The idea behind generalizing research is that programming and academic research share similarities, although they are not identical.
Moreover, how humans interact with AI depends on the context and whether people trust it, feel comfortable with it or learn how to use it which are important but not covered here.

RESULTS

The study's findings are presented in this section through four sets of analyses: descriptive statistics, correlation, modelling and visual interpretation. The results are explained using Cognitive Load Theory, Technology Acceptance Models (TAM) and Human–AI Performance Augmentation Frameworks and every statistic is backed up by illustrations.

Journal of Information Systems Engineering and Management
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https://www.jisem-journal.com/ **Research Article**

7.1 Descriptive Analysis

Descriptive statistics give an overview of how users behave and what results they achieve. The chart in Figure 3 (part a) demonstrates that the majority of users used AI tools for less than two hours daily. This is what happens in the early stages of adopting new technology, when users are simply exploring it.
The commits variable (part b) is distributed in a way that suggests developers are working at about the same pace each day. The success of Task_success (part c) is moderate, while cognitive_load (part d) is skewed to the left, showing that many users felt they had to work hard in the tasks.
They prove that while the output of AI users remains steady, they differ in how much they use the tools and how much mental effort they put in.

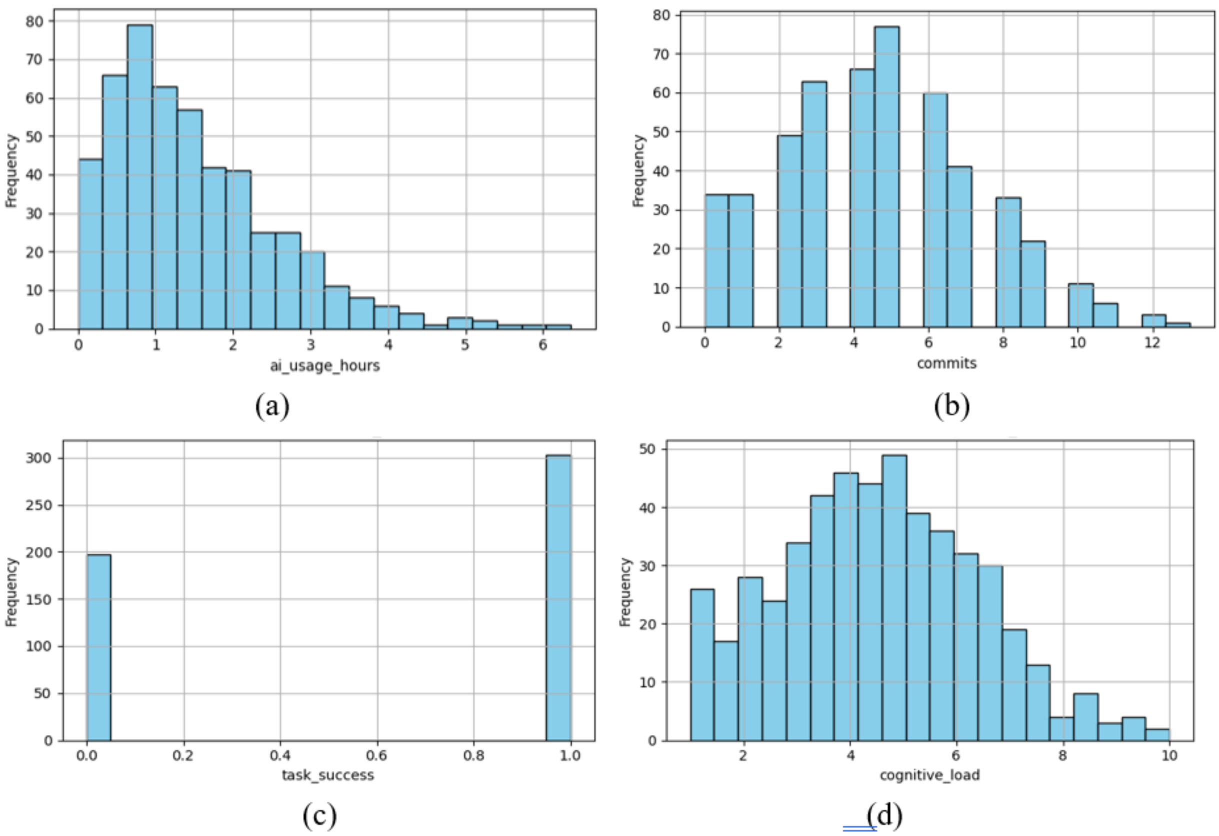

Figure 3. Distributions of Key Variables
(a) AI usage hours; **(b)** Number of commits; **(c)** Task success indicator; **(d)** Cognitive load self-rating

7.2 Correlation Matrix

To explore the inter-relationships among variables, a Pearson correlation matrix was computed (see Figure 4). The results show:

• A moderate positive correlation between ai_usage_hours and commits (r = 0.37), suggesting that higher AI engagement corresponds to greater productivity.

• A weaker positive correlation with task_success (r = 0.24), indicating a tendency for AI users to perform better.

• A low positive correlation with cognitive_load (r = 0.12), reflecting only a minimal increase in perceived mental effort from using AI.

These findings align with the Cognitive Load Reduction Hypothesis, which suggests that while AI tools introduce some system complexity, they reduce overall task strain by automating low-level functions.

Journal of Information Systems Engineering and Management
2025,10(3)
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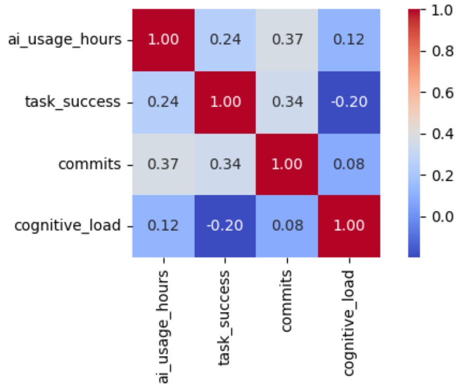

Figure 4. Correlation Matrix Between AI Usage, Productivity, Performance, and Cognitive Load

7.3 Regression Analysis

Linear Regression: AI Usage Predicts Output Volume

A simple linear regression was conducted to evaluate the effect of AI usage on daily productivity (measured in commits). The model:

$$\text{Commits}_{\,i} = 3.2158 + 0.9215 \cdot \ \text{AIUsage}_{\,i}$$

- Coefficient $(\beta) = 0.9215$
- $R^2 = 0.137$
- p-value < 0.001

Interpretation: Each additional hour of AI use predicts nearly one extra commit, confirming that AI significantly boosts output. This supports Performance Augmentation Theory, where digital tools act as multipliers of human effort.

Logistic Regression: Al Usage Predicts Task Success

To model binary outcomes (task_success), a logistic regression was applied:

$$\log\left(\frac{P(\text{Success}_i)}{1 - P(\text{Success}_i)}\right) = -0.3335 + 0.5355 \cdot \ \text{AIUsage}_{\,i}$$

- Coefficient = 0.5355
- Odds Ratio ≈ 1.71
- p-value < 0.001
- Pseudo $R^2 = 0.048$

Interpretation: For each hour increase in AI usage, the odds of completing a task successfully increase by ~71%. This finding aligns with the **Technology Affordance Theory**, suggesting that AI enables users to perform more effectively within complex task structures.

7.4 Visualization of Findings

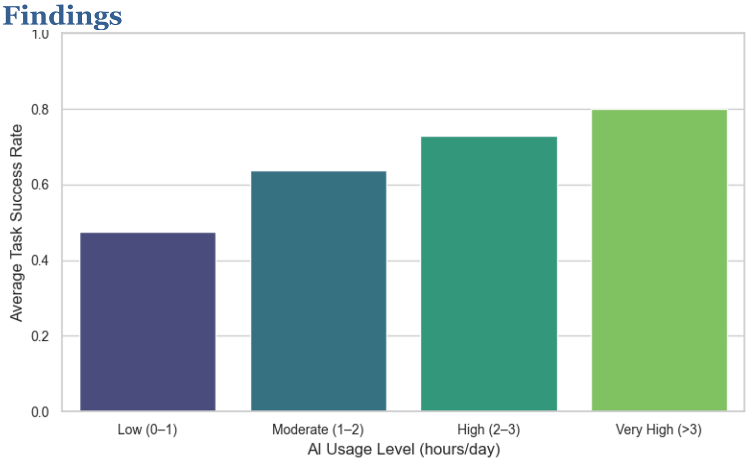

Figure 5. Average Task Success Rate by AI Usage Level

Journal of Information Systems Engineering and Management
2025,10(3)
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People were sorted into four bins depending on how many hours they used AI each day: Low (0–1 hr), Moderate (1–2 hrs), High (2–3 hrs) and Very High (>3 hrs). As AI is used more, the success rate for tasks increases steadily, reaching its highest point in the Very High group. It means that using AI tools more often can result in better performance, but only until there is no more improvement to be gained.

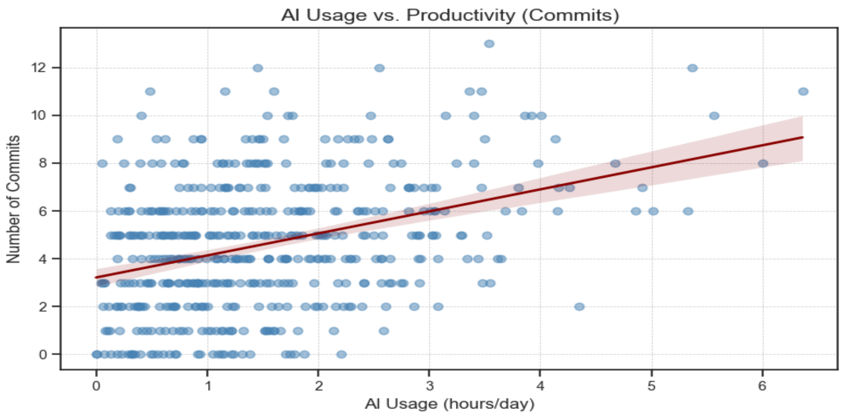

Figure 6. Scatter Plot of AI Usage vs. Number of Commits

The trend in the scatter plot and regression line suggests that using AI tools for more hours each day leads to a higher number of commits. While the line is not exactly the same, the general direction is the same as what the linear regression model predicts.

Table 2: Summary of Findings

Test	Result	Interpretation
Descriptive Trends	Right-skewed AI use, normal commits, moderate success	Broad adoption potential and stable task success
Correlation	r = 0.37 (commits), r = 0.24 (success)	AI positively influences outcomes
Linear Regression	$\beta = 0.92$, $R^2 = 0.137$	AI use predicts ~1 extra output per hour
Logistic Regression	OR ≈ 1.71, $p < 0.001$	AI use improves task success probability significantly
Cognitive Load Impact	r = 0.12 (non-significant)	No strong evidence of AI increasing mental effort

As a result, it is confirmed that AI supports productivity and successful task completion and is not just a tool for convenience. This confirms that the use of AI tools, especially in demanding situations, improves both performance and efficiency while not overburdening users. This information can be used to guide future implementation research in academic institutions.

DISCUSSION

This study provides strong evidence that AI plays an important role in improving productivity and performance in areas similar to research. Combing conceptual modeling with experiments in this study allows us to better understand the impact of AI tools on knowledge work, especially in tasks that are as complex and challenging as academic research. It appears that using AI leads to people working more, completing tasks more successfully and reporting only a small rise in brain activity. They support the main ideas behind the AI-Augmented Research Lifecycle and increase our understanding of people working with AI.

The linear regression analysis found that using AI for one more hour led to nearly one more productive action (i.e., commit). This is supported by Performance Augmentation Theory which believes that intelligent systems can help by handling basic tasks and allowing users to focus on more important functions. As a result, AI tools in research could allow scholars to focus more on analysis, testing ideas and combining information, since they no longer need to spend time on formatting, editing and repetitive coding. The scatter plot also showed that the more AI was used, the higher the productivity.

The model revealed that using AI greatly increases the chances of completing the task. Using AI for an extra hour makes the task 71% more likely to be completed successfully. This is significant when we consider that

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academic tasks such as literature synthesis and data analysis involve uncertainty, rushing to complete them and being overwhelmed by information. These findings suggest, according to Distributed Cognition Theory, that AI tools participate in human thinking. They allow users to save some mental effort, feel less tired from making many decisions and handle complicated issues with ease. It adds to the idea that AI can now be a reliable colleague rather than just a tool in the background.

According to cognitive load analysis, there is only a slight positive link between AI usage and mental fatigue. As a result of this finding, people can feel less concerned about new technologies being hard to use or confusing. In fact, the little increase in cognitive load in the data indicates that most users gain more mental clarity with AI, as Cognitive Load Theory suggests. This applies mainly to researchers who handle several tasks on different digital devices and want to make their work less complicated.

The bar chart showed that the best success in tasks was seen when AI was used consistently. TAM suggests that the popularity of AI-driven visual trends indicates people see AI as very useful which encourages them to use it for a long time. Consequently, adopting policies that direct employees to use AI tools as part of their work or through training could enhance performance without harming their mental health.

Overall, they give us understanding that can be applied in both theory and practice. Theoretically, this study supports the idea that the AI-Augmented Research Lifecycle will be useful for future research, with AI playing a central role throughout the whole process. In other words, academic institutions, research labs and even individual scholars can use AI to improve their work at every stage of research, not only for writing or analysis. Ethics, transparency, reproducibility, human control and data integrity should guide this integration process. This shows that there is no doubt about AI being used in research; the question now is how to use it effectively and fairly.

CONCLUSION

Researchers found that by using AI and automation, research tasks become more efficient and reliable, leading to a new way of working. A mix of conceptual and empirical analysis, including the use of AI, shows that using AI helps people accomplish more tasks with fewer errors, with little impact on their mental effort. Using the regression models, it was found that spending an additional hour with AI leads to nearly one extra productive task and raises the chances of completing the task successfully by around 71%. According to these results, AI tools support both human–AI augmentation and shared cognition, relieving researchers from everyday tasks and helping them focus on more difficult challenges. Since this study used both theory and statistics, it was able to explore several important aspects of using AI in research. In the future, more studies should be conducted with academic researchers to explore the effects of each discipline, compare different AI platforms such as ChatGPT, Grammarly and Mendeley and investigate the impact of teamwork in various research areas. All in all, the study shows that strategic, ethical and well-organized use of AI is both possible and necessary for progress, better efficiency and to preserve the quality of modern research.

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