



PEDAGOGICAL RECOMMENDATIONS FOR LEVERAGING THE USE OF ARTIFICIAL INTELLIGENCE IN WRITING DOCTORAL DISSERTATIONS TO ADDRESS THE EDUCATION ADOPTION GAP

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ABSTRACT

Aim/Purpose	The purpose of this study is to develop tactics for leveraging artificial intelligence (AI) in the writing of doctoral dissertations. These recommendations address the current lack of instructional materials that guide students in effectively and ethically integrating AI into this specific academic task. The paper outlines the challenges students face during the dissertation writing process and identifies specific AI tools that can help overcome these challenges.
Background	Despite AI's potential in doctoral education, its application in drafting dissertation documents remains limited. Students encounter numerous challenges during the writing phases of a doctoral dissertation. Traditional support systems are often slower and more constrained than AI tools, which can address these challenges more efficiently.
Methodology	As a theoretical piece, the study proposes recommendations for the practical application of Cognitive Load Theory (CLT) as a framework. The paper addresses the challenges inherent in doctoral research and dissertation writing, chief among which is the cognitive transformation that occurs during the writing process. Therefore, employing CLT as the theoretical underpinning is a logical approach.
Contribution	This paper can be a valuable resource for using AI tools in doctoral dissertation writing. It provides a foundational AI literacy, covering core concepts, a brief historical overview, ethical applications, and other important principles.

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	By describing the proper use of AI models and tools, this paper promotes their adoption to help address challenges in dissertation writing. By leveraging AI for writing tasks, students can free their minds from time-intensive, repetitive tasks, allowing them to focus more on analytical and interpretive work.
Findings	Students can effectively use AI tools and models to address challenges they face in writing doctoral dissertations. Tools such as Generative Artificial Intelligence (GenAI) and other specialized applications can significantly enhance the efficiency of the dissertation writing process. Limitations and drawbacks of using AI need to be discussed to help students avoid potential pitfalls.
Recommendations for Practitioners	Based on the research, four specific recommendations are proposed for doctoral mentors: (1) provide AI training and ethical guidelines: Integrate training on ethical AI tool usage into doctoral curricula; (2) encourage GenAI for ideation: promote the use of Generative AI (GenAI) for brainstorming and refining research topics; (3) promote AI for literature review and citation – encourage students to use AI tools to assist with literature reviews and ensure citation accuracy; and (4) establish clear AI usage policies: develop and communicate clear institutional policies regarding the use of AI in academic writing.
Recommendations for Researchers	Future research on AI in education should focus on several key areas. First, it is crucial to study AI adoption rates within doctoral programs, examining how institutional policies, training initiatives, and awareness campaigns influence integration. Additionally, research should explore how to prepare faculty advisors to guide students better in the ethical use of AI, potentially through specialized training programs. Finally, a study analyzing AI's impact on the quality and originality of dissertations would provide valuable insights.
Impact on Society	Integrating AI tools into doctoral education could accelerate knowledge creation. By streamlining the dissertation process, AI can reduce student burden and stress, leading to higher completion rates and, consequently, more successful doctoral graduates. Furthermore, an increase in the doctoral completion rate would make more trained educators available to contribute to student success and societal advancement.
Keywords	artificial intelligence and doctoral education, artificial intelligence and dissertation writing, leveraging GenAI in dissertation writing

INTRODUCTION

The proliferation of news regarding artificial intelligence (AI) consistently highlights its pervasive and powerful nature (Joshi, 2025; Pietsch & Mah, 2025; Walter, 2024). This constant stream of headlines, which spans new developments, expanding applications, and instances of harmful use, makes it clear that AI is a permanent feature and will be applied to an increasing range of purposes (Selvaraj et al., 2025; Singh et al., 2025).

These advancements necessitate the crucial integration of AI tools into many relevant fields. Delay or failure to do so could result in a significant disadvantage and the risk of being left behind (Sowa & Przegalinska, 2025; Sridhar et al., 2025). Consequently, individuals who incorporate AI into their work are likely to be more productive than those who do not.

AI tools have found diverse applications within education. They can be used for tasks such as personalized tutoring, customer service, writing computer programs, student registration, and many other tasks (Adair, 2023; Adhikari, 2024). Furthermore, AI is increasingly being utilized for research and various stages of the writing process (Eghosa, 2025). While the use of AI for research and writing may raise concerns about academic integrity, students and educators can ethically leverage these tools to their advantage (Kooli, 2023). In fact, many are already doing so to enhance their work (Holmes & Porayska-Pomsta, 2023).

The issue becomes particularly critical when considering the use of AI tools for writing doctoral dissertations. There is a notable gap in the application of AI tools to support this process (Torres & Statti, 2025). As a result, students who do not use these tools may take considerably longer to complete their dissertations than those who do (Grichko et al., 2025). AI holds significant potential to assist doctoral students in navigating the numerous challenges of dissertation writing (Rafi & Amjad, 2025). However, its integration is not without challenges (Suglo et al., 2024). A variety of AI tools are available for educational use, but while the application of some is well understood, others remain ambiguous (Rafi & Amjad, 2025). Additionally, there is general uncertainty regarding the availability and appropriate use of certain tools. Many educators are either unaware of these tools or lack the knowledge to use them effectively and maximize their potential (Adair, 2023).

These challenges are also relevant to the use of AI tools in doctoral dissertations. While some educators are not fully informed about their usage, others are concerned about ethical considerations and proper application (Suglo et al., 2024). This is further complicated by the sheer number of specialized AI tools currently in existence (Rafi & Amjad, 2025). Therefore, a comprehensive understanding of these available tools is a crucial prerequisite for their successful integration into academic fields.

RESEARCH PROBLEM

This study addresses the underutilization of AI tools in doctoral dissertation writing (Rafi & Amjad, 2025). This underutilization represents missed opportunities for doctoral students, as AI could be leveraged to streamline routine, repetitive tasks in dissertation writing (Suglo et al., 2024).

The limited use of these tools is partly due to a lack of pedagogical resources that specifically demonstrate to students how to apply AI models and tools in dissertation writing (Grichko et al., 2025). Consequently, many students are unaware of how to use these tools effectively, creating a gap in pedagogical resources. This gap, which this study aims to explore, is defined as the deficiency in the application of AI tools in doctoral dissertation writing.

RESEARCH OBJECTIVE

The primary objective of this research is to theoretically explore the opportunities that artificial intelligence (AI) presents for writing doctoral dissertations. This aim is pursued in two distinct phases, giving the research a two-fold purpose. The first is to establish a foundational understanding of AI in education, including its core concepts and terminology. This “AI literacy for dissertation writing” is essential for the second phase, which is to develop pedagogical recommendations for integrating AI into the doctoral dissertation writing process.

Before presenting the pedagogical recommendations, this paper will first define the foundational AI concepts necessary for understanding its application in academic writing. By doing so, the research aims to help students work “smarter, not harder” throughout their dissertation journey. This approach is intended to streamline the writing process and enhance productivity by leveraging AI capabilities.

THEORETICAL UNDERPINNING

This research utilizes Cognitive Load Theory (CLT) as its theoretical underpinning to formulate pedagogical recommendations. CLT posits that learning is influenced by the demands placed on an individual’s cognitive system (Paas & Ayres, 2014). The theory suggests that learning can be enhanced by

effectively managing cognitive load and strategically sequencing instructional materials (Prestine & LeGrand, 1991; Tennyson & Rasch, 1988). Therefore, an understanding of memory types and cognitive resource allocation is fundamental to the application of CLT.

A study by Duran et al. (2022) explored the application of Cognitive Load Theory (CLT) in computing education, highlighting several key concepts. Three constructs are relevant to the present research: working memory, long-term memory, and example-based learning (EBL). Working memory is defined as the active, readily accessible memory used during learning (Baddeley, 2020). Conversely, long-term memory represents a more permanent store of accumulated knowledge, which is generally slower to access than working memory (Alberini, 2011). When working memory is overloaded with information – a state known as cognitive overload – individuals must retrieve information from long-term memory (Duran et al., 2022), thereby slowing cognitive processing.

Pedagogical planning and tools can mitigate this cognitive overload. One such tool is example-based learning (Van Gog & Rummel, 2010), where students acquire new knowledge by studying worked examples that model the content being learned (Sukkar et al., 2023). This research adopts this approach, utilizing Cognitive Load Theory (CLT) as its theoretical foundation and employing Example by Learning (EBL) to formulate pedagogical recommendations.

CLT is typically noted in research as used in education to optimize learning by managing the load on working memory. Knowing the limitations of working memory compared to those of long-term memory, it would be more effective to delegate some non-critical workload to the long-term memory (Tennyson & Rasch, 1988). This paper explains how leveraging AI tools allows users to bypass routine cognitive hurdles, facilitating the encoding of core concepts into long-term memory while maintaining focus in working memory.

OUR APPROACH TO LITERATURE REVIEW

This study employs a scoping review methodology to conduct our literature review. This approach is particularly well-suited for providing a broad overview of a research topic, enabling a wide-ranging exploration of key terms and concepts (Pham et al., 2014). The efficacy of this methodology has been demonstrated in similar contexts, such as in defining competencies and design considerations for AI literacy (Long & Magerko, 2020). Accordingly, this paper utilizes a scoping review to delineate the core terms associated with AI literacy, establishing a conceptual framework for the pedagogical recommendations presented in subsequent sections. This literature review is structured into three distinct phases to organize the information gathered:

- **Phase I: Fundamentals of Artificial Intelligence** - This phase explains the evolving field of AI and its foundational terminology.
- **Phase II: AI Tools for Research Writing** - This section identifies specific AI tools that are utilized in the context of academic research and writing.
- **Phase III: Disadvantages of Using AI** - Examines the potential drawbacks and ethical considerations that may arise from the use of artificial intelligence.

RESEARCH OVERVIEW

The remainder of this study is structured as follows. First, we will introduce the knowledge base necessary for the pedagogical recommendations presented in this paper by discussing and defining AI literacy. Due to the wide variety of topics relevant to AI literacy, this discussion is presented in the three phases outlined previously. Following this, we will discuss the AI tools introduced in this paper, using practical examples and a review of the ensuing discourse. Based on this, we will present our pedagogical recommendations for using AI in doctoral dissertations. In the next section, we will explain how this study met the research objective and present our recommendations. Finally, the paper will conclude with a summary of key findings and suggestions for future research. Figure 1 presents a pictorial overview of the research for this paper.

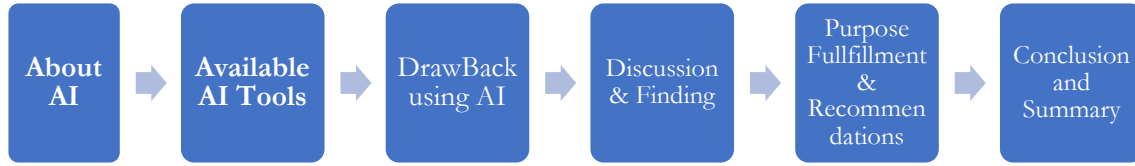


Figure 1. Overview of this study

AI LITERACY PHASE I - ABOUT ARTIFICIAL INTELLIGENCE

When discussing AI literacy, a range of divergent perspectives has emerged regarding the essential concepts, terminology, and knowledge required for an individual to be considered “AI literate.” These suggestions span a range of topics, including the technical foundations of AI, prompt engineering, and ethical considerations (Long & Magerko, 2020; Ng et al., 2021). However, a review of the field’s history reveals a substantial body of literature that informs and shapes our understanding of AI literacy (Rasheed et al., 2024). Consequently, this section begins by presenting the evolution of artificial intelligence to establish a foundational knowledge base for the pedagogical recommendations that follow.

THE EVOLUTION OF AI AND ITS IMPACT ON LITERACY

The capabilities of modern Artificial Intelligence (AI) are expansive, allowing it to engage in complex conversations, provide consistent answers to questions, and even write computer programs (Singh et al., 2025). This advanced functionality is presented in a manner that is accessible and easily understood through natural, human language (Rawat et al., 2024). However, this sophisticated state of AI is the result of a long developmental process marked by significant milestones. A deeper understanding of this evolution is crucial for grasping the full scope of AI literacy. Figure 2 provides an overview of these historical milestones, which began in the mid-twentieth century and have continued to shape the field to the present day.

The milestones presented in Figure 2 offer a comprehensive overview of AI’s development. While some are not directly relevant to the scope of this study or the evolution of AI literacy, others are crucial and warrant further discussion. This section focuses on the following key milestones:

- **The birth of AI:** The foundational event where the term “Artificial Intelligence” was first coined.
- **“Good Old-Fashioned AI” (GOFAI) and Symbolic AI:** An exploration of these early paradigms that relied on symbolic reasoning and logic.
- **Natural Language Processing (NLP):** A discussion of its significance in simplifying communication between humans and machines.
- **Chatbots:** An overview of their widespread use and impact.
- **Generative AI (GenAI).** An analysis of this modern advancement and its implications.

The academic discipline of artificial intelligence (AI) was formally established in 1956 during a summer research workshop at Dartmouth College. The primary objective of this gathering was to explore the possibility of creating machines capable of simulating human intelligence and thought processes (Russell, 2021). This workshop aimed at enabling machines to perform tasks traditionally exclusive to humans (M. Chen, 2020). It was at this time that the term “artificial intelligence” was coined to define this emerging field of study. Following its inception at Dartmouth, AI quickly gained traction in academia. Stanford University was among the first to offer a course on the subject, followed by other prominent institutions such as the Massachusetts Institute of Technology (MIT) and Carnegie Mellon University (CMU). This period also marked the beginning of discussions surrounding AI in education (AIEd), a field dedicated to leveraging AI to improve teaching and learning opportunities (Mustafa et al., 2024).

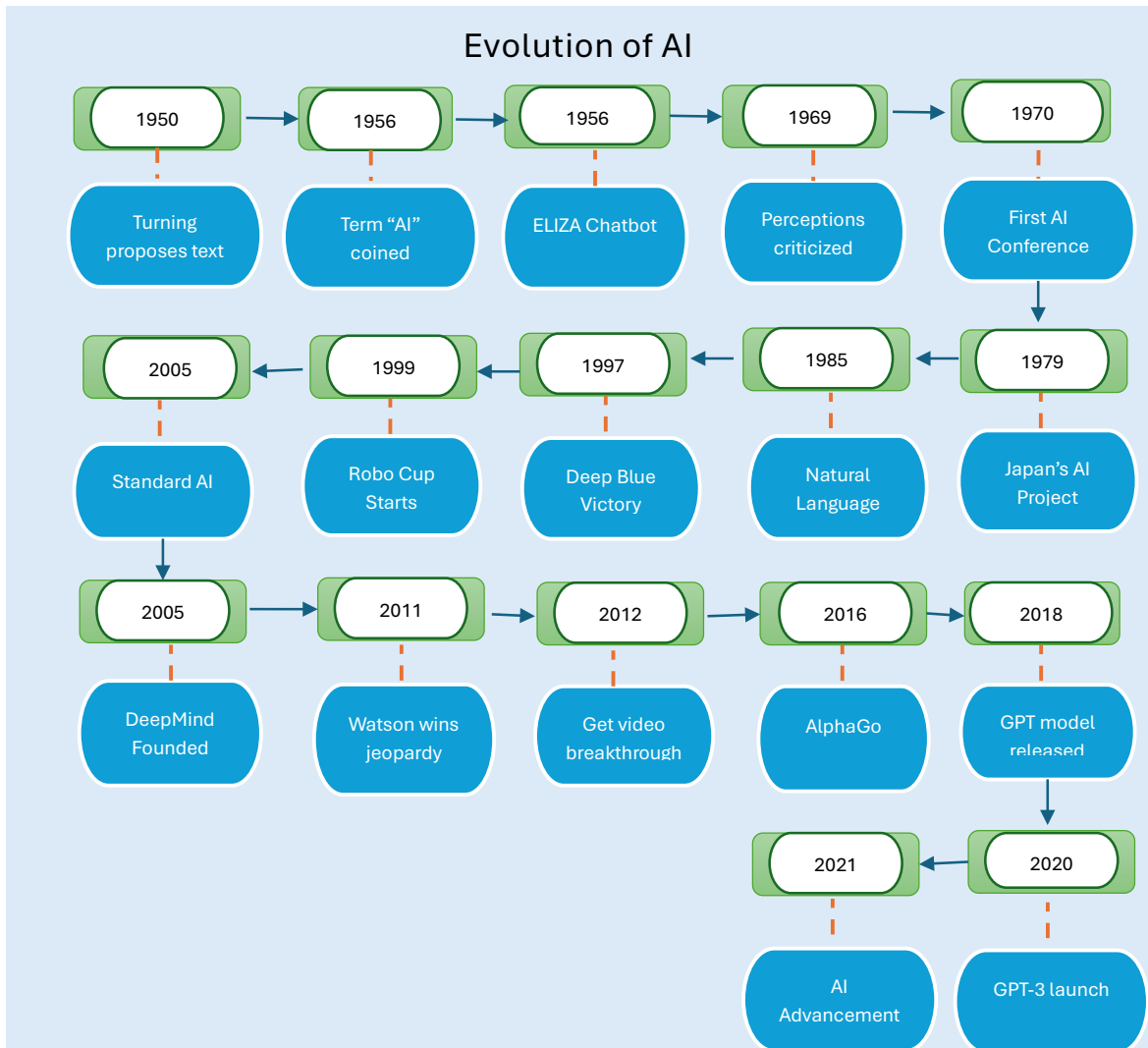


Figure 2. Evolution of AI (Vadapalli, 2025)

Source: upGrad (<https://www.upgrad.com/blog/history-of-ai/>)

Following its inception as an academic field, numerous versions of artificial intelligence emerged. A significant early paradigm is classical AI, also known as symbolic AI or GOFAI (Good Old-Fashioned AI). This approach to AI relies on symbolic representations and predefined rules programmed by humans (Singh et al., 2025). The name “GOFAI” helps distinguish this early form of AI from later, more sophisticated models. Two key concepts are central to GOFAI: expert systems and logic programming. Expert systems are designed to mimic human decision-making processes by applying programmed knowledge to solve problems. In contrast, logic programming focuses on formally defining the problem itself before attempting to find a solution (Sowa & Przegalinska, 2025).

A pivotal moment in the public perception and development of AI occurred when IBM’s Deep Blue defeated the reigning world chess champion, Garry Kasparov, in 1997. This victory marked the first time a computer had triumphed over a human champion in a chess match (Sridhar et al., 2025). AI’s success was not based on intuition or strategy in the human sense but on its ability to perform millions of calculations for each move, assessing potential gains and predicting the opponent’s responses based on prior moves (Shelke et al., 2025). While a symbolic triumph, this event was deeply meaningful. It demonstrated a machine’s ability to excel in a domain long considered a bastion of human in-

tellectual superiority (Bloomfield & Vurdubakis, 2008). This milestone set the stage for subsequent AI victories in other complex games and cemented the public's fascination with the potential of artificial intelligence (Zhang et al., 2025).

Another major advancement in AI's evolution is Natural Language Processing (NLP), which allows computers to understand and process human language (Scherbakov et al., 2025). This technology enables people to interact with computers in a conversational manner, much as humans do. The computer then provides answers to questions based on its vast database (Selvaraj et al., 2025). Unlike earlier forms of computer interaction, NLP eliminates the need for users to fill out forms, select from pre-set options, or navigate complex menus. In the past, interacting with a computer often involved indirect responses, such as a list of links or large amounts of information that were not always relevant to the user's query. NLP represents a significant departure from this, offering a more intuitive and direct way to get the needed information (Gavira-Durón & Jiménez-Preciado, 2026).

The development and widespread use of chatbots mark another important milestone in the history of AI (Kooli, 2023). A chatbot is a computer program designed to simulate human conversation (Li et al., 2025). Early versions were limited in their responses and often required detailed input before providing an answer. Later versions expanded their capabilities and were used in applications such as customer service and the automation of simple tasks. This development is particularly significant because it foreshadowed the interactive, user-driven nature of modern AI. Although limited in scope, these early chatbots prompted users to engage with AI in a conversational manner (Meincke et al., 2025). This paved the way for more sophisticated technologies, ultimately leading to the development of Generative AI, which enables more fluid, free-form interaction.

GENERATIVE ARTIFICIAL INTELLIGENCE

Generative Artificial Intelligence (GenAI) represents a significant new frontier in AI, with the potential to boost productivity and transform communication and workflows (Singh et al., 2025). This technology, which began as a single model, has since proliferated into numerous specialized models designed for diverse purposes (Joshi, 2025). Our research identified several of these GenAI models. Table 1 provides a quick reference listing some of these models, brief descriptions of their functions, and links to their websites. While this table serves as a useful guide for finding an appropriate GenAI model, we anticipate that the number and diversity of these models will continue to grow rapidly.

Table 1. Partial Listing of AI models

The AI model	Brief description	Link to the website
ChatGPT	Most widely used for content generation and brainstorming	https://chatgpt.com/
Gemini	Googol's chatbot, writing, and ideation	https://gemini.google.com/
OpenAI	Automate knowledge-based tasks	https://openai.com/
Adobe Firefly	Text-to-images and text-to-video generation	https://www.adobe.com/products/firefly.html
VoiceBox	Developed by Meta, the Text-to-Speech type of generation	https://voicebox.metademolab.com/

The GenAI models listed above share a fundamental feature: a similar interaction method. This similarity in functioning is a significant factor in their popularity. The communication method that allows users to interact with GenAI models is called prompt engineering.

PROMPT ENGINEERING

A prompt is the text that an individual enters to communicate with GenAI. The purpose of these prompts is to get answers to questions, complete specific tasks, and fulfill similar requests. The user provides a question or a request, and GenAI then generates a response by drawing from a massive

database (Walter, 2024). While this process may seem as simple as the fairy tale of Aladdin and his magic lamp, the text entered into the prompt significantly influences the relevance and accuracy of the output. Therefore, effective prompt engineering is a crucial skill for obtaining high-quality results from GenAI).

The popular adage GIGO, or “garbage in, garbage out,” applies directly to GenAI. If the prompts are incomplete or incomprehensible, the resulting output from GenAI will likely be of poor quality. However, if the questions are clear and follow the correct protocols, the likelihood of receiving consistent, relevant answers from GenAI is significantly higher (Hutson & Cotroneo, 2023). The key takeaway is that prompts entered into GenAI must be carefully crafted, or “engineered,” to increase the likelihood of receiving a direct, relevant response. This process of meticulously designing queries to enter GenAI is known as prompt engineering (B. Chen et al., 2025).

It is important to clarify that prompt engineering is not always a single question-and-answer exchange. If the initial response is not satisfactory, a user can ask follow-up questions. GenAI typically retains information from earlier prompts and builds upon it. This process of entering additional questions and related data is known as an “iterative prompt engineering” (Wang et al., 2025).

Figure 3 illustrates the iterative prompt engineering process. The process begins in Step 1, where a user enters an initial prompt. GenAI then generates a response, which the user can analyze for sufficiency. If the answer is not satisfactory, the user can refine the prompt with additional data to improve clarity, then submit a follow-up question. This iterative, back-and-forth process can continue until the user obtains the desired response or decides to pursue a different approach (Adair, 2023).

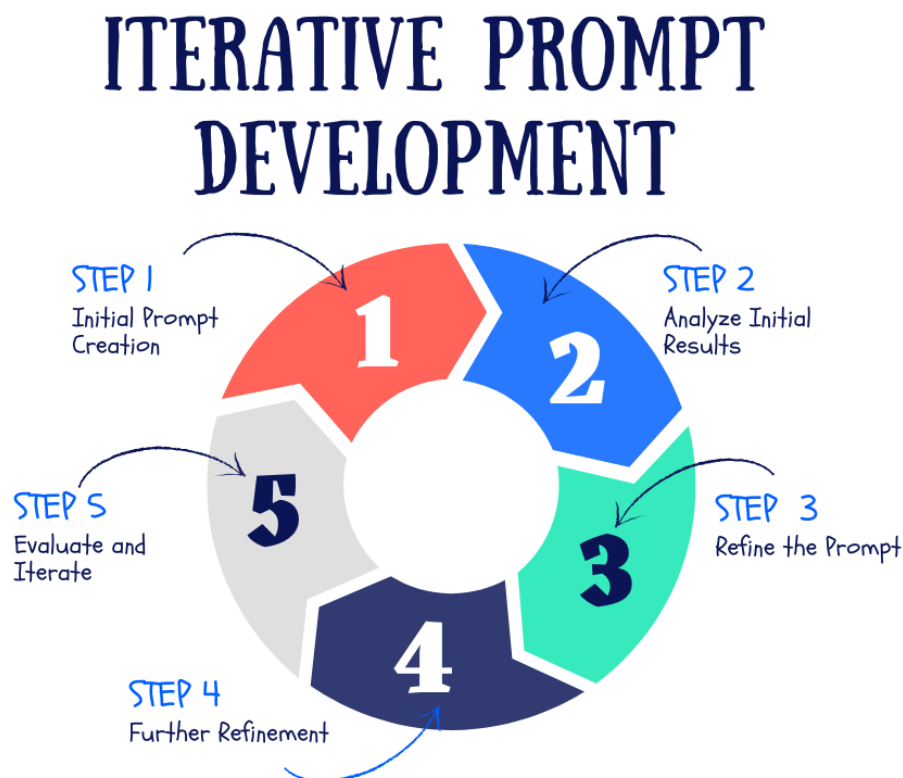


Figure 3. Iterative prompt engineering development (Ahmed, 2024)

Source: <https://aifordevelopers.io/prompt-engineering-for-software-developers-4/>

Prompt engineering has become an essential concept for effective GenAI use. Learning how to ask the right questions can significantly increase your chances of getting specific, accurate answers. We

will now introduce additional terms relevant to prompt engineering that are crucial for developing AI literacy (B. Chen et al., 2025).

A prompt engineering mindset involves understanding how to communicate effectively with GenAI to get the desired results. This process is a form of mutual learning, enhanced through experience. As users learn how GenAI responds, they can adjust their prompts, while GenAI, in turn, can refine its answers by learning from the user's question patterns and feedback (Pietsch & Mah, 2025).

Write, refine, and optimize prompts: Prompt engineering is not a one-and-done process. Prompts can be submitted, the results analyzed, and the prompt then refined and re-entered. The results can then be re-analyzed. A key feature of this process is that a prompt can build on previous ones. Alternatively, you can direct GenAI to disregard the previous conversation and generate an answer based on entirely new information (Walter, 2024).

Trial and error in learning prompt engineering: Learning prompt engineering is a process of trial and error, where both the user and GenAI learn from each other as they work together. This involves observing the outcomes, adjusting, and repeating the cycle (Singh et al., 2025).

Figure 4 illustrates the types of entries that are helpful for receiving the desired information from prompts. Additional entries, such as specific or sequential historical events, can also enhance the dialogue with GenAI (Wang et al., 2025). This is because GenAI is better at building and referencing specific information in its database rather than general or broadly stated information (B. Chen et al., 2025).

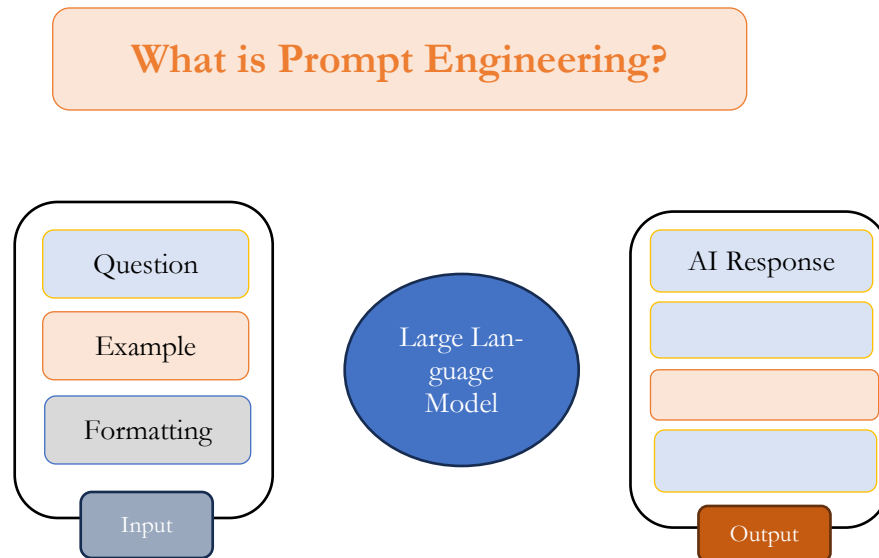


Figure 4. Helpful entries for prompt engineering (Tahir, n.d.)

Source: <https://cloudkitect.com/why-prompt-engineering-is-useful-for-generative-ai-models/>

BRAINSTORMING WITH GENAI

Brainstorming is the process of exchanging thoughts among a group to generate new ideas for a specific problem or topic (B. Chen et al., 2025). The core concept is “ideation,” which aims to stimulate discussion and produce a wide range of creative ideas (Suleri, 2020). In a group setting, participants talk freely about a given topic to develop a new plan, strategy, or fresh ideas. This can occur in person among teams, groups, or partners, and in an educational context, it often happens between students and educators (Suleri, 2020).

Despite its many advantages, brainstorming also has its drawbacks. These can be categorized into four key areas: groupthink, production blocking, social loafing, and evaluation apprehension (Lavrič & Škraba, 2023). Groupthink occurs when one person dominates the session, preventing others from contributing equally. Production blocking occurs when a participant speaks for too long without a time limit, preventing others from participating equally. Social loafing is when a person contributes less to the conversation than other participants (Meinke et al., 2025). Evaluation apprehension is particularly prevalent in education. Some students may be hesitant to ask questions out of concern that their inquiries might be incorrect or perceived as unintelligent (Ali et al., 2023). This type of apprehension can be significantly reduced when using GenAI for brainstorming, as it eliminates the fear of judgment (Lavrič & Škraba, 2023).

Through iterative prompt engineering, users can acquire new and potentially useful information from GenAI. While some of the information may not be helpful, each new question generates new data. The key is to refine the prompts to achieve the desired output consistently. Fortunately, GenAI will not get tired or look down on users for asking the same question multiple times. In their article, “Brainstorming Will Never be the Same Again,” Suleri (2020) suggests that group brainstorming can be enhanced with GenAI. They demonstrated the effectiveness of an AI brainstorming tool that used an iterative process to develop a regional plan for community improvement.

After establishing the fundamentals of AI in this section, we now shift our focus to using AI tools specifically for research writing.

AI LITERACY PHASE II - TOOLS FOR RESEARCH WRITING

Generative AI (GenAI) models are not the only AI tools available to researchers. While GenAI is useful for brainstorming and fact-finding (Eghosa, 2025), many other AI tools are designed to assist with various stages of research writing. We have identified numerous AI tools that serve specific purposes in the research writing process (Grichko et al., 2025). We believe these tools are an essential component of AI literacy and a necessary foundation for the pedagogical recommendations we will present in this study. Table 2 lists AI tools for research writing, which can also be helpful for dissertation writing.

Table 2. AI tools for research writing

Purpose	Software name	Link
Research with AI tools	Research Rabbit Scite	https://www.researchrabbit.ai/ https://scite.ai/
Organizing your research paper with AI	Scrivener	https://www.scrivenerai.com/
Writing the first draft	Perplexity AI Elicit: AI-Assisted Research Drafting	https://www.perplexity.ai/ https://elicit.com/
Editing and paraphrasing with AI	QuillBot Hemingway Editor	https://quillbot.com/ https://hemingwayapp.com/
Managing references and avoiding plagiarism	EndNote PaperPile	https://endnote.com/downloads/styles/artificial-intelligence/ https://paperpile.com/
Final check: proofreading and polishing the research	Gammarly Co-writer	https://www.grammarly.com/ https://cowriter.com/
To gain knowledge or learn about a topic	LearnAbout	https://learnaboutai.ai/
To organize a group of articles into one document	NotebookLM	https://notebooklm.google/
References and citations check	reciteworks	https://reciteworks.com/

It is important to clarify that the tools listed in Table 2, although categorized as “AI tools,” do not use the same prompt engineering model as GenAI. Unlike the free-format nature of GenAI, each of these tools is designed for a specific purpose and requires unique input and processes. For instance, “Learnabout” can be used to gain an initial understanding of a topic, which a researcher can then explore further to determine whether it fits the research study under consideration.

BRAINSTORMING WITH AI TOOLS

In addition to using GenAI for brainstorming through prompt engineering, other tools have been developed specifically for brainstorming. Numerous different AI tools are designed for this same purpose. The EdrawMind Team (2026) lists many of these tools, summarizes their content, and adds other links for more examples. Table 3 partially lists some of these AI tools used in research writing.

Brainstorming can be taken to a new level with the tools listed above. They can generate and polish mind maps and also produce text and ideas to contribute to the session. A mind map is a visual way of organizing information, ideas, and tasks around a central theme or concept. This is considered to be critically helpful in research writing (Suleri, 2020).

While the tools discussed above offer immense productivity gains, their effective use also depends on understanding the inherent risks, drawbacks, and ethical ‘red lines’ that we explore next.

Table 3. List of brainstorming tools
(EdrawMind Team, 2026)

Name of brainstorming tool	Explanation	Link
Wondershare EdrawMind	Mindmap, outline, kanban, presentations EdrawMind, a full-featured collaborative mind mapping and brainstorming tool	https://edrawmind.wondershare.com/ai-features/ai-brainstorm.html
HyperWrite	Content generation, editing, and improvement	https://www.hyperwriteai.com/
Whimsical	Integrated project space for tasks, documents, and communication.	https://whimsical.com/
Context Minds	Hub for content creation. Research, brainstorm, plan, and visualize your content ideas all in one place.	https://www.contextminds.com/
Ayoa	Ideation and brainstorming, all-in-one mind mapping and task management tool designed to boost creativity and productivity	https://www.ayoa.com/
Visual Brainstorming	Enriches the idea of brainstorming by including images, diagrams, and visual models	https://symbio6.nl/en/blog/visual-brainstorming-ai

AI LITERACY PHASE III - DRAWBACKS OF USING GENAI

Despite the many advantages GenAI tools offer, they also come with significant drawbacks. Many studies have noted and cautioned against these drawbacks (Maleki et al., 2024; Westenberger et al., 2022). Therefore, we consider them an essential component of AI literacy and present them in this study as Phase 3 of AI literacy. Gaining insight into these drawbacks can help users avoid potential pitfalls and mishaps, as discussed below.

ERRORS IN AI OUTPUT

It is crucial to understand that the output generated by GenAI is not always accurate. Deviations from the expected or correct outcome can manifest in several ways:

- **Factual Inaccuracies:** AI can provide misleading or incorrect information. These inaccuracies often stem from the AI's training data (Basak et al., 2025). Although inaccuracies may be corrected as more data is introduced, they remain a significant problem.
- **Hallucination:** AI may fabricate information, create non-existent stories, or present false information as fact. This phenomenon is known as hallucination; it is not based on facts but on inaccuracies within the AI's training data (Maleki et al., 2024).
- **Biases:** AI can produce discriminatory results due to flaws in its training data (Saumure et al., 2025). This biased information can originate from historical misinformation, incomplete data, or data that does not accurately represent the population from which it was gathered (Banerjee & Chanda, 2020).
- **Context Handling Failure:** GenAI sometimes fails to understand the context of a question or conversation fully. This can lead to misunderstandings, inaccurate responses, or even the program shutting down. This is similar to a program "crashing," though in the case of AI, it may simply stop responding or revert to the operating system's display (Westenberger et al., 2022).
- **Deepfakes:** AI can create fabricated images, videos, or audio that appear realistic, misleading people about their authenticity. This can occur when a person's face or voice is digitally altered to look or sound like someone else's. These are often created for malicious purposes, such as extortion or the spread of false information (Sharma & Kaur, 2022). Jargon (2025) reported an incident where criminals called a mother, claiming her daughter was kidnapped. They used an AI deepfake to play audio of her daughter begging to be freed. The mother rushed to transfer the ransom money, only to later discover her daughter was safe, and the audio had been generated by AI.

LINGUISTIC AND CULTURAL BIASES WITHIN AI TRAINING DATA

In addition to the limitations identified in the previous section, a further concern that has received increasing scholarly attention is the presence of linguistic and cultural biases in AI training data. This issue has become more noticeable as artificial intelligence systems are more deeply integrated into everyday societal functions. Scholars suggest that training datasets are disproportionately composed of Western languages and cultural perspectives, resulting in the underrepresentation or misrepresentation of many non-Western societies and cultures (Beták & Szűts, 2025).

AI training data sources may consist of large-scale, aggregated datasets drawn from multiple sources, which systems analyze, synthesize, and transform into outputs in response to user prompts. However, these datasets are predominantly derived from widely spoken languages, particularly English, and are heavily influenced by Western cultural norms and frameworks. Consequently, languages with fewer digital resources and cultures outside dominant paradigms are often insufficiently represented (Foka et al., 2025). Given that many topics are subject to interpretive variation, the absence of diverse cultural and linguistic perspectives may result in outputs perceived as biased or incomplete (Beták & Szűts, 2025).

While such limitations may have minimal impact in routine informational use of AI, they carry significant implications in academic research contexts, particularly in doctoral-level data collection and analysis. Bias in AI-generated insights may affect the interpretation of findings and the validity of conclusions (Ali et al., 2023). This concern is especially relevant in light of the growing number of international doctoral students, whose research increasingly engages with culturally and linguistically diverse contexts that remain underrepresented in AI training data.

THE NEVER-ENDING DISCUSSION ABOUT CHEATING IN AI

Concerns about using AI for academic dishonesty are widespread among educators. While there is no consensus on the issue, many are concerned about students using GenAI to cheat (Chanpradit, 2025). This concern is valid; the ease of generating content with GenAI makes it tempting for students to submit AI-created work as their own. What complicates the matter is that the boundaries between violating academic integrity and acceptable AI use aren't always clear (Holmes & Porayska-Pomsta, 2023). Fortunately, many academic institutions are now developing specific AI policies, often referred to as “the red lines of academic integrity,” to address this challenge.

THE RED LINE OF ACADEMIC INTEGRITY

The term “red line” is commonly used to describe a set of firm rules or boundaries that should not be crossed. These rules are specific and rigid, allowing no exceptions. Different studies identified some of these red lines (Ersöz & Engin, 2024) for the use of AI in research writing, as listed in the following:

- *Avoid direct copying from GenAI:* Do not copy and paste information verbatim. Instead, paraphrase the content or, better yet, find other sources that can be cited more easily.
- *Cite GenAI for ideas:* If you get an idea from GenAI and include it in your document, you should cite the AI model as the source.
- *Use a decision-making algorithm:* Refer to the algorithm in Figure 5 to determine when information from GenAI needs to be cited.

We want to emphasize two distinct points. First, we do not recommend using direct quotes from GenAI in any situation. Second, we recommend the principle of “erring on the side of caution.” If a researcher uses any information from an AI, this information should be cited. At the same time, we agree with Sheng’s (2025) chart in Figure 5, which offers guidance on when to cite GenAI. We believe it is safest to cite any new information you get from AI.

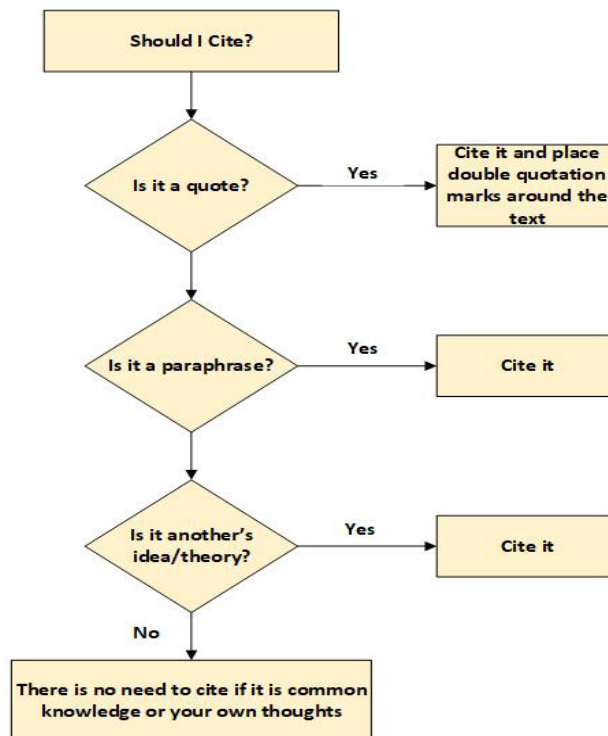


Figure 5. Decision to cite or not cite a source (Sheng, 2025)

Source: https://www.academia.edu/4116194/20_How_to_Harvard_reference

In the three phases listed above, we have covered the relevant concepts of AI literacy. Understanding these concepts is essential to developing pedagogical strategies that close the AI adoption gap in dissertation writing. The next section presents the discussion and findings of the research.

DISCUSSION AND FINDINGS

This section discusses how GenAI can be used in writing a doctoral dissertation. It begins by outlining the dissertation writing process, then focuses on three key areas where AI models and tools can be most helpful to students:

- **Topic Selection:** Assisting students in contemplating and focusing on a dissertation topic.
- **Literature Review:** Specifically aiding in the writing of the literature review chapter.
- **Citation Management:** Helping to match references with in-text citations.

ABOUT THE DOCTORAL DISSERTATION WRITING PROCESS

A dissertation is the culminating document required for doctoral students to complete their research program. This document often represents the student's first publication (Ali et al., 2024), which is typically lengthy and poses various challenges. The dissertation is conventionally divided into named chapters and sections that serve as a guide for students during the writing process. To successfully earn their degree, students must not only complete this document but also defend it before a committee of academic and/or industry experts. Both the completion of the written dissertation and a successful defense are mandatory requirements for graduation.

The dissertation process can be challenging from its inception to the defense (Ali et al., 2023). Right from the start, students enter uncharted territory and encounter various obstacles. One of the main challenges is cognitive transformation. Students typically could face a significant shift in their thinking when adapting to a new process. A study by Ali et al. (2024) highlighted this transformation and provided a table to illustrate it. Table 4 shows this transformation in thinking.

Table 4. The Transformation in the Dissertation Writing Stage (Ali et al., 2024)

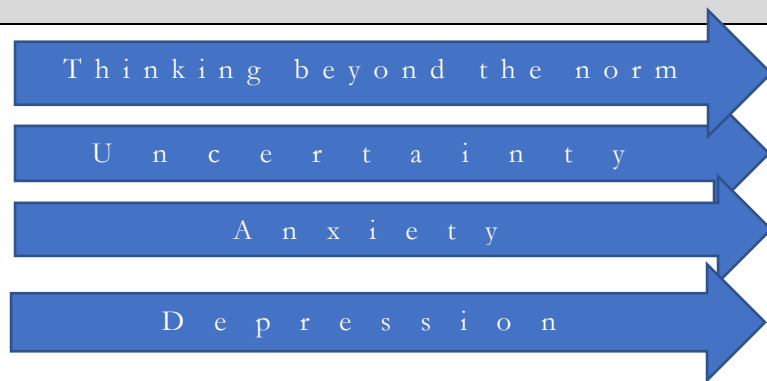
Pre-dissertation phase	Cognitive transformation	Dissertation writing phase
• Dependent stage • Teacher control • Given assignments • Passive adoption of knowledge • Undertake guided research	 Thinking beyond the norm Uncertainty Anxiety Depression	• Independent stage • Intellectual autonomy • Assign themselves • Self-directed • Independent learning • Creating own knowledge

Table 4 highlights the significant adjustment steps doctoral students undergo. These steps may be unfamiliar, leading to a period of mental adaptation. One common experience is the uncertainty surrounding dissertation topic selection, which can lead to a “mental fog” that makes it difficult to focus on a specific topic (Ali & Pandya, 2021).

An effective technique for overcoming this “mental fog” is through repeated brainstorming (Suleri, 2020). Traditionally, students brainstorm with their advisors or mentors. However, as previously discussed, repeated brainstorming sessions can lead to “evaluation of apprehension” (Lavrič & Škraba, 2023). Additionally, scheduling conflicts and limited access to advisors can be problematic. This is where generative AI (GenAI) can be helpful. With its free-form iterative prompt engineering, GenAI makes brainstorming much easier and more convenient (Lopes et al., 2024). Students can brainstorm with GenAI for a focused research topic for their dissertation.

BRAINSTORMING WITH GENAI FOR A FOCUSED RESEARCH TOPIC

Doctoral programs typically require students to start with a research topic in mind, but in reality, this is often not the case. Students may have multiple ideas or no topic at all. The challenge for an advisor is to work with the student to narrow the focus to a single, manageable topic while considering constraints such as funding, time, and viability. and others (Ali & Pandya, 2021).

It is common for students to propose projects that are too ambitious to be completed within a reasonable timeframe. Educators often joke that this is “trying to solve the world’s problems.” The exaggeration accurately reflects a student’s tendency to propose a topic that is beyond their control or their institution’s reach. The advisor’s job is to help scale these grand ideas down to a feasible project within the surrounding constraints (Ali et al., 2024). This process often requires numerous brainstorming sessions between the student and the advisor. However, as previously mentioned, too many sessions can have drawbacks. As an alternative, students can use GenAI to brainstorm and focus on their topic. This involves prompt engineering, which requires careful planning and adherence to specific protocols with GenAI.

To illustrate this, we will use a common dissertation topic: “The level of risk appetite that IT managers are willing to take when planning their cybersecurity plan.” This topic is similar to one our students have chosen. Our goal was to identify similar topics to explore, so we began our first session with ChatGPT. We went through four prompts with ChatGPT to narrow our research focus. Each subsequent prompt was built on the previous one and provided additional information - a process known as iterative prompt engineering. We prepared these prompts based on the responses we received. To illustrate the dialogue, we have included our first prompt in Figure 6 and ChatGPT’s response in Figure 7. The complete dialogue is available in the Appendix, Demonstration in Principles,” to avoid disrupting the flow of this discussion.

I want to write a dissertation on the level of risk appetite IT managers are willing to take when planning their cybersecurity strategies. Can you help me find five topics that are relevant to what I am looking for? I want a list of five related topics that have been discussed in the last three years.

Figure 6. Our first prompt to ChatGPT

Certainly! Based on recent developments in cybersecurity and IT management, here are five dissertation topics that align with your interest in the risk appetite of IT managers during cybersecurity planning:

1. **Evaluating IT Managers’ Risk Appetite in the Adoption of Autonomous AI Agents for Cybersecurity Operations**

This topic explores how IT managers assess and manage the risks of integrating autonomous AI agents into cybersecurity frameworks, including the potential for AI-driven breaches and the need for robust identity and access controls.

2. **The Influence of Regulatory Compliance on IT Managers’ Cybersecurity Risk Appetite**

Investigate how evolving regulations, such as the New York Department of Financial Services’ AI cybersecurity guidance, affect IT managers’ willingness to assume cybersecurity risks and their compliance strategies.

3. **Assessing the Impact of Cyber Insurance on IT Managers' Risk Appetite in Cybersecurity Planning**
Analyze how the availability and terms of cyber and data privacy insurance influence IT managers' decisions regarding risk tolerance and the implementation of cybersecurity measures.
 4. **The Role of Cybersecurity Culture in Shaping IT Managers' Risk Appetite**
Examine how the development and maturity of an organization's cybersecurity culture affect IT managers' perceptions of risk and their approach to cybersecurity planning.
 5. **Impact of Security Convergence on IT Managers' Risk Appetite in Cybersecurity Strategies**
Explore how the integration of physical and information security functions (security convergence) influences IT managers' risk assessments and decision-making processes in cybersecurity planning.
- These topics are grounded in recent research and industry developments, providing a contemporary perspective on the factors influencing IT managers' cybersecurity risk appetite.

Figure 7. ChatGPT's response to our First Prompt

LEVERAGING AI TOOLS FOR WRITING THE LITERATURE REVIEW

Doctoral students typically begin their literature review with some foundational knowledge of their chosen topic (Ali & Pandya, 2021). From there, they seek more information. Much like other researchers, they often start with a web search. The term “Googling” is commonly used to describe this process. However, this method rarely yields just the right amount of information. Instead, it often produces an overwhelming number of results, many of which are only tangentially related to the topic. Students can quickly become overwhelmed by a tangled web of links and information, leading to feelings of “information overload” or “swimming in information” (Duran et al., 2022). As a result of this information overload, a major challenge emerges in managing the vast amount of information for the literature review. Engaging in prompt engineering can even make the situation worse, leading to a state of “cognitive overload” in which the brain becomes overwhelmed by the sheer volume of information (Croskerry, 2013). Figure 8 illustrates the negative outcomes that can result from both “swimming in information” and “cognitive overload.”

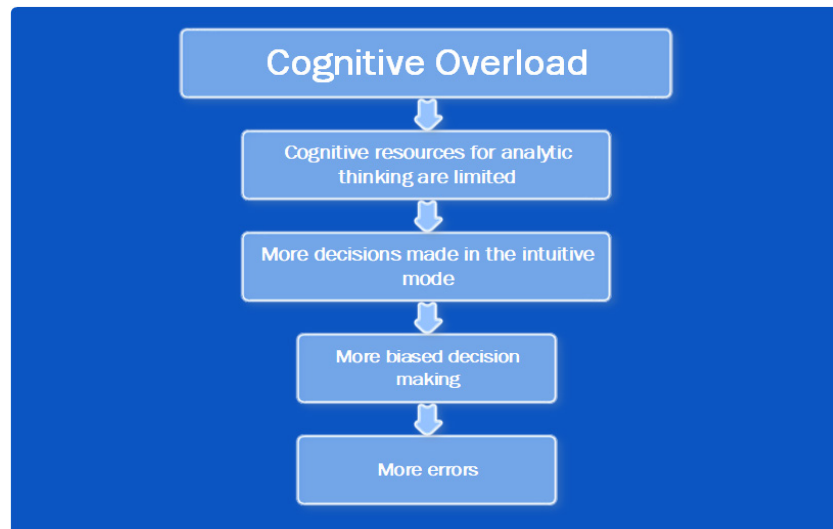


Figure 8. Cognitive overload (Source: Croskerry (2013))

(https://www.researchgate.net/figure/Effects-of-cognitive-overload_fig1_262147339)

While cognitive overload can result from processing a massive amount of information, AI tools designed to handle and manage this “information overload” can help students minimize its negative effects. We experimented with two such tools: NoteBookLM and “Learn About”. NoteBookLM allows students to upload various documents. It then analyzes the content, summarizes the information, and organizes it with keywords. This tool also provides links that guide the user through menus and categories, reducing the time a researcher needs to review the material. This allows students to let the AI tool organize the information while they focus on the analysis and writing phases (Dihan et al., 2025).

The second tool, “Learn About”, uses AI to answer questions with visual and interactive guides. Students can explore various topics, ask different questions, or upload their own materials to delve deeper into a chosen subject. This tool helps users gain an initial understanding of a new subject, after which they can decide whether to explore it further or move on. In essence, students can delegate tasks to the software to produce summaries and reports, then shift their focus to analyzing the reports from Learn About and deciding what to include in their work.

MATCHING IN-TEXT CITATIONS WITH REFERENCES USING AI TOOLS

One of the challenges doctoral students face when writing their dissertations is matching references with in-text citations. While this may seem like a simple, straightforward task, our experience with dissertation committees shows that it is far from error-free.

This “easy thinking” may stem from prior experience writing smaller papers with fewer references. In those cases, matching citations and references is less problematic because the limited number of sources allows for manual checking and correction of spellings and dates.

However, the situation is different in doctoral dissertations. The number of references and citations is significantly higher, and the quality of the document is often measured by the number of sources listed (Ali et al., 2022). With so many references, the likelihood of mistakes increases. Common errors we have observed include:

- *Mismatched names*: Reference names and citation names do not match due to different spellings.
- *Incorrect dates*: The date listed in the reference is different from the one in the citation.
- *Uncited references*: A reference is listed in the bibliography but never cited in the text.
- *Missing references*: A citation is included in the text but has no corresponding entry in the references section.

While these types of errors may seem small, they are common and can be a major source of frustration for students. An analogy can be drawn to learning a programming language, where a simple syntax error, like a single typo, can render a program inoperable for hours (Liu & Wu, 2018). Students may meticulously review their code without finding the issue until they realize it was a simple misspelling or a name mismatch.

Similarly, in a dissertation, a high number of references can be confusing, especially when authors are cited multiple times or have long names. These routines, though not complex, are often best handled with specialized tools. We believe this is a seamless application for an AI tool like ReciteWorks.

USING RECITEWORKS

Reciteworks is a software designed to find mismatches between references and citations, ensuring accuracy in both “in-text citations” and the reference list. The research document is submitted, and Reciteworks generates three types of reports:

- The first report identifies mismatches between references and citations, specifically noting errors in:
 - Differences in author names between the reference list and in-text citations.

- Discrepancies in the date of the reference between the two locations.
- Differences in a combination of both the author's name and the date.
- The second report lists all references and the number of times each is cited. It also flags references that are not cited in the document.
- The third report highlights the document, showing where the references have been cited.

Reciteworks also provides other useful information, such as misaligned references when they are not sorted correctly. Another valuable piece of information is the Digital Object Identifier (DOI), which is increasingly important for academic publications as it indicates the integrity of the source (Mondal & Mondal, 2023).

The ease with which dissertation reviewers can find these errors is notable. They can run the dissertation through Reciteworks, which generates error reports. It is not uncommon to see a report with hundreds of errors that students must fix gradually. This process can be iterative as students work to find and correct every error. Therefore, we strongly suggest that students do not submit their dissertations for review until they have addressed the errors identified by Reciteworks.

Now that we have completed the sections of AI literacy and the discussion and findings of this study, our next step is to explain how this article achieved its research goals and offer pedagogical recommendations.

FULFILLMENT OF THE RESEARCH PURPOSE & RECOMMENDATIONS

This section is divided into two parts: (1) a review of our initial goals, and (2) a consolidated list of recommendations for reducing cognitive overload.

FULFILLMENT OF THE RESEARCH PURPOSE

This paper aimed to provide practical pedagogical recommendations for using AI to streamline the dissertation process. By delegating repetitive tasks to AI, doctoral students can significantly reduce cognitive overload and redirect their mental energy toward high-level critical analysis. While these tools and strategies were discussed throughout the previous two sections, this section centralizes them into a definitive set of explicit recommendations.

PEDAGOGICAL RECOMMENDATIONS

Our recommendations are derived from both a review of current literature and our own practical experience. Grounded in Cognitive Load Theory, these strategies aim to leverage AI for time-consuming, repetitive tasks, thereby freeing working memory for high-level critical analysis:

- *Develop AI Literacy:* To use these tools effectively, it is essential to master AI literacy concepts, most notably Prompt Engineering and Iterative Prompting.
- *Acknowledge AI Limitations:* AI output should never be treated as “faultless.” Users must remain vigilant, as models frequently exhibit biases or generate factually incorrect information (e.g., hallucinations).
- *Streamline Data and Literature Management:* Managing the high volume of articles and data required for a dissertation can be overwhelming. Tools like Scrivener, Perplexity, and Elicit can help organize this information more efficiently.
- *Refine Research Scope through Brainstorming:* Narrowing a dissertation topic is an iterative process. Generative AI is highly effective for brainstorming and refining research questions.
- *Utilize Specialized Visualization Tools:* For more structured brainstorming and mind-mapping, specialized tools such as Wondershare EdrawMind, Hypotenuse (Hypewrite), Whimsical, ContextMinds, and Ayoa are recommended.

- *Enhance the Literature Review:* To navigate the challenges of a comprehensive literature review, researchers could utilize tools like ResearchRabbit, Scrivener, and NotebookLM.
- *Ensure Citation Accuracy:* Discrepancies between in-text citations and reference lists are a major source of error. We recommend using Reciteworks or Grammarly to ensure all references are accurately matched and formatted.
- *Adhere to Ethical AI Principles:* Maintaining academic integrity is of paramount importance. While we have introduced the “Red Line of Academic Integrity,” researchers must also consult their specific institutional guidelines. Tools like Grammarly or Co-Writer can further help identify duplicate content and avoid plagiarism.

CONCLUSION

This study addressed the significant adoption gap of Artificial Intelligence (AI) tools in doctoral education, focusing on the complex process of dissertation writing. While AI technology is evolving rapidly, academic institutions have been slow to adopt it, primarily due to concerns about ethical use. It has become essential to explore how powerful AI tools can be leveraged effectively and ethically within the academic environment. Through a comprehensive literature review, this paper delineated the challenges doctoral students face during the dissertation process and identified specific AI tools and models that can mitigate these difficulties at various stages of the dissertation.

Our findings strongly indicate that doctoral students can benefit from integrating AI tools into their dissertation writing process. While we acknowledge valid concerns about academic integrity and potential misuse, the proper application of AI can streamline processes, improve efficiency, and help students navigate the complexities of doctoral research.

We have discussed the utility of Generative AI (GenAI) models like ChatGPT and Gemini for brainstorming and refining research topics through iterative prompt engineering. This interactive approach can help students overcome “mental fog” and narrow broad ideas into manageable dissertation topics. This serves as an alternative to traditional advisor-student brainstorming sessions, which are sometimes limited by the advisor’s availability or the student’s evaluation of anxiety.

We have also highlighted the role of specialized AI tools in managing the “information overload” that is common during a dissertation literature review. Tools like NotebookLM and LearnAbout can organize and summarize vast amounts of information and present data in a more manageable format. This reduces cognitive load, allowing students to focus on critical analysis and synthesis. Another crucial, but often overlooked, challenge is accurately matching in-text citations to reference lists, a problem ReciteWorks addresses robustly.

We discussed the inherent drawbacks and ethical considerations associated with AI. AI is prone to factual inaccuracies or “hallucinations,” biases stemming from questionable training data, and failures in context handling; for example, mixing up Apple, Inc. with the fruit apple, which one of the authors sadly observed in a student’s paper. This also includes the concerning proliferation of “deep-fakes.” Therefore, users must exercise discernment and ethical judgment.

RECOMMENDATIONS FOR FUTURE STUDIES

The use of AI in education is continually evolving, which presents numerous avenues for future research. One critical area is to examine AI adoption rates in doctoral programs, specifically assessing how institutional policies, faculty training, and student awareness influence the integration and effective use of AI tools. Such studies could provide valuable insights into the best practices for fostering an AI-literate academic environment. Once a baseline is established, it would be interesting to conduct a longitudinal study of the AI adoption rate.

Further research could also examine the pedagogical implications of AI integration. How can doctoral advisors and mentors be better equipped to guide students in the ethical and effective use of

AI? This could involve developing specialized training programs, creating standardized curricula for AI literacy in doctoral studies, or exploring the impact of AI on the mentor-mentee relationship.

Finally, another area of future investigation that would be beneficial is the impact of AI tools on the quality and originality of dissertations. While this suggested study focuses on the utility of AI, an analytical study comparing the characteristics of dissertations written with AI assistance versus those without it could be undertaken in the future. Such an analysis could provide empirical evidence of AI's influence on research depth and overall academic contribution.

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APPENDIX: DEMONSTRATION IN PRINCIPLES

A common teaching/learning method educators use when asking students to complete assignments is through the “demonstration in principles”. In this method, the educator presents concepts or principles, demonstrates to students the steps to complete the assignment, and then assigns students’ work that follows the demonstrated steps in different settings. We followed this approach in writing this paper. We presented concepts and principles before; now is the time to demonstrate how to use iterative prompt engineering to focus the dissertation topic. This lays the ground for students to use the iterative prompt engineering concept, to follow these steps, and to narrow down the topic of their dissertation.

Our demonstration goes through four steps of using iterative prompt engineering. We start with an open and general question about a particular topic. We used ChatGPT for our demonstration. ChatGPT replied to us, we used its prompt and, with our experience and through iterations, developed a more focused research topic that is being discussed for a doctoral dissertation. To demonstrate our approach (and the four iterative questions we asked ChatGPT), we present our first question below. Figure A1 shows the first question we asked ChatGPT.

I want to write a dissertation about the level of risk appetite that IT managers are willing to take when planning for their cybersecurity plan. Can you help me with finding five topics that are relevant to what I am looking for. I just want a list of five related topics that have been discussed in the last three years.

Figure A1. Our first question to ChatGPT

Figure A2 is the ChatGPT response we received to the first question about the dissertation topic. As shown, ChatGPT listed five narrower (focused) topics as relevant to the general topic we listed first.

Certainly! Based on recent developments in cybersecurity and IT management, here are five dissertation topics that align with your interest in the risk appetite of IT managers during cybersecurity planning:

1. **Evaluating IT Managers’ Risk Appetite in the Adoption of Autonomous AI Agents for Cybersecurity Operations**
This topic explores how IT managers assess and manage the risks associated with integrating autonomous AI agents into cybersecurity frameworks, considering the potential for AI-driven breaches and the need for robust identity and access controls.
2. **The Influence of Regulatory Compliance on IT Managers’ Cybersecurity Risk Appetite**
Investigate how evolving regulations, such as the New York Department of Financial Services’ AI cybersecurity guidance, impact IT managers’ willingness to assume cybersecurity risks and their strategies for compliance.
3. **Assessing the Impact of Cyber Insurance on IT Managers’ Risk Appetite in Cybersecurity Planning**
Analyze how the availability and terms of cyber and data privacy insurance influence IT managers’ decisions regarding risk tolerance and the implementation of cybersecurity measures.
4. **The Role of Cybersecurity Culture in Shaping IT Managers’ Risk Appetite**
Examine how the development and maturity of an organization’s cybersecurity culture affect IT managers’ perceptions of risk and their approach to cybersecurity planning.
5. **Impact of Security Convergence on IT Managers’ Risk Appetite in Cybersecurity Strategies**
Explore how the integration of physical and information security functions (security con-

vergence) influences IT managers' risk assessments and decision-making processes in cybersecurity planning.

These topics are grounded in recent research and industry developments, providing a contemporary perspective on the factors influencing IT managers' cybersecurity risk appetite.

Figure A2. ChatGPT's prompt to our first question

ChatGPT answered our question and listed the five topics we asked about, each with a brief description. But we want to narrow the topic further, so our iterative question this time focused on one of the five questions listed. So, our follow-up question (question #2) in Figure A3.

ChatGPT, thanks for this information, but please give us about one more page of information on this topic. Evaluating IT Managers' Risk Appetite in the Adoption of Autonomous AI Agents for Cybersecurity Operations.

Figure A3. ChatGPT's prompt to our iterative Question #2

ChatGPT's response to the follow-up question (Question #2) is shown in Figure A4. It focused the answer on the topic we selected and explained it further.

As artificial intelligence continues to evolve, many organizations are exploring autonomous AI agents to bolster cybersecurity defenses. These agents can automate threat detection, incident response, and even predictive analysis. However, the adoption of such technology introduces new and complex risk considerations. This dissertation examines the risk appetite of IT managers when integrating AI-driven agents into their cybersecurity frameworks.

The core of the study would examine how IT managers evaluate the trade-offs between increased efficiency and potential vulnerabilities introduced by AI. Key concerns include algorithmic bias, lack of transparency in decision-making, and the possibility of adversarial attacks exploiting the AI systems themselves. IT managers must balance the desire for innovation and automation with the necessity for control, accountability, and compliance with regulatory standards.

This topic would benefit from interviews, surveys, or case studies of organizations that have begun adopting AI tools in their security architecture. It could also explore how different sectors (e.g., finance, healthcare, government) approach AI risk differently, as well as how factors like organizational culture, budget, and leadership support influence risk tolerance. By understanding these dynamics, this research can contribute to a deeper understanding of how risk appetite shapes the adoption of transformative cybersecurity technologies.

Figure A4. ChatGPT's prompt to our Question #2

ChatGPT's prompt gave us more information about the topic we selected. We want to focus more on the one topic we selected. So we asked ChatGPT another iterative question to give us more information about the topic we selected. Our iterative Question #3 is shown in Figure A5.

Can you list three articles on this topic published in the last two years? Include the information in APA format, including DOI for the three articles.

Figure A5. Our iterative Question #3 to ChatGPT

ChatGPT was properly prompted and provided information on the three relevant references and the DoI (Figure A6).

Certainly! Here are three scholarly articles from the past two years that discuss the adoption of autonomous AI agents in cybersecurity and the associated risk considerations for IT managers. Each entry is formatted in APA style, including DOI links where available:
1. Ligo, A. K., Kott, A., & Linkov, I. (2022). <i>Autonomous cyber defense introduces risk: Can we manage the risk?</i> arXiv. https://doi.org/10.48550/arXiv.2201.11148 This paper examines the integration of autonomous cyber defense systems, highlighting the potential risks such as unintended harm due to machine learning training, algorithmic feedback, and constraints. It emphasizes the need for trust in autonomous cyber defenses, which is crucial for IT managers when considering the adoption of such technologies. arXiv
2. Ee, S., O'Brien, J., Williams, Z., El-Dakhakhni, A., Aird, M., & Lintz, A. (2024). <i>Adapting cybersecurity frameworks to manage frontier AI risks: A defense-in-depth approach.</i> arXiv. https://doi.org/10.48550/arXiv.2408.07933 This article discusses the evolving threat landscape due to frontier AI development and proposes a multi-layered approach to risk management. It outlines strategies such as functional, lifecycle, and threat-based approaches to identify and manage AI-related risks, providing IT managers with frameworks to assess their risk appetite in the context of AI adoption. arXiv
3. Farber, S. (2024). <i>Tackling AI risk requires a new governance framework.</i> Palo Alto Networks Blog. https://www.paloaltonetworks.com/blog/cloud-security/ai-risk-governance-framework/ This blog post addresses the novel security risks and governance challenges introduced by rapidly advancing AI technologies. It emphasizes the importance of developing a nuanced governance framework to assess and manage AI risks, which is essential for IT managers when determining their organization's risk appetite in cybersecurity planning.

Figure A6. ChatGPT provides article list with DoI information

A note to make here: although ChatGPT listed the references with DoI, there were some mismatches between the references and the DoI information; thus, we recommend always checking the accuracy of GenAI's prompts. After going through all the iterative steps with ChatGPT, we wanted to express our thanks (Figure A7).

Thanks, ChatGPT, that was very useful, I will come back to you tomorrow.

Figure A7. Thanks to ChatGPT after iterative prompts

ChatGPT was even more professional and kindly responded to our earlier request (Figure A8).

You're very welcome—I'm glad I could help! Good luck with your research, and I'll be here whenever you're ready to continue. Have a great day!

Figure A8. ChatGPT responded to our thanking it for working with us

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