Predicting Undergraduate Students' Behavioral Intention to Use Large Language Models for Academic Productivity: A Technology Acceptance Model Study Across Majors

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Chapter One

Introduction

Background and Problem Statement

Large language models (LLMs) and generative artificial intelligence tools such as ChatGPT and Copilot became increasingly visible in higher education as students used them to support the completion of coursework-related tasks (Albadarin et al., 2024; Baig & Yadegaridehkordi, 2024; Yu et al., 2024). Prior research showed that students often viewed these tools as helpful when they reduced effort, improved efficiency, or supported productivity-oriented academic work (Abdi et al., 2025; Albayati, 2024; Morell-Mengual et al., 2025). As these tools became more integrated into routine academic workflows across a large undergraduate population in the United States, the need to better understand how students perceived and accepted them for productivity-oriented use became more pronounced.

The background for this study was further shaped by evidence that LLM-based tool use and acceptance did not appear to be uniform across academic disciplines. Prior studies found that perceptions and usage varied across fields of study, academic levels, and disciplinary task demands (Elshaer et al., 2024; Qu et al., 2024; Stöhr et al., 2024). Students in technical or applied majors often engaged with LLM-based tools for programming, problem solving, technical explanation, or code-related support, whereas students in other majors more often used them for drafting, summarization, and comprehension support (Bernabei et al., 2023; García-Alonso et al., 2024; Peslak & Kovalchick, 2024). Because coursework demands and tasks differed across majors, prior research suggested that students could also differ in how useful and easy to use they perceived these tools to be (Baig & Yadegaridehkordi, 2024; Elshaer et al., 2024; Yu et al., 2024). This pattern emphasized a need for further study.

The problem addressed in this study was that, although undergraduate students increasingly used LLM-based tools for academic productivity, the literature had not sufficiently established whether perceived usefulness and perceived ease of use could predict behavioral intention to use these tools for productivity-oriented academic tasks across multiple majors. Existing studies showed that students often reported favorable views of generative AI tools. However, much of the literature focused on general perceptions of AI, single-discipline samples, single-institution contexts, or extended acceptance models that added multiple external variables (Abdi et al., 2025; Albayati, 2024; García-Alonso et al., 2024; Strzelecki, 2024). As a result, the core Technology Acceptance Model relationships had not been examined clearly enough in a broader undergraduate context centered on productivity-oriented use across majors (Al-Adwan et al., 2023; Davis, 1989).

If this problem had not been studied, colleges and universities could continue making instructional, policy, and support decisions regarding student LLM use without sufficient evidence on what drives acceptance across disciplines (Bittle & El-Gayar, 2025; Cotton et al., 2024; Wang et al., 2024). Instructors and institutions could remain uncertain about whether students across majors perceive these tools similarly or differently with respect to academic productivity, which could contribute to uneven guidance, inconsistent classroom integration, and poorly targeted support (Elshaer et al., 2024; Qu et al., 2024; Stöhr et al., 2024). Further research was therefore needed to examine whether the core Technology Acceptance Model explained undergraduate students' behavioral intention to use LLM-based tools for productivity-oriented academic tasks across multiple majors.

Chapter Two

Review of Literature

Introduction

Large language models (LLMs) and generative artificial intelligence (AI) have become increasingly visible in undergraduate education as students have adopted LLMs such as ChatGPT and Copilot to support their academic work (Albadarin et al., 2024; Baig & Yadegaridehkordi, 2024). Within higher education settings, students used LLM-based tools to summarize readings, generate ideas, draft and revise work, and obtain explanations that supported the comprehension of complex ideas and task completion (Albadarin et al., 2024). Students pursuing degrees in technical domains also used LLMs for programming-related tasks such as generating code, troubleshooting errors, and explaining programming concepts (Peslak & Kovalchick, 2024). The rapid diffusion of these tools, combined with their expanding capabilities, has positioned generative AI as a productivity-oriented technology that can reshape how students approach coursework across multiple disciplines (Albadarin et al., 2024; Baig & Yadegaridehkordi, 2024; Yu et al., 2024). At the same time, adoption has not occurred uniformly or automatically (Strzelecki, 2024; Yu et al., 2024; Abdi et al., 2025). Students' willingness to use LLM-based tools can depend on how they perceive the value of the tool for completing academic tasks and how easy they believe the tool is to use effectively (Davis, 1989; Al-Adwan et al., 2023; Strzelecki, 2024). These acceptance factors are important because students' adoption choices can influence how LLM-based tools are incorporated into coursework practices, academic support structures, and institutional guidelines regarding responsible and ethical use of such technologies (Cotton et al., 2024; Bittle & El-Gayar, 2025; Wang et al., 2024).

The purpose of this quantitative, cross-sectional, survey-based study is to examine undergraduate students' acceptance of LLM-based tools across multiple academic majors by applying the Technology Acceptance Model to assess behavioral intention to use LLM-based tools for productivity-oriented academic tasks. The TAM provides a structured explanation of technology adoption in which perceived usefulness and perceived ease of use contribute to the behavioral intention to use a technology (Al-Adwan et al., 2023; Davis, 1989). In this dissertation, perceived usefulness refers to the extent to which undergraduate students believe that LLM-based tools improve academic productivity, including completing academic tasks more efficiently or effectively (Davis, 1989; Venkatesh & Davis, 2000; Venkatesh et al., 2003). For this study, academic productivity refers to students' perceived ability to complete coursework-related tasks more efficiently, effectively, or with less effort by using LLM-based tools. Perceived ease of use represents the extent to which students believe that using an LLM-based tool is understandable, manageable, and requires minimal effort to obtain valuable outputs (Davis, 1989; Venkatesh & Davis, 2000; Venkatesh et al., 2003). Behavioral intention reflects the likelihood that students will use LLM-based tools for productivity-focused coursework activities (Davis, 1989; Venkatesh & Davis, 2000; Venkatesh et al., 2003). Although prior research has examined LLM use among specific student groups, such as students pursuing degrees in computer science, the literature has noted a need to better understand acceptance and productivity-oriented use across a wider range of majors (Aljohani, 2025). Because academic disciplines can differ in typical task demands, assessment formats, and types of information studied, a cross-major perspective is important for clarifying whether the predictors of LLM adoption remain consistent across disciplines or whether acceptance patterns may vary in meaningful ways (Baig & Yadegaridehkordi, 2024; Yu et al., 2024).

This chapter provides the theoretical and empirical foundation for the dissertation by synthesizing recent literature on LLM use in higher education through the lens of the TAM. The literature review is designed to establish conceptual clarity regarding the productivity-oriented academic use of LLM-based tools, justify the selection of the TAM constructs as study variables, and position the dissertation as relevant to current empirical research. In alignment with quantitative research conventions, the literature review emphasized empirical studies that reported measurable relationships among technology acceptance constructs and usage intentions, while incorporating foundational theory that supports construct definitions and model structure. The chapter's organizing logic is theme-based rather than study-by-study. Themes are used to synthesize evidence across research designs and educational settings so that the chapter develops a cohesive rationale for the dissertation's predictive model and clarified the gap addressed by the study.

The literature gathering process for this chapter followed a structured search strategy designed to identify foundational TAM literature and recent empirical research relevant to LLM adoption and productivity-oriented academic use in higher education. Because widespread student adoption of LLMs and similar tools emerged recently, the search strategy prioritized current literature, with an emphasis on research primarily published within the past five years for generative AI topics. Seminal works were included where necessary to define TAM constructs and to establish theoretical precedence, consistent with the dissertation's expectations that a literature review incorporate both historical and recent scholarship when appropriate. The search process emphasized peer-reviewed journal articles and peer-reviewed conference proceedings relevant to information technology and educational technology research. Doctoral dissertations were also considered when they addressed constructs, populations, or methods closely aligned with the current study’s framing.

Searches were conducted across multidisciplinary and discipline-specific databases and indexing platforms. These included education-focused databases, broad scholarly indexing services, and repositories of technology and information systems. To improve coverage, the literature search also included backward reference searching. Backward reference searching involved reviewing reference lists in high-relevance studies and reviews to identify foundational TAM publications and related acceptance research that informed construct definitions and measurements (Page et al., 2021).

Keyword selection and query construction were organized into concept clusters, which were then combined using standard database search operators (Page et al., 2021). The first cluster focused on TAM constructs and adoption terminology, including the Technology Acceptance Model, TAM, perceived ease of use, PEOU, perceived usefulness, PU, behavioral intention, BI, intention to use, acceptance, and adoption. The second cluster focused on LLM and generative AI terminology, including large language model, LLM, generative AI, AI, conversational AI, ChatGPT, Copilot, and AI writing tools. The third cluster targeted the higher education and productivity context, including higher education, undergraduate, college, and university students, academic productivity, studying, writing support, summarization, coursework, coding support, code generation, and learning support. Search strings were iteratively refined when early results suggested additional terminology was used in the literature, such as performance expectancy and effort expectancy, which can be conceptually aligned with perceived usefulness and perceived ease of use in acceptance research (Davis, 1989; Venkatesh & Davis, 2000; Venkatesh et al., 2003).

Inclusion criteria were applied to maintain relevance to the dissertation topic and to support an in-depth synthesis. Sources were included when they addressed higher education learners or a closely comparable population, examined adoption or intention to use generative AI tools or similar educational technologies, or provided foundational theory and measurement guidance related to TAM constructs. Sources were generally excluded when they were non-scholarly, lacked methodological transparency, did not address student populations or educational contexts, or did not provide evidence that could be mapped to the dissertation's constructs. When multiple versions of a work were available, peer-reviewed versions were prioritized. Systematic reviews were used to summarize broader trends in early empirical findings and to identify clusters of research questions and methodological patterns relevant to LLM adoption in education (Albadarin et al., 2024; Baig & Yadegaridehkordi, 2024). Across all included sources, the goal was to select literature that supported conceptual definitions, instrument development considerations, and empirical expectations for relationships among perceived usefulness, perceived ease of use, and behavioral intention to use.

The scope of the literature review is aligned with the dissertation's purpose and theoretical framework. The dissertation focuses on undergraduate students in the United States, who are a large population enrolled across a wide range of institutions and fields of study (National Center for Education Statistics, 2023). Because the study examined adoption across majors, the literature review includes research that clarified how academic tasks and technology exposure can vary by discipline and how such differences may influence perceptions of usefulness and ease of use (Baig & Yadegaridehkordi, 2024; Wang et al., 2024; Yu et al., 2024). The scope also emphasized productivity-oriented academic use rather than non-academic, exploratory, or novelty-driven use. Productivity-oriented use is defined as student use of LLM-based tools to support completion of coursework tasks more effectively or efficiently, including writing and revision, comprehension support, summarization, planning, and related academic workflows (Albadarin et al., 2024; Baig & Yadegaridehkordi, 2024; Yu et al., 2024).

The literature review was organized into major thematic areas that build from the general context to the specific theoretical and empirical foundations needed for the dissertation's model. First, the review established a grounding in LLM technology as it appears in higher education by defining LLM-based tools, describing their core capabilities, and summarizing common student use patterns. This initial section provided contextual clarity for why generative AI can be framed as a productivity-oriented technology in academic settings (Albadarin et al., 2024; Baig & Yadegaridehkordi, 2024; Yu et al., 2024). It also addressed constraints such as accuracy limitations and academic integrity concerns that may influence adoption decisions (Cotton et al., 2024; Bittle & El-Gayar, 2025; Wang et al., 2024). Second, the review presented TAM as the guiding theoretical framework by defining perceived usefulness, perceived ease of use, and behavioral intention and by summarizing how these constructs have been applied and tested in educational technology research (Al-Adwan et al., 2023; Davis, 1989). Establishing these definitions is essential for aligning survey items with construct meaning and for ensuring that the dissertation's variables accurately reflect the theoretical model. Third, the review synthesized empirical applications of the TAM and closely related acceptance models in educational technology and AI contexts. This section clarified how acceptance predictors have been examined in higher education settings, how measurement and validity were addressed, and how results were interpreted across different technology types. This is important because generative AI tools differ from many other educational technologies in their general-purpose nature, their reliance on user-prompting skills, and their probabilistic outputs (Albadarin et al., 2024; Baig &

Yadegaridehkordi, 2024; Yu et al., 2024). Fourth, the review focused specifically on students' acceptance of LLM-based tools, emphasizing empirical findings on determinants of intention to use, perceived benefits, and adoption barriers (Strzelecki, 2024; Abdi et al., 2025; García-Alonso et al., 2024). This section was positioned as the closest evidence base to the dissertation topic and is used to justify expected relationships among the TAM constructs in productivity-oriented use contexts. Fifth, the review examined major-based differences in technology use and academic workflows to support the dissertation's cross-major design (Baig & Yadegaridehkordi, 2024; Wang et al., 2024; Yu et al., 2024). This section considered how discipline-specific task structures may affect students' perceptions of LLMs' usefulness for productivity and the effort required to use these tools effectively.

Throughout these sections, the TAM served as the theoretical framework, and the discussion explicitly connects each theme back to perceived usefulness, perceived ease of use, and behavioral intention. For example, when prior studies used constructs labeled as performance expectancy or effort expectancy, these constructs are evaluated in relation to the TAM's definitions to ensure the dissertation's theoretical structure remains consistent and coherent (Davis, 1989; Venkatesh & Davis, 2000; Venkatesh et al., 2003). This approach supported a consistent interpretation of results and prevented the literature review from becoming a set of disconnected summaries. The literature was synthesized across studies by comparing populations, contexts, constructs, measurement approaches, and analytic methods. Convergent findings provided stronger support for the expectations tested in the dissertation, whereas divergent findings identified boundary conditions, limitations, and unresolved questions that reinforce the need for additional research.

The chapter's literature analysis followed a synthesis-oriented process that emphasizes integration of evidence rather than simple description (Page et al., 2021). After sources were identified through the search strategy, the literature was grouped into thematic sections that were aligned with the chapter's organization, rather than randomly or study-by-study. Within each theme, studies were evaluated based on methodological rigor, relevance to undergraduate populations, how clearly key constructs were defined and measured, and the extent to which outcomes align with the dissertation's focus on productivity-oriented academic use. Evidence across studies was compared to identify consistent patterns in the effects of perceived usefulness and perceived ease of use on behavioral intention, as well as discrepancies arising from differences in institutional context, measurement approaches, or the specific academic tasks supported by LLM-based tools. This synthesis approach supported the development of a logical and defensible research gap statement and clarified how the dissertation extends and enhances existing research.

In sequence, Chapter Two began with a literature review of LLM-based tools in higher education and the types of academic activities in which students have used them. The chapter then established the TAM as the theoretical foundation and synthesized prior acceptance research to define perceived usefulness, perceived ease of use, and behavioral intention. Next, the empirical findings from TAM-based and related adoption studies in educational technology and AI contexts were reviewed to provide an evidence base for expected relationships between the defined constructs. The review then focused on students' acceptance of large language models, emphasizing determinants of intention, productivity-oriented benefits, and potential barriers to adoption. The chapter subsequently examined major-based differences that may shape how students perceive usefulness and ease of use across disciplines. Finally, the chapter synthesized convergent and divergent findings to identify the literature gap regarding productivity-oriented LLM acceptance across diverse majors and to justify the dissertation's TAM testing approach. This synthesis transitioned to Chapter Three, which describes the quantitative methodology used to test whether perceived usefulness and perceived ease of use predict behavioral intention, including the study's sampling plan and analytic strategy.

Large Language Models in Higher Education

Large language models became one of the most visible forms of generative artificial intelligence in higher education because they combined broad functionality with accessible, conversational interfaces (Albadarin et al., 2024; Baig & Yadegaridehkordi, 2024; Peláez-Sánchez et al., 2024). Across recent reviews, the literature increasingly treated tools such as ChatGPT and Copilot not as short-lived novelties with narrow use cases, but as multipurpose academic technologies associated with writing support, explanation, feedback, summarization, and general coursework assistance (Albadarin et al., 2024; Baig & Yadegaridehkordi, 2024; Guizani et al., 2025). This convergence mattered because it showed broad agreement that LLMs had become part of the contemporary higher education landscape, even though the empirical base remained recent and context dependent.

A second pattern in the literature was that the educational relevance of LLMs came largely from their versatility. Unlike narrower academic technologies designed for a single function, LLM-based systems supported brainstorming, drafting, revision, explanation, and discipline-specific support within a single interface (Peláez-Sánchez et al., 2024; Morell-Mengual et al., 2025; Stöhr et al., 2024). At the same time, the literature did not portray this versatility as producing uniform academic experiences. Instead, studies repeatedly suggested that perceptions and uses varied by discipline, prior experience, training, and institutional context, meaning that the same tool could be interpreted differently across majors and learning environments (Elshaer et al., 2024; García-Alonso et al., 2024; Pan & Ni, 2024; Stöhr et al., 2024). In that sense, the literature converged on the presence of broad capability while diverging on how consistently that capability translated into meaningful academic value.

Recent systematic reviews reinforced this interpretation by showing that AI-supported learning expanded across tutoring, feedback, writing support, assessment, and task assistance, while concerns about quality, readiness, and responsible use persisted across settings (Abdallah et al., 2025; Ali et al., 2024; Lo, 2023; Montenegro-Rueda et al., 2023; Naznin et al., 2025). Taken together, these studies suggested that LLMs were best understood as academically beneficial but conditional technologies. They offered strong productivity-oriented promise, but their perceived value depended on context, student judgment, and the institutional policies that governed appropriate use.

Definitions and Core Capabilities of Large Language Models

Large language models are artificial intelligence systems trained on massive datasets to identify patterns in language and generate contextually relevant responses to prompts (Peláez-Sánchez et al., 2024; Guizani et al., 2025). At a functional level, these models produce output by predicting likely word sequences based on patterns learned during training (Guizani et al., 2025). Although their underlying technical architecture is complex, their relevance in higher education lies less in the engineering details and more in the practical capabilities they make available to users (Peláez-Sánchez et al., 2024). In academic settings, large language models can generate explanations, summaries, examples, revisions, outlines, and responses to questions through natural language interaction, making them especially accessible to students without technical expertise (Peláez-Sánchez et al., 2024; Guizani et al., 2025).

One of the defining features of large language models is that they operate as general-purpose systems rather than single-function applications (Albadarin et al., 2024; Baig & Yadegaridehkordi, 2024; Guizani et al., 2025). In higher education, this means the same tool may be used for brainstorming, language refinement, concept explanation, tutoring-like interaction, and support for course-related problems (Peláez-Sánchez et al., 2024; Guizani et al., 2025). This broad functional range distinguishes large language models from many earlier academic technologies designed to perform a single limited task (Peláez-Sánchez et al., 2024). Reviewed literature has accordingly emphasized that these systems are being adopted precisely because they can support multiple forms of academic work within a single interface, making them especially attractive in environments where students must manage diverse and recurring cognitive demands (Albadarin et al., 2024; Baig & Yadegaridehkordi, 2024; Guizani et al., 2025).

Another core capability of large language models is their adaptability across subject areas (Pan & Ni, 2024; Bernabei et al., 2023; García-Alonso et al., 2024; Peslak & Kovalchick, 2024). These tools can be used in writing-intensive courses, social science contexts, technical coursework, and professional programs, although the forms of support they provide may differ across disciplines (Pan & Ni, 2024; Bernabei et al., 2023). For some students, the most salient capability may be language generation or revision support. For others, it may be concept explanation, problem-solving assistance, or help with technical workflows (García-Alonso et al., 2024; Peslak & Kovalchick, 2024). This cross-disciplinary adaptability is particularly important for the present dissertation because it helps explain why student acceptance may vary across majors while still centering on the same underlying technology.

Despite these capabilities, large language models should not be understood as equivalent to expertise, nor should their results be interpreted as completely accurate (Baig & Yadegaridehkordi, 2024; Cotton et al., 2024; Bittle & El-Gayar, 2025). The literature consistently notes that these systems can generate polished and convincing responses that may nonetheless contain factual inaccuracies, or incomplete explanations lacking important context (Baig & Yadegaridehkordi, 2024; Cotton et al., 2024). In educational settings, this means that the usefulness of large language models depends not only on what they can produce, but also on how critically students evaluate and apply their output (Bittle & El-Gayar, 2025). Thus, the defining capabilities of large language models must be understood alongside their limitations, particularly in higher education environments where quality, originality, and academic judgment remain central expectations (Cotton et al., 2024; Bittle & El-Gayar, 2025).

Student Use Patterns and Academic Applications

The literature indicated that student adoption of LLMs expanded rapidly after public release, but it did not portray use as a single, uniform pattern (Albadarin et al., 2024; Baig & Yadegaridehkordi, 2024). Across descriptive, acceptance-based, and review studies, students used tools such as ChatGPT and Copilot for clusters of related academic purposes, especially writing support, explanation, summarization, studying, and workflow assistance (Abdi et al., 2025; Albayati, 2024; Stöhr et al., 2024; Yu et al., 2024). This convergence across studies suggested that LLMs were adopted less as specialty tools and more as flexible supports that could be used in everyday coursework.

At the same time, the literature also showed that use was context sensitive. Studies from social science, medical, engineering, and computing settings indicated that students used the same broad technology in discipline-specific ways, with some emphasizing explanation and writing support while others emphasized technical clarification, code-related help, or specialized problem support (Bernabei et al., 2023; García-Alonso et al., 2024; Pan & Ni, 2024; Peslak & Kovalchick, 2024). This pattern mattered because it suggested that common use categories existed across higher education, but the relative importance of each category depended on course demands, disciplinary expectations, and academic background. Rather than simply using LLMs more or less, students often used them differently depending on what kinds of work dominated their field.

Writing, revision, and idea generation emerged as one of the clearest and most consistently documented application areas. Across reviews and empirical studies, students used LLMs to brainstorm topics, generate outlines, refine wording, improve clarity, and revise grammar or organization (Albadarin et al., 2024; Albayati, 2024; Morell-Mengual et al., 2025; Romero-Rodríguez et al., 2023). Writing-focused studies in English, pharmacological studies, and broader undergraduate contexts reported similar patterns even though they differed in sample and setting. Students tended to value these tools most when they reduced the difficulty of starting, structuring, or refining written work (Abd Hadi et al., 2024; Boudouaia et al., 2024; Launonen et al., 2024; Lee & Cakir, 2024; Lubis et al., 2025; Othman, 2025; Untari & Trisanti, 2026; Xhaferi, 2024). Across these studies, the more consistent finding was that students viewed LLMs as useful when the tools reduced the effort needed to move from initial uncertainty to a workable draft

A second recurring application area involved summarization, studying, and comprehension support. Reviews and primary studies consistently described students using LLMs to condense readings, simplify difficult concepts, generate examples, and produce study-oriented explanations that made content more manageable under time constraints (Albadarin et al., 2024; Baig & Yadegaridehkordi, 2024; Peláez-Sánchez et al., 2024; Stöhr et al., 2024; Yu et al., 2024). These benefits appeared across disciplines, but the specific academic content changed by field. Students in general higher education contexts often used LLMs for reading and concept support, whereas students in technical and professional fields used them to clarify specialized material or solve task-specific problems (Bernabei et al., 2023; Pan & Ni, 2024; Peslak & Kovalchick, 2024). Thus, the literature suggested that comprehension support was a cross-disciplinary use case, but its perceived usefulness depended on the complexity and type of material students were working with.

The literature also converged on workflow efficiency as a major part of perceived academic value. Even when studies did not explicitly label the phenomenon as task management, they repeatedly showed that students used LLMs to shorten the time required to interpret instructions, generate examples, begin assignments, revise text, and solve difficult coursework problems (Albayati, 2024; Stöhr et al., 2024; Yu et al., 2024). This efficiency-related value became especially evident in environments where students faced multiple simultaneous demands, which helped explain why usefulness, satisfaction, and continued intention featured prominently in recent acceptance studies (Abdi et al., 2025; Alshammari & Babu, 2025; Yu et al., 2024). In this sense, the literature did not merely show that students liked LLMs. It showed that they often interpreted them as tools that reduced friction in everyday academic workflows.

Discipline-specific studies strengthened this interpretation by showing that efficiency gains were not limited to one type of coursework. Programming and engineering studies, for example, showed that students and instructors often valued ChatGPT for code explanation, debugging, brainstorming, and rapid problem solving, even while debating the effects on collaboration, integrity, and potential security issues with untested code (Peslak & Kovalchick, 2024; Stoyanova et al., 2025; Stoyanova et al., 2026). Taken together with writing-focused studies, these findings suggested that the strongest use cases were not random. They clustered around tasks in which students perceived the tool as reducing effort, increasing speed, or improving the early stages of academic production, even though the specific task varied by field.

Risks, Limitations, and Academic Integrity

The literature did not present LLMs as unambiguously beneficial. The same studies that emphasized writing support, comprehension assistance, and efficiency also raised concerns about originality, superficial learning, inaccurate summaries, and overreliance on AI-generated output (Bittle & El-Gayar, 2025; Cotton et al., 2024; Wang et al., 2024). This pattern was consistent across both empirical and review studies, suggesting that educational value and educational risk often developed together rather than as separate issues.

A second area of convergence involved uncertainty about acceptable use. Even when students viewed LLMs as useful, institutional policies and instructor expectations varied considerably, leading to adoption within changing, sometimes unclear boundaries (Bamasoud et al., 2025; Wang et al., 2024). This mattered because it suggested that acceptance did not depend only on what the technology could do. It also depended on whether students believed use was legitimate, responsible, and compatible with course and institutional policies.

These limitations are central to the present dissertation because they help connect descriptive use patterns back to TAM. Students may have recognized clear functional value while remaining selective about whether they intended to incorporate the technology into routine academic behavior. In that sense, the literature suggested that adoption judgments reflected more than simple enthusiasm. They reflected students’ attempts to balance efficiency and support against concerns about trust, originality, and educational appropriateness.

Technology Acceptance Model Foundations

The Technology Acceptance Model provided the primary theoretical foundation for the present study (Davis, 1989). Developed by Davis (1989), TAM was designed to explain why users accept or reject information technologies by focusing on two core beliefs, which are perceived usefulness and perceived ease of use. The model proposed that users are more likely to form positive intentions toward a technology when they believe it will enhance their performance and when they perceive it as relatively easy to use (Davis, 1989). Because the present dissertation examined undergraduate students' acceptance of large language models for academic productivity, TAM offers a conceptually appropriate framework for understanding how students' beliefs about these tools may shape their intention to use them.

One reason TAM remained highly influential was its simplicity (Davis, 1989; Al-Adwan et al., 2023). Rather than attempting to explain technology adoption through an excessively large set of variables, the model centers on a small number of conceptually powerful constructs that have been widely tested across information systems, educational technologies, and digital platforms (Davis, 1989). This simplicity makes TAM especially useful in higher education research, where scholars often seek to understand how students evaluate the usefulness and usability of emerging tools (Al-Adwan et al., 2023). In the context of large language models, this framework is particularly relevant because students often judge whether these tools save time, support academic tasks, or reduce effort in coursework-related activities.

The continuing relevance of TAM is also evident in the development of later acceptance models and extensions (Venkatesh & Davis, 2000; Venkatesh et al., 2003). Venkatesh and Davis (2000) expanded the model through TAM2, showing that perceived usefulness and usage intentions may also be shaped by social influence and cognitive instrumental factors. Venkatesh et al. (2003) later synthesized multiple technology acceptance theories into the Unified Theory of Acceptance and Use of Technology, further demonstrating the central role that belief-based adoption models play in technology research. Although the present study uses TAM rather than UTAUT or other extended models, TAM is preferable for this dissertation because its core constructs align directly with the study's purpose and research questions (Davis, 1989; Venkatesh & Davis, 2000; Venkatesh et al., 2003). The focus of the present study is not to test a broad multivariable acceptance framework, but to examine whether perceived usefulness and perceived ease of use predict behavioral intention to use LLM-based tools for academic productivity. A more expansive model, such as UTAUT, may introduce additional constructs that are valuable in other contexts but not essential to the narrower predictive aim of this dissertation. Accordingly, TAM provided a simpler and theoretically aligned framework for the present study.

The literature on student adoption of LLMs such as ChatGPT, Copilot, and related tools further supported the appropriateness of TAM as a guiding framework for this dissertation (Abdi et al., 2025; Alshammari & Babu, 2025; Albayati, 2024; Al-Adwan et al., 2023). Recent higher education studies applied TAM directly or used closely related acceptance models to examine how students perceived and adopted generative AI systems (Abdi et al., 2025; Alshammari & Babu, 2025; Albayati, 2024). These studies reinforced the view that student acceptance of large language models was strongly tied to beliefs about usefulness, ease of use, value, and intention (Al-Adwan et al., 2023). At the same time, this body of research was still developing and was often limited by single-institution samples, self-reported perceptions, or discipline-specific populations (Abdi et al., 2025; Albayati, 2024). Accordingly, TAM provided both a theoretically grounded and empirically relevant framework for examining how undergraduate students evaluated large language models as academic productivity tools while also addressing a still-developing evidence base.

Perceived Usefulness

Perceived usefulness referred to the degree to which an individual believed that using a specific system would improve performance or outcomes in a given context (Davis, 1989). Within the present study, that construct was especially relevant because LLM adoption in higher education often centered on whether students believed the technology enhanced productivity, improved coursework efficiency, or supported better academic task completion (Abdi et al., 2025; Alshammari & Babu, 2025; Yu et al., 2024). Across the recent literature, usefulness repeatedly emerged as one of the most stable predictors of intention to use LLM-based tools in academic contexts (Abdi et al., 2025; Sharma & Ha, 2025; Yu et al., 2024). This consistency suggested that students' willingness to adopt LLM-based tools depended heavily on whether they perceived clear academic value rather than novelty alone.

That value often included assistance with writing, explanations, studying, task completion, or managing coursework demands. Although these activities differed by discipline and assignment type, the literature consistently indicated that students were more likely to express favorable attitudes toward LLM use when they believed the tools reduced effort, increased speed, or improved the quality of their work (Abd Hadi et al., 2024; Albayati, 2024; Morell-Mengual et al., 2025; Sousa & Cardoso, 2025). In this sense, perceived usefulness functioned as both a theoretical construct and a practical explanation for why LLMs became embedded in academic routines.

Perceived Ease of Use

Perceived ease of use referred to the degree to which an individual believed that using a system would be effort-minimizing (Davis, 1989). In the context of large language models, ease of use was especially important, as conversational interfaces reduced many of the technical barriers commonly associated with digital tools. Students did not need advanced programming skills or extensive training to begin experimenting with systems such as ChatGPT and Copilot. This natural language accessibility lowered barriers to experimentation and may help explain why LLMs such as ChatGPT and Copilot were adopted so rapidly across varied educational settings (Albayati, 2024; Yu et al., 2024).

Recent empirical studies suggest that ease of use remains important, though its effect is not always identical across models. In some studies, ease of use directly predicted intention. In others, it influenced intention indirectly through usefulness or satisfaction (Abdi et al., 2025; Alshammari & Babu, 2025; Yu et al., 2024). This pattern suggested that ease of use was most important when it helped students recognize the tool’s value more quickly. For the present study, that distinction was important because it supported continued attention to ease of use even when usefulness appeared to be the stronger predictor overall.

Behavioral Intention to Use

Behavioral intention to use represented an individual’s stated likelihood of adopting or continuing to use a technology (Davis, 1989). In the context of higher education, intention was especially relevant because many studies on LLM adoption examined planned or expected use rather than direct observation of long-term behavior (Abdi et al., 2025; Strzelecki, 2024; Yu et al., 2024). This emphasis reflected the practical importance of intention as a bridge between attitudes and behavior. Students may have recognized benefits or experienced ease of use, but those beliefs only mattered for adoption if they translated into an intention to incorporate the tool into academic work.

The recent literature consistently suggests that behavioral intention is shaped by beliefs about usefulness, effort, trust, and context, although the strength of these relationships varies by study design and population (Abdi et al., 2025; Sharma & Ha, 2025; Wahdah et al., 2025). For the present dissertation, behavioral intention served as the logical outcome variable because it captured whether undergraduate students saw LLM-based tools as worth using for productivity-oriented academic purposes across majors.

Empirical Research on TAM and LLM Acceptance

Recent empirical research increasingly applied the Technology Acceptance Model and closely related adoption frameworks to explain how students evaluated and adopted large language model-based tools in higher education (Abdi et al., 2025; Albayati, 2024; Alshammari & Babu, 2025; Yu et al., 2024). This body of literature was important because it moved beyond descriptive discussion of ChatGPT and related systems and instead tested how specific beliefs shaped students' willingness to use these tools for academic purposes. Across studies, acceptance was typically examined through variables such as perceived usefulness, perceived ease of use, behavioral intention, satisfaction, trust, and social influence (Abdi et al., 2025; Alshammari & Babu, 2025; Strzelecki, 2024). The cumulative evidence suggested that students' adoption of LLM-based tools was not random or merely trend-driven. Rather, it reflected patterned judgments about whether the tools were useful, manageable, legitimate, and worth integrating into academic work. Prior studies also varied in construct measurement, model specification, and reliance on self-reported data, which affected how acceptance findings were interpreted across contexts.

At the same time, the empirical literature on LLM acceptance remained uneven. Many studies were conducted in single institutions, within one country, or among one academic subgroup, which limited generalizability across broader student populations (Abd Hadi et al., 2024; García-Alonso et al., 2024; Pan & Ni, 2024). In addition, some studies used TAM, while others used UTAUT, UTAUT2, or extended adoption models, creating a diverse but fragmented evidence base (Grassini et al., 2024; Romero-Rodríguez et al., 2023; Strzelecki, 2024). Even so, this line of research consistently reinforced the value of acceptance-based frameworks for understanding how students interpreted the role of large language models in higher education. The present dissertation builds on that literature by focusing specifically on whether perceived usefulness and perceived ease of use predict undergraduate students' behavioral intention to use LLM-based tools for productivity-oriented academic tasks across majors.

TAM in Higher Education

The empirical use of TAM in higher education had a long history that extended well beyond generative AI, which helped explain why it remained an appropriate framework for the present study (Davis, 1989; Al-Adwan et al., 2023). Researchers repeatedly used TAM to examine how students adopted instructional technologies, digital learning platforms, and other academic systems, often finding that usefulness and ease of use were central to adoption judgments (Davis, 1989; Al-Adwan et al., 2023). This broader educational technology literature was relevant because it demonstrated that student technology use was often shaped by practical academic considerations rather than by novelty alone. In other words, students were more likely to accept a tool when they believed it supported performance and did not create unnecessary effort.

This pattern continued in research on generative AI and large language models. Recent higher education studies applying TAM to ChatGPT and related tools generally found that TAM remained effective for explaining student acceptance of AI-based tools (Abdi et al., 2025; Alshammari & Babu, 2025; Albayati, 2024; García-Alonso et al., 2024). Even when researchers extended TAM with additional variables such as credibility, trust, privacy, or social influence, the core constructs remained central to the model logic (Abdi et al., 2025; Albayati, 2024). This was important for the present dissertation because it suggested that TAM continued to offer explanatory value, even in relation to rapidly developing technologies such as ChatGPT and Copilot. The model's continued relevance in higher education also supported its use as a simple framework for examining productivity-oriented LLM acceptance, without introducing an unnecessarily large number of variables that are not the study's direct focal point.

The empirical literature further suggested that TAM-based studies were especially useful when researchers wanted to focus on practical student judgments rather than institutional or technical complexity. Large language models could be described in many ways, including as communication tools, content generators, writing assistants, study aids, or discipline-specific supports. TAM helped organize these possibilities by returning attention to a basic question, which asks whether students believe the technology was useful and easy enough to use that they intended to adopt it. In that sense, TAM provided theoretical continuity across older educational technology studies and newer AI-focused studies, making it especially suitable for a dissertation that aimed to test a focused acceptance model within a contemporary higher education context (Davis, 1989; Abdi et al., 2025; Alshammari & Babu, 2025; García-Alonso et al., 2024).

Additional acceptance studies reinforced the continued relevance of TAM and related models in AI-enabled higher education. Recent work applied TAM, UTAUT, and UTAUT2 to student adoption of ChatGPT and broader generative AI tools across multiple countries, again showing that value, effort, contextual support, and risk perceptions remained central to student adoption decisions (Habibi et al., 2023; Aldreabi et al., 2025; Howlader et al., 2025; Wahdah et al., 2025; Suryawidjaja & Gozali, 2025; Alshammari et al., 2025). Together, these studies suggested that acceptance frameworks remained useful even as the technology evolved, because students still evaluated AI tools based on beliefs about usefulness and ease of use.

Predictors of Intention to Use AI Tools

One of the most consistent findings in the literature was that students' intention to use AI tools was shaped by perceived academic value. Across TAM-based and related studies, perceptions of usefulness repeatedly emerged as one of the strongest predictors of intention, continued use, or satisfaction (Abdi et al., 2025; Alshammari & Babu, 2025; Yu et al., 2024; Sharma & Ha, 2025). When students believe an LLM-based tool helps them complete tasks more effectively, understand concepts more clearly, or save time in coursework, they are more likely to express an intention to use it. This pattern is theoretically aligned with Davis (1989) and also highly relevant to the present dissertation, which focuses on productivity-oriented academic use. Much of the current literature suggested that the key question for students is whether the tool produces enough value to justify integration into ongoing academic routines.

Perceived ease of use also remained an important predictor, though the effect's strength and direction varied across studies (Abdi et al., 2025; Alshammari & Babu, 2025; Yu et al., 2024). In some models, ease of use directly predicted intention. In others, it influenced intention indirectly by increasing satisfaction or perceived usefulness (Alshammari & Babu, 2025; Yu et al., 2024). This distinction is important because ease of use may have functioned both as a direct belief about effort and as a supporting condition that enabled students to recognize value more quickly. For large language models, which were often accessed through conversational interfaces, ease of use was especially relevant during early experimentation and first adoption. However, once students become familiar with the interface, usefulness became the stronger determinant of whether they continue to use the tool regularly.

Beyond usefulness and ease of use, the literature also identified a range of additional predictors that may shape intention to use AI tools. These include social influence, credibility, trust, performance expectancy, hedonic motivation, habit, and institutional context (Abdi et al., 2025; Strzelecki, 2024; Grassini et al., 2024; Wahdah et al., 2025). Although these variables are not the central focus of the present study, they help explain why intention does not develop identically across all students and settings. Students interpreted large language models within broader social and academic environments, including faculty expectations, policy uncertainty, and prior experience. Thus, the empirical literature suggests that intention to use AI tools is shaped by both core acceptance beliefs and contextual factors, even when usefulness and ease of use remain central.

Recent predictor studies also added nuance to the literature by showing that intention is not only driven by usefulness and ease of use. Social persuasion, facilitating conditions, habit, readiness, ethical awareness, perceived cost, and risk can strengthen or weaken adoption depending on the setting and model specification (Sharma & Ha, 2025; Aldreabi et al., 2025; Howlader et al., 2025; Baharin et al., 2025; Alshammari et al., 2025). This pattern does not undermine TAM. Instead, it suggests that the core TAM relationships operate within broader academic and institutional contexts that may intensify or constrain students' willingness to use AI tools.

Student Acceptance of LLMs

The empirical literature generally indicated that students hold favorable or at least moderately favorable views toward the use of large language models in higher education, particularly when the tools are perceived as relevant to academic tasks (Abd Hadi et al., 2024; Albayati, 2024; Morell-Mengual et al., 2025; Sousa & Cardoso, 2025). Many students reported positive perceptions of ChatGPT and related systems for writing, idea generation, concept explanation, studying, and general coursework support (Abd Hadi et al., 2024; Launonen et al., 2024; Morell-Mengual et al., 2025). This general pattern of acceptance is reinforced by systematic reviews that describe growing interest in LLM use across higher education contexts (Albadarin et al., 2024; Baig & Yadegaridehkordi, 2024). Taken together, these findings suggest that acceptance of large language models is no longer a marginal issue in the literature. It became a central topic in research on student technology use.

At the same time, student acceptance was not uniform. Studies showed that acceptance varied by discipline, training, country, prior experience, institutional expectations, and subgroup characteristics such as academic level (Elshaer et al., 2024; Stöhr et al., 2024; Qu et al., 2024; Pan & Ni, 2024). Students in technical or applied fields often emphasized discipline-specific support such as coding, problem solving, or specialized explanation, whereas students in writing-intensive or general education contexts often focused more on drafting, summarization, and comprehension support (Bernabei et al., 2023; Peslak & Kovalchick, 2024; García-Alonso et al., 2024). This mattered because it suggested that acceptance was shaped not only by the tool itself, but also by the kinds of academic problems students expected it to solve. For the present study, this supported the importance of examining undergraduate students across majors rather than assuming that acceptance developed in the same way across all disciplinary environments.

The literature also indicated that acceptance may be broad even when actual patterns of use remained mixed or conditional. Students expressed interest in using large language models while still questioning accuracy, ethics, or appropriateness in certain assignments or courses (Cotton et al., 2024; Bittle & El-Gayar, 2025; Wang et al., 2024). This distinction was important because it prevented acceptance from being interpreted too narrowly as simple enthusiasm. Instead, the literature suggested that student acceptance of LLMs often involved a balancing process in which perceived value was weighed against concern and uncertainty. That complexity made acceptance research particularly valuable for understanding why some students integrated these tools into everyday academic work while others remained hesitant or selective in their use.

Perception studies from additional contexts likewise showed broad but qualified student acceptance. U.S. undergraduates, Greek social science students, and large cross-disciplinary student samples reported generally positive views of AI-supported learning, especially when the tools helped clarify concepts, generate ideas, or improve academic efficiency. However, these positive views were tempered by persistent concerns about plagiarism, privacy, uneven faculty guidance, and the effect of AI on independent learning (Klimova et al., 2025; Katsantonis & Katsantonis, 2024; Jwair, 2025; Petricini et al., 2024; Pan, 2025). Descriptive studies of student perceptions also showed that favorable views did not necessarily translate into uniform use or acceptance, particularly when students were uncertain about institutional boundaries or the educational legitimacy of AI-generated support (Annur & Sujarwati, 2023; Pan, 2025).

Benefits, Motivation, and Barriers

A major theme in the literature was that students were drawn to large language models because they perceived meaningful academic benefits. These benefits often included writing assistance, idea generation, language refinement, summarization, concept clarification, task support, and time savings (Albadarin et al., 2024; Naznin et al., 2025; Sousa & Cardoso, 2025; Yu et al., 2024). Across both review and empirical studies, students generally did not adopt LLMs because the technology itself was novel. Rather, they tended to adopt them when they believed the tools improved the efficiency or manageability of academic work (Abd Hadi et al., 2024; Morell-Mengual et al., 2025). This convergence was especially relevant to the present dissertation because the study was framed around academic productivity and therefore depended on students' perceptions of these systems' benefits in the context of coursework demands.

Student motivation also appeared to be shaped by convenience and practical fit. Large language models were often available on demand, responded quickly, and supported multiple academic functions within a single interface, making them appealing to students balancing varied assignments and deadlines (Morell-Mengual et al., 2025; Peláez-Sánchez et al., 2024). In that sense, motivation did not depend only on expected performance gains. It also depended on whether the tools fit naturally into students' existing workflows. This helped explain why satisfaction, compatibility, and continued use intention have become increasingly evident in recent acceptance studies, particularly when students evaluate LLMs as part of routine academic activity rather than one-time experimentation (Alshammari & Babu, 2025; Yu et al., 2024).

At the same time, the literature did not portray benefits and motivation as sufficient for adoption on their own. Barriers persisted across settings, including concerns about accuracy, overreliance, academic integrity, privacy, weak institutional guidance, and uncertainty about acceptable classroom use (Bittle & El-Gayar, 2025; Cotton et al., 2024; Kooli, 2023; Wang et al., 2024). These barriers mattered because they suggested that students could recognize the usefulness of the tools while still hesitating to rely on them. In other words, favorable perceptions of utility did not automatically translate into strong behavioral intention if students also questioned legitimacy, trustworthiness, or educational appropriateness.

The literature, therefore, suggested that benefits, motivation, and barriers were best understood together rather than as isolated themes. A student may have viewed ChatGPT as helpful for drafting and explanation, while remaining cautious due to concerns about authorship, credibility, or instructor approval. Another student may have found the tool easy to use but not sufficiently beneficial to justify regular use. This interaction between positive and negative perceptions reinforced the importance of acceptance models, which aim to explain how students translate multiple judgments into intention. For the present dissertation, these findings supported the view that perceived usefulness and perceived ease of use operated within a broader environment shaped by both motivation and constraint.

Cross-Major and Disciplinary Differences in LLM Use and Acceptance

Across the literature, one of the clearest context effects involved discipline and major. Studies did not simply show that students used LLMs differently. They suggested that students interpreted usefulness through the task structures of their fields, such as writing-intensive assignments, technical problem solving, coding support, or concept explanation (Elshaer et al., 2024; Stöhr et al., 2024; Pan & Ni, 2024; Qu et al., 2024). This mattered for the present study because perceived usefulness is unlikely to be entirely subjective, since it was shaped by the coursework demands students were actually trying to meet, and by how effectively LLMs helped them address them.

Several empirical studies supported that conclusion from different angles. Stöhr et al. (2024) found meaningful differences in perceptions and usage across fields of study, while Elshaer et al. (2024) showed that study discipline affected certain aspects of the acceptance relationship. Discipline-specific studies then added substantive detail to those model-level findings by showing that medical, engineering, social science, and computing students emphasized different types of support, including technical explanation, writing help, code-related assistance, and domain-specific academic guidance (Pan & Ni, 2024; Bernabei et al., 2023; García-Alonso et al., 2024; Peslak & Kovalchick, 2024). Together, these studies suggested that disciplinary differences appeared in both reported attitudes and the specific academic uses students prioritized.

Direct comparisons of disciplinary groupings strengthened the same pattern. Qu et al. (2024) reported that students in applied technical disciplines demonstrated stronger AI knowledge and higher usage intentions than students in non-technical fields. More recent work similarly found that U.S. usage patterns varied by major, institution type, and policy environment, and that students in STEM or applied disciplines often reported stronger perceptions of AI's value for demanding academic work than peers in non-STEM fields (Baek et al., 2024; Alghamdi, 2025). These studies did not imply that one field uniformly accepted AI while another rejected it. Rather, they indicated that adoption patterns were filtered through disciplinary task demands and local academic expectations.

This cross-major evidence strengthened the rationale for the present dissertation. Although the literature increasingly recognized disciplinary variation, many empirical studies still relied on single-discipline or single-institution samples, which limited what could be concluded about whether core acceptance relationships remained stable across a broader undergraduate population (Abd Hadi et al., 2024; García-Alonso et al., 2024; Pan & Ni, 2024; Bernabei et al., 2023). A cross-major design, therefore, addresses more than sample diversity. It directly responds to evidence that the perceived value and effort associated with LLM use may vary across academic contexts, even when the same technology and theoretical model are under study.

Synthesis of the Literature and Research Gap

This section synthesized the major empirical and theoretical patterns that emerged across the reviewed literature and identified the specific gap addressed by the present study. It brought together findings on LLM use in higher education, TAM-based acceptance research, and cross-major differences to clarify what the literature had established and what remained insufficiently examined.

Converging and Diverging Findings

Across the reviewed literature, several patterns were clear. First, large language models became an established topic in higher education research and were commonly described as flexible tools for writing support, explanation, summarization, studying, and task assistance (Albadarin et al., 2024; Baig & Yadegaridehkordi, 2024; Naznin et al., 2025). Second, student acceptance research consistently showed that beliefs about value and usability mattered. Whether examined through TAM or related models such as UTAUT and UTAUT2, studies repeatedly found that intention to use AI tools was shaped by perceptions of usefulness and ease of use (Abdi et al., 2025; Grassini et al., 2024; Sharma & Ha, 2025; Strzelecki, 2024). Third, the literature broadly agreed that student use was motivated by practical academic goals rather than curiosity alone. Students often used these tools because they believed the tools could save time, improve the quality of their work, or make coursework more manageable (Morell-Mengual et al., 2025; Sousa & Cardoso, 2025).

A second area of convergence involved the mixed nature of LLM adoption. Even when students expressed favorable perceptions, the literature consistently noted concerns regarding academic integrity, overreliance, output accuracy, and institutional uncertainty (Bittle & El-Gayar, 2025; Cotton et al., 2024; Wang et al., 2024). This suggested that acceptance was often conditional rather than unconditional. Students may have been willing to use the tools in some contexts but not others or may have seen them as useful while still questioning their legitimacy in formal academic work. This convergence is important because it prevents the literature from being interpreted too optimistically. Student acceptance appeared substantial, but it also remained challenged by ethical, educational, and policy-related concerns.

At the same time, the literature also contained meaningful divergence. One area of divergence involved the relative strength of acceptance predictors. Some studies identified perceived usefulness or performance expectancy as the strongest determinant of intention, while others showed more complex roles for ease of use, satisfaction, trust, habit, or social influence (Abdi et al., 2025; Alshammari & Babu, 2025; Grassini et al., 2024; Murthiningtyas et al., 2025). Another area of divergence involved context. Results varied across countries, institutions, academic fields, and tool types, making it impossible to generalize findings from one setting to others (García-Alonso et al., 2024; Pan & Ni, 2024; Qu et al., 2024; Stöhr et al., 2024). In addition, some studies focused on general attitudes toward AI, whereas others focused specifically on academic writing, coding, or classroom support, making direct comparisons across studies more difficult.

The reviewed literature also diverged in methodological emphasis. Many studies relied on self-reported surveys of intention, satisfaction, or perception rather than direct measures of long-term behavior or objective performance. While this is common and appropriate in acceptance research, it also means that the evidence base remained strongest for perceived adoption rather than sustained real-world outcomes. Similarly, a substantial number of empirical studies used single-discipline, single-institution, or country-specific samples. These choices were understandable in early-stage research, but they also left open questions about how broadly current findings applied to diverse undergraduate populations and cross-major settings.

Research Gap and Study Rationale

The reviewed literature clearly established that student acceptance of large language models is an important and growing area of inquiry. However, several gaps remained. One major gap was that many studies focused on general perceptions of AI rather than on productivity-oriented academic use specifically. While writing support, summarization, explanation, and task assistance are frequently mentioned, the literature often treats them descriptively rather than testing acceptance in relation to the broader concept of academic productivity (Albadarin et al., 2024; Albayati, 2024; Stöhr et al., 2024; Naznin et al., 2025). For a dissertation centered on whether undergraduate students view LLM-based tools as useful and easy to use for productivity-oriented coursework tasks, this leaves room for a more targeted empirical contribution.

A second gap involved population scope. Much of the literature had been conducted with students from a single institution, a single country, or one disciplinary group such as ESL students, social science students, medical students, or engineering students (Abd Hadi et al., 2024; García-Alonso et al., 2024; Pan & Ni, 2024; Bernabei et al., 2023). Although these studies were valuable, they often did not capture how acceptance may vary across undergraduate majors within a broader student population. However, several studies suggested that field of study, discipline, and contextual task demands may influence how students interpreted usefulness, ease of use, and intention (Elshaer et al., 2024; Stöhr et al., 2024; Qu et al., 2024). This created a clear need for additional research that examined LLM acceptance across majors rather than within only one disciplinary context.

A third gap concerned theoretical focus. Many recent studies on ChatGPT adoption used extended frameworks that included numerous additional predictors such as trust, social influence, habit, or hedonic motivation (Abdi et al., 2025; Strzelecki, 2024; Wahdah et al., 2025). These studies were informative, but they could also divert attention from the core TAM relationships among perceived usefulness, perceived ease of use, and behavioral intention. The present study addresses this issue by returning to a more focused TAM design centered on two foundational predictors and one key outcome. This approach was appropriate because it enabled the dissertation to examine whether the core acceptance framework continued to explain undergraduate students' productivity-oriented use of LLM-based tools.

Accordingly, the rationale for the present study was grounded in both the strengths and the limitations of the existing literature. Prior studies showed that students often viewed large language models favorably and that usefulness-related beliefs were especially important in shaping intention (Abd Hadi et al., 2024; Abdi et al., 2025; Alshammari & Babu, 2025; Yu et al., 2024). However, there remained a need for research that specifically examined undergraduate acceptance of LLM-based tools for academic productivity across majors using a focused TAM framework. By testing whether perceived usefulness and perceived ease of use predict behavioral intention in a cross-major undergraduate sample, the present dissertation addresses a meaningful gap in the literature and contributes to a more targeted understanding of student acceptance in higher education (Qu et al., 2024; Stöhr et al., 2024; Yu et al., 2024).

Taken together, the most recent literature suggested that future studies should continue to narrow the gap between broad descriptive enthusiasm for generative AI and more focused explanatory models of student acceptance based on productivity-oriented use. Conceptual and empirical work alike now point to the need for studies that keep the theoretical model simple, using clearly defined academic outcomes, and compare student groups whose coursework demands may shape how usefulness and ease of use are interpreted (Alhammadi & Alhazmi, 2025; Sharma & Ha, 2025; Howlader et al., 2025; Alghamdi, 2025). For the present dissertation, this reinforced the value of examining productivity-oriented behavioral intention among undergraduates across majors rather than limiting the analysis to one discipline or to a broad, non-specific notion of AI use.

Summary

Chapter Two reviewed the literature relevant to undergraduate students' acceptance of LLM-based tools in higher education. The chapter first established the broader educational context of LLMs by discussing their capabilities, student use patterns, productivity-oriented functions, and major concerns related to accuracy, overreliance, and academic integrity. It then presented the Technology Acceptance Model as the theoretical foundation for the study. It defined the core constructs of perceived usefulness, perceived ease of use, and behavioral intention to use. The chapter next synthesized empirical research on TAM and related acceptance models, showing that students' intentions to use AI tools were commonly shaped by judgments about value, effort, trust, and context. The literature further suggested that student acceptance of LLMs was generally positive but varied across disciplines, settings, and use cases, and that perceived benefits were often balanced against institutional and ethical concerns.

The final sections synthesized converging and diverging findings and identified the research gap addressed by the present dissertation. The literature converged on the importance of usefulness-oriented beliefs, practical academic value, and the growing relevance of LLMs in higher education, while diverging across disciplines, institutional settings, and model specifications. Most importantly, the review revealed a need for more focused research on undergraduate students' productivity-oriented acceptance of LLM-based tools across majors using a parsimonious TAM framework. Chapter Three described the methodology used to examine whether perceived usefulness and perceived ease of use predicted behavioral intention to use LLM-based tools for academic productivity.

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