Chapter Two

Review of Literature

Introduction

Large language models (LLMs) and generative artificial intelligence (AI) have become increasingly visible in undergraduate education as students 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 comprehension of ideas and completion of tasks (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 the context of this dissertation, perceived usefulness reflects 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 the purposes of this study, academic productivity refers to students' perceived ability to complete coursework-related tasks more efficiently, effectively, or with less effort through the use of LLM-based tools. Perceived ease of use reflects 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 around productivity-oriented academic use of LLM-based tools, to justify the selection of the TAM constructs as study variables, and to position the dissertation as relevant within current empirical research. In alignment with quantitative research conventions, the literature review emphasizes empirical studies and systematic syntheses that reported measurable relationships among technology acceptance constructs and usage intentions, while incorporating foundational theory that supports construct definitions and model structure (Cramer & Howitt, 2004). 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 clarifies the gap addressed by the study (Page et al., 2021).

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 dissertation expectations that a literature review incorporates 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 closely aligned constructs, populations, or methods that informed 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 technology and information systems repositories. 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 usefulness, PU, perceived ease of use, PEOU, 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 student, university student, 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 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.

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, which is a large population enrolled across a wide range of institutions and fields of study (National Center for Education Statistics, 2023). Because the study examines adoption across majors, the literature review includes research that clarifies 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 emphasizes 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 is organized into major thematic areas that build from general context to the specific theoretical and empirical foundations needed for the dissertation's model. First, the review establishes 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 provides 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 addresses 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 presents 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 synthesizes empirical applications of the TAM and closely related acceptance models in educational technology and AI contexts. This section clarifies 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 dependence on user prompting skill, and their probabilistic outputs (Albadarin et al., 2024; Baig

& Yadegaridehkordi, 2024; Yu et al., 2024). Fourth, the review focuses specifically on student acceptance of LLM-based tools, with an emphasis on empirical findings describing determinants of intention to use, perceived benefits, and barriers to adoption (Strzelecki, 2024; Abdi et al., 2025; García-Alonso et al., 2024). This section is 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 examines 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 considers how discipline-specific task structures may affect students' perceptions of LLM usefulness for productivity and their perceptions of effort required to use these tools effectively.

Throughout these sections, the TAM serves 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 performance expectancy or effort expectancy, these are evaluated in relation to the TAM's definitions so that the dissertation's theoretical structure remains consistent and coherent (Davis, 1989; Venkatesh & Davis, 2000; Venkatesh et al., 2003). This approach supports a consistent interpretation of results and prevents the literature review from becoming a set of disconnected summaries. The literature is synthesized across studies by comparing populations, contexts, constructs, measurement approaches, and analytic methods. Convergent findings are presented as stronger support for expectations tested in the dissertation, whereas divergent findings are used to identify boundary conditions, limitations, and unresolved questions that reinforce the need for additional research.

The chapter's literature analysis follows 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 aligned with the chapter's organization, rather than randomly or study-by-study. Within each theme, studies are 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 is compared across studies to identify consistent patterns regarding the effects of perceived usefulness and perceived ease of use on behavioral intention, as well as discrepancies that may arise from differences in institutional context, measurement approaches, or the specific academic tasks being supported by the LLM-based tools. This synthesis approach supports the development of a logical and defensible research gap statement and clarifies how the dissertation extends and enhances existing research.

In sequence, Chapter Two begins with the literature describing LLM-based tools in higher education and the types of academic activities in which students have used these tools. The chapter then establishes the TAM as the theoretical foundation and synthesizes 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 are reviewed to provide an evidence base for expected relationships between the defined constructs. The review then focuses on student acceptance of large language models, emphasizing determinants of intention, productivity-oriented benefits, and barriers that may influence adoption. The chapter subsequently examines major-based differences that may shape how students perceive usefulness and ease of use across disciplines.

Finally, the chapter synthesizes 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 transitions 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 have rapidly emerged as one of the most visible forms of generative artificial intelligence used in higher education (Albadarin et al., 2024; Baig & Yadegaridehkordi, 2024). In contrast to earlier educational technologies that were often designed for narrower instructional purposes, large language model-based tools can support multiple academic functions through a single conversational interface (Peláez-Sánchez et al., 2024). Within university settings, these tools are increasingly associated with drafting assistance, idea generation, explanation of course concepts, summarization, and general academic support (Albadarin et al., 2024; Baig & Yadegaridehkordi, 2024; Peláez-Sánchez et al., 2024). These functions have contributed to their growing prominence in both educational practice and scholarly literature (Albadarin et al., 2024; Baig & Yadegaridehkordi, 2024).

The expansion of research on LLMs such as ChatGPT, Copilot, and related tools suggests that large language models are no longer being treated as a short-lived novelty in higher education (Albadarin et al., 2024; Baig & Yadegaridehkordi, 2024; Guizani et al., 2025). Instead, the literature increasingly presents these technologies as meaningful academic tools whose implications extend across teaching, learning, assessment, and institutional policy (Peláez-Sánchez et al., 2024; Wang et al., 2024). Recent reviews have documented rapid growth in studies examining generative AI in educational contexts (Albadarin et al., 2024; Baig & Yadegaridehkordi, 2024). Recurring themes include learning support, academic productivity, learner engagement, and concerns regarding appropriate use (Albadarin et al., 2024; Baig & Yadegaridehkordi, 2024; Guizani et al., 2025). This pattern indicates that large language models have become an established topic within contemporary higher education literature (Albadarin et al., 2024; Baig & Yadegaridehkordi, 2024; Guizani et al., 2025). However, much of the current literature remains recent, fast-developing, and context-dependent, which means conclusions should be interpreted cautiously and on a case-by-case basis rather than treated as fully settled across all higher education environments.

A major reason large language models have become so significant in higher education is their versatility (Peláez-Sánchez et al., 2024; Stöhr et al., 2024; Morell-Mengual et al., 2025). These systems can perform multiple support functions that would otherwise require separate tools, resources, or forms of human assistance (Peláez-Sánchez et al., 2024). Students may use them to brainstorm, refine written language, request explanations, generate examples, or obtain assistance with course-related tasks (Albadarin et al., 2024; Morell-Mengual et al., 2025). Because these capabilities can be accessed quickly and iteratively, large language models are frequently perceived as convenient and adaptable forms of academic support (Stöhr et al., 2024; Morell-Mengual et al., 2025). As a result, the higher education literature has increasingly framed them not merely as technical innovations, but as technologies that may reshape how students access information and complete coursework (Peláez-Sánchez et al., 2024; Stöhr et al., 2024; Morell-Mengual et al., 2025).

The literature also indicates that student engagement with large language models is shaped by context rather than occurring uniformly across all users (Elshaer et al., 2024; García-

Alonso et al., 2024; Stöhr et al., 2024; Pan & Ni, 2024). Empirical research has shown that student perceptions and patterns of use may differ by field of study, prior experience, training, and other background variables (Stöhr et al., 2024; Pan & Ni, 2024). Studies examining acceptance and use have found that discipline and subgroup differences may influence how students evaluate and adopt LLMs (Elshaer et al., 2024; García-Alonso et al., 2024). This strengthens the rationale for examining undergraduate students across multiple majors rather than limiting analysis to one disciplinary setting.

At the same time, the role of large language models in higher education remains ambiguous (Cotton et al., 2024; Wang et al., 2024; Bittle & El-Gayar, 2025). While the literature frequently identifies potential benefits related to accessibility, efficiency, and academic support (Albadarin et al., 2024; Baig & Yadegaridehkordi, 2024), it also emphasizes concerns involving academic integrity, overreliance, accuracy, and institutional uncertainty (Cotton et al., 2024; Wang et al., 2024; Bittle & El-Gayar, 2025). Universities have responded in varied ways, often adopting cautious or mixed approaches through policies, guidelines, and support resources (Wang et al., 2024). These responses reflect the fact that large language models are being interpreted not only as tools of support, but also as technologies that challenge existing norms regarding authorship, assessment, and acceptable academic assistance (Cotton et al., 2024; Bittle & El-Gayar, 2025; Wang et al., 2024).

Definitions and Core Capabilities of Large Language Models

Large language models are artificial intelligence systems trained on massive collections of text in order 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 sequences of words 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 question responses through natural language interaction, which makes 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 course-related problem support (Peláez-Sánchez et al., 2024; Guizani et al., 2025). This broad functional range distinguishes large language models from many earlier academic technologies that were designed to perform one limited task (Peláez-Sánchez et al., 2024). Review 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 or guaranteed accuracy (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, fabricated information, shallow reasoning, or incomplete explanations (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 the output they receive (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).

Adoption Trends and Common Student Use Patterns

The literature indicates that adoption of LLMs such as ChatGPT, Copilot, and related large language model-based tools expanded rapidly in higher education following their widespread public availability (Albadarin et al., 2024; Baig & Yadegaridehkordi, 2024). This growth is reflected not only in student experimentation and everyday academic use, but also in the sharp increase in scholarly attention given to these tools across educational journals and reviews (Albadarin et al., 2024; Baig & Yadegaridehkordi, 2024). Recent literature has shown that higher education researchers quickly began examining student attitudes, acceptance, awareness, and patterns of use of such technologies (Albadarin et al., 2024; Baig & Yadegaridehkordi, 2024). This suggests that large language models became embedded in academic discourse in a relatively short period of time.

A common theme across the literature is that students do not use these tools for a single isolated purpose (Stöhr et al., 2024; Abdi et al., 2025; Yu et al., 2024; Albayati, 2024). Instead, large language models appear to be adopted as flexible academic supports that can assist with writing, explanations, idea development, summarization, studying, and discipline-specific tasks (Albadarin et al., 2024; Baig & Yadegaridehkordi, 2024; Stöhr et al., 2024). Large-sample evidence on student AI chatbot use suggests that patterns of adoption are related to factors such as field of study and academic background (Stöhr et al., 2024). Other empirical studies have found that students evaluate these tools in relation to usefulness, convenience, and intention to continue use (Abdi et al., 2025; Yu et al., 2024; Albayati, 2024). Collectively, these findings indicate that adoption is tied not only to access, but also to students' judgments regarding whether the tools improve academic work or reduce effort.

Common student use patterns also vary by disciplinary context (Pan & Ni, 2024; Bernabei et al., 2023; García-Alonso et al., 2024; Peslak & Kovalchick, 2024). In social science and general university contexts, students may focus on explanation, writing support, and academic assistance (García-Alonso et al., 2024). In medical or engineering contexts, they may use large language models to assist with more specialized, hands-on educational demands (Pan & Ni, 2024; Bernabei et al., 2023). Similarly, students in programming or computing environments may engage with LLM-based tools for code explanation, troubleshooting, and task-specific learning support (Peslak & Kovalchick, 2024). These patterns matter because they suggest that the perceived usefulness of large language models is not fixed but is often shaped by the nature of the coursework and the kinds of problems students are trying to solve.

The literature further suggests that adoption should not be confused with universal acceptance (Strzelecki, 2024; Grassini et al., 2024; Morell-Mengual et al., 2025; Elshaer et al., 2024). Some students may view large language models as highly useful and integrate them into regular academic routines, whereas others may be more hesitant because of concerns about trust, accuracy, institutional expectations, or ethical boundaries (Elshaer et al., 2024; Grassini et al., 2024). Studies of acceptance and continued use indicate that student engagement with LLMs can be shaped by perceptions, experiences, and context rather than by exposure alone (Strzelecki, 2024; Morell-Mengual et al., 2025). For that reason, adoption trends are best understood as evidence of growing relevance rather than as proof that all students use or value these tools in the same way. In addition, many existing studies rely on self-reported use and intention data, which are useful for understanding perceptions but may not fully capture actual patterns of sustained academic use, or objective academic outcomes.

Limitations, Risks, and Academic Integrity

Although large language models offer substantial convenience and flexibility, the literature consistently identifies important limitations and risks associated with their use in higher education (Baig & Yadegaridehkordi, 2024; Cotton et al., 2024; Bittle & El-Gayar, 2025). One of the most frequently discussed concerns is accuracy (Baig & Yadegaridehkordi, 2024; Cotton et al., 2024). Large language models can generate responses that are fluent and convincing even when they contain incomplete, misleading, or incorrect information (Cotton et al., 2024). In academic settings, this creates a particular challenge because students may mistake polished language for trustworthy content, which can undermine learning quality if outputs are used without verification or critical review (Baig & Yadegaridehkordi, 2024; Cotton et al., 2024).

A second major concern is overreliance (Peláez-Sánchez et al., 2024; Cotton et al., 2024; Bittle & El-Gayar, 2025). Because large language models can reduce the effort associated with drafting, brainstorming, explaining, and early-stage problem solving, students may become dependent on the technology for tasks that are also central to academic development (Cotton et al., 2024; Bittle & El-Gayar, 2025). Higher education is not concerned solely with task completion. It is also intended to cultivate critical thinking, writing ability, content mastery, and independent problem solving. The literature therefore raises the possibility that even when large language models improve short-term efficiency, they may also discourage deeper engagement if used as substitutes rather than as support tools (Peláez-Sánchez et al., 2024; Cotton et al., 2024; Bittle & El-Gayar, 2025).

Academic integrity is among the most prominent themes in the higher education literature on generative AI (Cotton et al., 2024; Bittle & El-Gayar, 2025; Bernabei et al., 2023). Scholars have emphasized that ChatGPT and similar tools complicate longstanding assumptions about authorship, originality, and acceptable assistance in academic work (Cotton et al., 2024; Bittle & El-Gayar, 2025). Concerns about cheating, plagiarism, misrepresentation of authorship, and the difficulty of detecting AI-generated content have become especially important as these tools have grown more capable and more widely accessible (Cotton et al., 2024). This body of literature is essential for the present dissertation because student acceptance cannot be interpreted solely through usefulness and ease of use. It should also be understood in relation to the ethical and institutional constraints that shape whether use is considered acceptable (Bittle & El-Gayar, 2025; Bernabei et al., 2023).

Institutional context further complicates the use of large language models in higher education (Wang et al., 2024; Bamasoud et al., 2025). Universities have not responded uniformly to generative AI, and studies of institutional policies and guidelines suggest that many institutions are still working to define appropriate boundaries for use (Wang et al., 2024). Some universities emphasize openness and experimentation, whereas others frame generative AI through caution, regulation, and risk management (Wang et al., 2024; Bamasoud et al., 2025). This variation matters because students form beliefs about these technologies within a broader academic environment shaped by policy, faculty expectations, and available support resources. Consequently, the limitations and risks associated with large language models are not merely technical concerns. They are also social and institutional concerns that affect how students interpret the legitimacy of use. At the same time, much of this literature is still emerging, and institutional guidance may continue to change as universities adapt their policies and practices.

Productivity-Oriented Academic Use of LLM-based Tools

Large language model-based tools are increasingly discussed in higher education as productivity-oriented technologies that may support how students complete academic work (Albadarin et al., 2024; Baig & Yadegaridehkordi, 2024). Rather than functioning only as novel conversational systems, these tools have been examined as practical academic aids that can help students generate ideas, revise written work, explain concepts, summarize content, and assist with course-related tasks more efficiently (Albadarin et al., 2024; Peláez-Sánchez et al., 2024). Review literature has shown that educational studies commonly focus on writing support, tutoring-like interaction, academic assistance, and feedback-related functions (Albadarin et al., 2024; Baig & Yadegaridehkordi, 2024). These functions position large language model-based tools as flexible supports for academic productivity.

The productivity-oriented value of these tools is closely tied to their versatility (Peláez-Sánchez et al., 2024; Morell-Mengual et al., 2025; Stöhr et al., 2024). Unlike older academic technologies that often supported a single stage of learning or assignment completion, large language model-based tools can be applied across multiple parts of student workflow (Peláez-Sánchez et al., 2024). A student may use the same system to brainstorm an idea, clarify a reading, revise written language, generate a practice explanation, or request help with a technical task (Morell-Mengual et al., 2025; Stöhr et al., 2024). This multi-functionality helps explain why these tools have gained attention so quickly in higher education and why students may evaluate them in terms of practical academic value rather than technological novelty alone.

The student acceptance literature reinforces this productivity framing by showing that students often evaluate ChatGPT and related tools through beliefs about usefulness, convenience, satisfaction, and ongoing intention to use (Abdi et al., 2025; Albayati, 2024; Yu et al., 2024; Alshammari & Babu, 2025). Empirical studies have examined behavioral intention to use ChatGPT for academic purposes, perceptions of ChatGPT as a regular assistance tool, and factors influencing continued use in higher education (Abdi et al., 2025; Albayati, 2024; Yu et al., 2024). Taken together, these studies suggest that students are not simply experimenting with generative AI because it is new. Rather, they are assessing whether the tool helps them manage academic demands more effectively, which aligns closely with the present dissertation's focus on academic productivity.

At the same time, productivity-oriented use should not be interpreted as evidence that these tools are uniformly beneficial (Cotton et al., 2024; Wang et al., 2024; Bittle & El-Gayar, 2025). The same characteristics that make large language models efficient, such as speed, accessibility, and broad functionality, may also increase the risk of superficial engagement, overreliance, or inappropriate academic use (Cotton et al., 2024; Bittle & El-Gayar, 2025). The literature supports understanding these tools as academic productivity technologies while also recognizing that their value depends on how students use them, how institutions frame them, and how academic norms shape their adoption (Wang et al., 2024; Bittle & El-Gayar, 2025).

Writing, Revision, and Idea Generation Support

One of the most frequently discussed academic uses of large language models in higher education involves support for writing, revision, and idea generation (Albadarin et al., 2024; Baig & Yadegaridehkordi, 2024). Students may use these tools to brainstorm topics, generate outlines, rephrase sentences, improve clarity, refine grammar, or develop early drafts of written assignments (Albadarin et al., 2024; Morell-Mengual et al., 2025). This pattern appears consistently in the literature and helps explain why large language models have become especially prominent in university contexts where written communication plays a central role across disciplines (Baig & Yadegaridehkordi, 2024).

The usefulness of large language models for writing support lies partly in their capacity to reduce the difficulty of beginning and refining written work (Morell-Mengual et al., 2025; Albayati, 2024; Romero-Rodríguez et al., 2023). For many students, the most challenging stages of writing occur before a full draft exists, such as selecting an angle, generating initial ideas, or translating vague thoughts into structured language. Large language models can support these early stages by providing suggestions, scaffolding language, and helping students move from uncertainty to an editable draft (Romero-Rodríguez et al., 2023; Morell-Mengual et al., 2025). This is one reason they are often perceived as useful academic support tools, particularly in settings where students face repeated writing demands across courses (Albayati, 2024).

Writing-related uses of large language models also extend into revision and language improvement (Boudouaia et al., 2024; Launonen et al., 2024; Abd Hadi et al., 2024). In higher education, students may rely on these tools to simplify wording, increase coherence, improve tone, or revise text for clarity and organization (Launonen et al., 2024; Abd Hadi et al., 2024). This is particularly relevant in contexts where students are learning in a second language or navigating academically demanding writing conventions (Boudouaia et al., 2024). Studies in writing-focused educational settings support the claim that students increasingly view LLMs such as ChatGPT, and similar systems as assistance tools for producing and refining written content, even if the educational implications of that use remain debated (Boudouaia et al., 2024; Launonen et al., 2024; Abd Hadi et al., 2024).

However, the literature also suggests that writing support through large language models should be interpreted carefully (Cotton et al., 2024; Bittle & El-Gayar, 2025). While these tools may increase efficiency and reduce barriers to drafting, they also raise important questions about originality, authorship, and the boundary between assistance and substitution (Cotton et al., 2024). As a result, writing, revision, and idea generation support represent one of the clearest examples of both the usefulness and the controversy associated with large language model adoption in higher education (Bittle & El-Gayar, 2025).

Summarization, Studying, and Comprehension Support

A second major form of productivity-oriented academic use involves summarization, studying, and comprehension support (Albadarin et al., 2024; Baig & Yadegaridehkordi, 2024; Peláez-Sánchez et al., 2024). Large language models can condense information, explain complex ideas in simpler language, generate examples, and provide question-and-answer style interaction that resembles tutoring or study assistance (Peláez-Sánchez et al., 2024). In higher education, these capabilities are especially appealing because students frequently encounter dense readings, unfamiliar terminology, and compressed academic timelines that increase the value of tools capable of accelerating comprehension (Albadarin et al., 2024; Baig & Yadegaridehkordi, 2024).

The literature suggests that students often use these tools not only to retrieve information, but to make academic content more manageable (Yu et al., 2024; Morell-Mengual et al., 2025; Stöhr et al., 2024). A student may ask a large language model to summarize a reading, explain a concept in simpler terms, generate a study guide, or provide an example that clarifies an abstract principle (Morell-Mengual et al., 2025; Stöhr et al., 2024). This type of interaction is particularly relevant to academic productivity because it reduces the time and effort needed to reach an initial level of understanding, even if deeper learning still depends on the student's own judgment and engagement (Yu et al., 2024). Studies on student use and continued use intention support the idea that convenience and perceived value are important in shaping how students integrate these tools into academic routines (Yu et al., 2024; Morell-Mengual et al., 2025; Stöhr et al., 2024).

This comprehension-oriented use also appears across disciplines (Pan & Ni, 2024; Bernabei et al., 2023; Peslak & Kovalchick, 2024). In general higher education settings, students may use large language models to explain course concepts or clarify readings. In more specialized fields such as medicine, engineering, or computer science, they may use them to support understanding of technical material or domain-specific tasks (Pan & Ni, 2024; Bernabei et al., 2023; Peslak & Kovalchick, 2024). The consistency of this pattern across fields supports the view that large language models function as flexible comprehension aids, even though the specific form of support may differ by course type and disciplinary expectations.

At the same time, summarization and comprehension support raise important concerns (Baig & Yadegaridehkordi, 2024; Cotton et al., 2024). When students rely heavily on AI-generated summaries or explanations, there is a risk that they may accept incomplete or inaccurate content too readily (Cotton et al., 2024). Thus, while these tools may improve efficiency and accessibility, the literature suggests that their educational value depends on students' ability to evaluate outputs critically rather than treating them as unquestioned substitutes for reading, analysis, or reasoning (Baig & Yadegaridehkordi, 2024).

Task Management and Efficiency Gains in Coursework

Large language models may also support academic productivity by improving efficiency across coursework-related tasks (Yu et al., 2024; Albayati, 2024; Stöhr et al., 2024). Although the literature does not always frame this explicitly as task management, many studies indicate that students use LLMs such as ChatGPT, and related tools because they reduce the time and effort associated with recurring academic demands (Yu et al., 2024; Albayati, 2024). These demands may include beginning assignments, generating examples, checking phrasing, clarifying instructions, organizing ideas, or obtaining assistance on technical problems (Stöhr et al., 2024). In this sense, large language models can be understood as workflow support tools that help students move more quickly through early or repetitive stages of coursework.

This efficiency-related value is particularly relevant in higher education environments where students must manage multiple simultaneous tasks across courses (Abdi et al., 2025; Alshammari & Babu, 2025; Yu et al., 2024). A tool that shortens the time required to interpret a reading, draft an initial response, refine written text, or obtain a working explanation may be perceived as highly useful even when it does not replace deeper academic effort (Yu et al., 2024). This helps explain why constructs such as perceived usefulness, satisfaction, and continued intention to use are so prominent in the acceptance literature (Abdi et al., 2025; Alshammari & Babu, 2025). Students are often evaluating these tools not simply on technical novelty, but on whether the tools make coursework more manageable within real academic constraints.

In technical and computing-related contexts, efficiency gains may become even more visible (Peslak & Kovalchick, 2024; Bernabei et al., 2023). Studies involving programming students and AI-assisted coding tools suggest that generative AI can assist with debugging, concept explanation, code-related problem solving, and workflow support in applied tasks (Peslak & Kovalchick, 2024). Although these sources are narrower than the present dissertation's cross-major focus, they strengthen the broader claim that large language model-based tools may be adopted because they improve efficiency in discipline-specific academic work (Bernabei et al., 2023). These findings also support the argument that productivity gains may be one of the key mechanisms through which students perceive such tools as useful.

However, efficiency gains should not be automatically viewed as educational benefits (Cotton et al., 2024; Wang et al., 2024; Bittle & El-Gayar, 2025). If students rely on large language models only to minimize effort, the short-term advantages of speed and convenience may conflict with deeper learning goals (Cotton et al., 2024; Bittle & El-Gayar, 2025). For that reason, the literature supports treating efficiency as an important component of academic productivity while also recognizing that the educational value of such efficiency depends on how the tools are used, how instructors frame them, and whether students remain actively engaged in the learning process (Wang et al., 2024).

Technology Acceptance Model Foundations

The Technology Acceptance Model provides 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: perceived usefulness and perceived ease of use. The model proposes 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 examines 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 remains highly influential is its parsimony (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 parsimony 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 are often making judgments about 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 are not essential to the narrower predictive aim of this dissertation. Accordingly, TAM provides a more parsimonious and theoretically aligned framework for the present study.

The literature on student adoption of LLMs such as ChatGPT, Copilot, and related tools further supports 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 have applied TAM directly or used closely related acceptance models to examine how students perceive and adopt generative AI systems (Abdi et al., 2025; Alshammari & Babu, 2025; Albayati, 2024). These studies reinforce the view that student acceptance of large language models is 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 is still developing and is often limited by single-institution samples, self-reported perceptions, or discipline-specific populations (Abdi et al., 2025; Albayati, 2024). Accordingly, TAM provides both a theoretically grounded and empirically relevant framework for examining how undergraduate students evaluate large language models as academic productivity tools while also addressing a still-developing evidence base.

Perceived Usefulness

Perceived usefulness is one of the two core constructs of the Technology Acceptance Model and is central to the present dissertation (Davis, 1989). According to Davis (1989), perceived usefulness refers to the extent to which a person believes that using a system will improve their performance in the completion of a task. In educational contexts, this construct is commonly interpreted in terms of whether a technology helps students complete academic tasks more effectively, more efficiently, or with greater confidence (Davis, 1989). Because the present study focuses on undergraduate students' acceptance of large language models for academic productivity, perceived usefulness is especially important as a predictor of whether students view these tools as worth adopting.

The higher education literature on ChatGPT and related tools strongly supports the relevance of perceived usefulness (Romero-Rodríguez et al., 2023; Abdi et al., 2025; Albayati, 2024). Studies of student adoption and intention frequently suggest that students evaluate generative AI systems in relation to the academic value they believe the tools provide (Abdi et al., 2025; Albayati, 2024). This value may include assistance with writing, explanations, studying, task completion, or managing coursework demands (Romero-Rodríguez et al., 2023). In other words, students are often asking whether the technology helps them do academic work better or faster. That question is fundamentally aligned with the logic of perceived usefulness.

Recent empirical studies further indicate that usefulness is not merely a background perception, but a substantive driver of intention and related acceptance outcomes (Alshammari & Babu, 2025; Abdi et al., 2025). In TAM-based research on ChatGPT, perceived usefulness has been linked to behavioral intention and, in some models, to mediating variables such as satisfaction (Alshammari & Babu, 2025). This suggests that students' judgments about academic benefit play a central role in whether they intend to continue using large language models in educational settings (Abdi et al., 2025). For the present study, this is especially important because academic productivity is closely tied to the concept of usefulness. If students believe large language models improve drafting, clarification, studying, or efficiency, they are more likely to form positive intentions toward use.

Perceived usefulness may also vary across students and academic contexts (Elshaer et al., 2024; Pan & Ni, 2024; Bernabei et al., 2023). A student in a writing-intensive major may define usefulness primarily in terms of drafting or revision support, whereas a student in a technical field may define it in terms of explanation, debugging, or discipline-specific problem support (Pan & Ni, 2024; Bernabei et al., 2023). This potential variation further supports the present dissertation's cross-major design, as it suggests that usefulness may not operate identically across all majors even if it is modeled consistently in theory (Elshaer et al., 2024). In addition, many current studies focus on perceived usefulness in broad academic terms, which leaves room for more targeted examination of usefulness as it relates specifically to productivity-oriented coursework tasks.

Perceived Ease of Use

Perceived ease of use is the second core construct of the Technology Acceptance Model and refers to the degree to which an individual believes that using a particular system will be effort minimizing (Davis, 1989). Within higher education, this construct is especially relevant when examining emerging tools such as large language models because students are more likely to engage with a technology when it appears accessible, intuitive, and manageable within the constraints of their coursework (Davis, 1989). A system may be highly capable, but if students perceive it as difficult to use, difficult to interpret, or difficult to integrate into their academic routines, acceptance may be reduced.

Large language models are particularly interesting in relation to perceived ease of use because their interface is often one of their most attractive features (Peláez-Sánchez et al., 2024; Stöhr et al., 2024). Students can interact with these tools through ordinary conversational prompts rather than through specialized commands or technical procedures (Peláez-Sánchez et al., 2024). This natural language accessibility lowers barriers to experimentation and may help explain why LLMs such as ChatGPT and Copilot were adopted so rapidly across varied educational settings (Stöhr et al., 2024). The ability to ask questions, request revisions, or seek explanations in plain language makes these tools appear approachable even to users with limited technical experience, supporting ease of use.

The empirical literature on LLM acceptance also supports the continued importance of perceived ease of use (Alshammari & Babu, 2025; Albayati, 2024; Abdi et al., 2025). Recent studies grounded in TAM have shown that ease of use remains meaningfully related to student satisfaction, behavioral intention, and overall acceptance (Alshammari & Babu, 2025; Abdi et al., 2025). When students perceive ChatGPT as straightforward and efficient to interact with, they may be more willing to explore its functions and incorporate it into academic workflows (Albayati, 2024). In this sense, ease of use does not merely reflect convenience. It also affects whether the technology becomes integrated into routine educational behavior.

At the same time, perceived ease of use should not be confused with educational simplicity (Davis, 1989; Cotton et al., 2024). A tool may be easy to access and operate while still requiring substantial judgment for effective and responsible use (Cotton et al., 2024). Students may find large language models easy to prompt, but more difficult to evaluate critically, verify, or use ethically. Therefore, perceived ease of use remains an important predictor of acceptance, but its educational significance should be understood alongside the more complex skills required to use these tools well in academic contexts.

Behavioral Intention to Use

Behavioral intention to use is a central outcome in the Technology Acceptance Model and represents the degree to which an individual intends to use a technology in the future (Davis, 1989). Within TAM, behavioral intention is closely linked to perceived usefulness and perceived ease of use, serving as the most immediate predictor of actual usage behavior (Davis, 1989). For the present dissertation, behavioral intention to use large language models is a particularly important construct because it captures students' willingness to adopt these tools as part of their academic productivity practices.

In the recent higher education literature, behavioral intention has become one of the most frequently studied outcomes in research on LLM acceptance (Abdi et al., 2025; Yu et al., 2024; Strzelecki, 2024). Scholars have examined whether students intend to use LLMs for academic purposes, continue using it in educational settings, or integrate it into routine coursework (Yu et al., 2024; Strzelecki, 2024). This emphasis reflects the practical importance of intention as a bridge between attitudes and behavior. Students may perceive a tool positively in principle, but intention more directly reflects whether they are likely to make that tool part of ongoing academic activity (Abdi et al., 2025).

The literature also suggests that behavioral intention is shaped by multiple interacting perceptions (Alshammari & Babu, 2025; Albayati, 2024; Elshaer et al., 2024). Students are more likely to intend to use large language models when they believe the tools are useful, easy to use, satisfying, or supportive of academic performance (Alshammari & Babu, 2025; Albayati, 2024). Conversely, intention may be weakened by doubts about trust, ethics, institutional expectations, or the legitimacy of use in specific classroom contexts (Elshaer et al., 2024). This makes behavioral intention an especially valuable construct for the present study because it reflects the point at which perceived benefits and perceived concerns are translated into a decision about whether to use the technology.

Behavioral intention is also important because it allows the present dissertation to focus on acceptance without requiring direct observation of all future use behaviors (Davis, 1989; Abdi et al., 2025; Alshammari & Babu, 2025). In higher education research, it is often more feasible to assess students' stated intention to use a technology than to track long-term behavior across varied courses and contexts (Davis, 1989). For this reason, behavioral intention remains one of the most theoretically and practically useful outcomes in adoption research. In the present study, it serves as the key dependent construct through which the effects of perceived usefulness and perceived ease of use can be examined in relation to undergraduate students' acceptance of large language models for academic productivity (Abdi et al., 2025; Alshammari & Babu, 2025). However, intention should still be interpreted carefully, as stated intention does not always translate perfectly into sustained real-world behavior.

References

Abd Hadi, N. A., Mohamad, F., Johar, E., & Kadir, Z. A. (2024). Exploring the acceptance of ChatGPT as an assisting tool in academic writing among ESL undergraduate students. International Journal of Research and Innovation in Social Science, 8(10), 330–345. https://doi.org/10.47772/IJRISS.2024.8100242

Abdi, A.-N. M., Omar, A. M., Ahmed, M. H., & Ahmed, A. A. (2025). The predictors of behavioral intention to use ChatGPT for academic purposes: Evidence from higher education in Somalia. Cogent Education, 12(1), Article 2460250. https://doi.org/10.1080/2331186X.2025.2460250

Al-Adwan, A. S., Li, N., Al-Adwan, A., Abbasi, G. A., Albelbisi, N. A., & Habibi, A. (2023). Extending the Technology Acceptance Model to predict university students' intentions to use metaverse-based learning platforms. Education and Information Technologies, 28(11), 15381–15413. https://doi.org/10.1007/s10639-023-11816-3

Albadarin, Y., Saqr, M., Pope, N., & Tukiainen, M. (2024). A systematic literature review of empirical research on ChatGPT in education. Discover Education, 3(1), Article 60. https://doi.org/10.1007/s44217-024-00138-2

Albayati, H. (2024). Investigating undergraduate students' perceptions and awareness of using ChatGPT as a regular assistance tool: A user acceptance perspective study. Computers and Education: Artificial Intelligence, 7, Article 100203. https://doi.org/10.1016/j.caeai.2024.100203

Aljohani, M. (2025). The impact of LLMs usage on learning outcomes for software development students: A focus on prompt engineering (Order No. 32170183). Available from ProQuest Dissertations & Theses Global. (3244717798). Retrieved from https://www.proquest.com/dissertations-theses/impact-llms-usage-on-learning-outcomes-software/docview/3244717798/se-2

Alshammari, S., & Babu, E. (2025). The mediating role of satisfaction in the relationship between perceived usefulness, perceived ease of use and students’ behavioural intention to use ChatGPT. Scientific Reports, 15, Article 91634. https://doi.org/10.1038/s41598-025-91634-4

Baig, M. I., & Yadegaridehkordi, E. (2024). ChatGPT in higher education: A systematic literature review and research challenges. International Journal of Educational Research, 127, Article 102411. https://doi.org/10.1016/j.ijer.2024.102411

Bamasoud, D. M., Mohammad, R., & Bilal, S. (2025). Adopting generative AI in higher education: A dual-perspective study of students and lecturers in Saudi universities. Big Data and Cognitive Computing, 9(10), Article 264. https://doi.org/10.3390/bdcc9100264

Bernabei, M., Colabianchi, S., Falegnami, A., & Costantino, F. (2023). Students' use of large language models in engineering education: A case study on technology acceptance, perceptions, efficacy, and detection chances. Computers and Education: Artificial Intelligence, 5, Article 100172. https://doi.org/10.1016/j.caeai.2023.100172

Bittle, K., & El-Gayar, O. (2025). Generative AI and academic integrity in higher education: A systematic review and research agenda. Information, 16(4), Article 296. https://doi.org/10.3390/info16040296

Boudouaia, A., Mouas, S., & Kouider, B. (2024). A study on ChatGPT-4 as an innovative approach to enhancing English as a foreign language writing learning. Journal of Educational Computing Research. Advance online publication. https://doi.org/10.1177/07356331241247465

Cotton, D. R. E., Cotton, P. A., & Shipway, J. R. (2024). Chatting and cheating: Ensuring academic integrity in the era of ChatGPT. Innovations in Education and Teaching International, 61(2), 228–239. https://doi.org/10.1080/14703297.2023.2190148

Cramer, D., & Howitt, D. L. (2004). The SAGE dictionary of statistics: A practical resource for students in the social sciences. SAGE. https://doi.org/10.4135/9780857020123

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly, 13(3), 319–340. https://doi.org/10.2307/249008

Elshaer, I., Hasanein, A., & Sobaih, A. (2024). The moderating effects of gender and study discipline in the relationship between university students' acceptance and use of ChatGPT. European Journal of Investigation in Health, Psychology and Education, 14(7), 132. https://doi.org/10.3390/ejihpe14070132

García-Alonso, E. M., León-Mejía, A. C., Sánchez-Cabrero, R., & Guzmán-Ordaz, R. (2024). Training and technology acceptance of ChatGPT in university students of social sciences: A netnographic analysis. Behavioral Sciences, 14(7), Article 612. https://doi.org/10.3390/bs14070612

Grassini, S., Aasen, M. L., & Møgelvang, A. (2024). Understanding university students' acceptance of ChatGPT: Insights from the UTAUT2 model. Applied Artificial Intelligence, 38(1), Article 2371168. https://doi.org/10.1080/08839514.2024.2371168

Guizani, S., Mazhar, T., Shahzad, T., Ahmad, W., Bibi, A., & Hamam, H. (2025). A systematic literature review to implement large language model in higher education: Issues and solutions. Discover Education, 4, Article 35. https://doi.org/10.1007/s44217-025-00424-7

Launonen, P., Talalakina, E., & Dubova, G. (2024). Students' perceptions of using ChatGPT for academic writing in English. Tertium, 9(1), 1–20. https://doi.org/10.7592/tertium.2024.9.1.274

Morell-Mengual, V., Fernández-García, O., Berenguer, C., Ortega-Barón, J., Gil-Llario, M. D., & Estruch-García, V. (2025). Characteristics, motivations and attitudes of students using ChatGPT and other language model-based chatbots in higher education. Education and Information Technologies, 30, 22257–22274. https://doi.org/10.1007/s10639-025-13650-1

National Center for Education Statistics. (2023). Undergraduate Enrollment. https://nces.ed.gov/programs/coe/indicator/cha

Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., Shamseer, L., Tetzlaff, J. M., Akl, E. A., Brennan, S. E., Chou, R., Glanville, J., Grimshaw, J. M., Hróbjartsson, A., Lalu, M. M., Li, T., Loder, E. W., Mayo-Wilson, E., McDonald, S., ... Moher, D. (2021). The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. BMJ, 372, n71. https://doi.org/10.1136/bmj.n71

Pan, G., & Ni, J. (2024). A cross sectional investigation of ChatGPT-like large language models application among medical students in China. BMC Medical Education, 24, Article 5871. https://doi.org/10.1186/s12909-024-05871-8

Peláez-Sánchez, I. C., Velarde-Camaqui, D., & Glasserman-Morales, L. D. (2024). The impact of large language models on higher education: Exploring the connection between AI and Education 4.0. Frontiers in Education, 9, Article 1392091. https://doi.org/10.3389/feduc.2024.1392091

Peslak, A., & Kovalchick, L. (2024). AI for coders: An analysis of the usage of ChatGPT and GitHub Copilot. Issues in Information Systems, 25(4), 252–260. https://doi.org/10.48009/4_iis_2024_120

Romero-Rodríguez, J.-M., Ramírez-Montoya, M. S., Buenestado-Fernández, M., & Lara-Lara, F. (2023). Use of ChatGPT at university as a tool for complex thinking: Students' perceived usefulness. Journal of New Approaches in Educational Research, 12(2), 323–339. https://doi.org/10.7821/naer.2023.7.1458

Stöhr, C., Ou, A. W., & Malmström, H. (2024). Perceptions and usage of AI chatbots among students in higher education across genders, academic levels and fields of study. Computers and Education: Artificial Intelligence, 7, Article 100259. https://doi.org/10.1016/j.caeai.2024.100259

Strzelecki, A. (2024). Students' acceptance of ChatGPT in higher education: An extended unified theory of acceptance and use of technology. Innovative Higher Education, 49(2), 223–245. https://doi.org/10.1007/s10755-023-09686-1

Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the Technology Acceptance Model: Four longitudinal field studies. Management Science, 46(2), 186–204. https://doi.org/10.1287/mnsc.46.2.186.11926

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. MIS Quarterly, 27(3), 425–478. https://doi.org/10.2307/30036540

Wang, H., Dang, A., Wu, Z., & Mac, S. (2024). Generative AI in higher education: Seeing ChatGPT through universities' policies, resources, and guidelines. Computers and

Education: Artificial Intelligence, 7, Article 100326. https://doi.org/10.1016/j.caeai.2024.100326

Yu, C., Yan, J., & Cai, N. (2024). ChatGPT in higher education: Factors influencing ChatGPT user satisfaction and continued use intention. Frontiers in Education, 9, Article 1354929. https://doi.org/10.3389/feduc.2024.1354929