Enhancing Preconstruction Education Through Applied Uses of Artificial Intelligence

by

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Abstract

This dissertation examines the intersection of Building Information Modeling (BIM)-based Quantity Takeoff (QTO), preconstruction education, and customized generative AI tools to address the growing need for digital upskilling in construction management (CM), industry skill gaps, and changing expectations for graduate competencies. The study was guided by three related research questions. First, a systematic review was conducted using the PRISMA method to examine the current state of BIM-based QTO research. The review found that BIM-based QTO can improve productivity, accuracy, and completeness in estimating tasks, while challenges remain related to professional skills, CM graduate competencies, and software functionality. Second, the dissertation developed and evaluated DrCGPT, a custom AI teaching assistant created in Microsoft Copilot Studio to support undergraduate students in construction estimating tasks. Student feedback indicated neutral-to-positive experiences and suggested that the AI agent was a useful learning resource, although students continued to value interaction with instructors and peers. Third, the dissertation examined the use of AI agents as primary instructional tools for asynchronous BIM-based QTO learning. Findings indicate that dialogue-tree-based AI agents, supported by controlled knowledge bases, successfully guided students through structured technical tasks and supported self-paced learning, while limitations remained in flexibility and contextual understanding. Overall, this dissertation provides a case-based framework for educators and industry professionals with limited programming experience to responsibly integrate AI agents into teaching and upskilling practices.

Artificial Intelligence (AI) Use Disclosure Statement

In the preparation of this dissertation, the following Artificial Intelligence (AI) tools were used: ChatGPT 5.2 and Grammarly. These tools were used primarily to improve readability, clarity, grammar, and academic style. The author acknowledges full responsibility for the intellectual content of this work and has ensured that all AI-assisted sections have been reviewed and revised for accuracy and appropriate academic style. All AI-generated content was reviewed and validated for relevance, appropriateness, and accuracy before incorporation into the final document to maintain the scholarly integrity of this research.

Digital Accessibility Use Disclosure Statement

In the preparation of this dissertation, the following digital accessibility tools were used to ensure this document complies with federal requirements: Microsoft Word Accessibility Checker. The author acknowledges full responsibility for the intellectual content of this work and has made a good faith effort to comply with digital accessibility requirements in publishing, wherein the nature of the content does not significantly change in order to do so. Furthermore, all content has been reviewed and revised to meet these requirements prior to final publication.

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Shadi Alathamneh

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List of Abbreviations

AACE	Association for the Advancement of Cost Engineering
AEC	Architecture, Engineering, and Construction
AI	Artificial Intelligence
API	Application Programming Interface
ASR	Automatic Speech Recognition
ASPE	American Society of Professional Estimators
BIM	Building Information Modeling
BoQ	Bill of Quantity
CM	Construction Management
GPT	Generative Pre-trained Transformer
IRB	Institutional Review Board
ITS	Intelligent Tutoring System
LCC	Life Cycle Cost
LLM	Large Language Model
LOD	Level of Development
MCS	Microsoft Copilot Studio
NLP	Natural Language Processing
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
QTO	Quantity Takeoff
RICS	Royal Institution of Chartered Surveyors
SMM	Standard Method of Measurement

List of Related Publications

- Alathamneh, S., Collins, W., & Azhar, S. (2024). BIM-based quantity takeoff: Current state and future opportunities. Automation in Construction, 165, 105549. https://doi.org/10.1016/j.autcon.2024.105549

- Alathamneh, S., Collins, W., Sands, K., Leathem, T., & Liu, J. (2025). Artificial Intelligence and Building Information Modeling in Construction: Applications, Challenges, and Future Opportunities. CIB Conferences. https://doi.org/10.7771/3067-4883.1913

- Alathamneh, S., & Collins, W. (2026). Leveraging Generative AI for Asynchronous Learning in Construction Education: A Pilot Case Study on BIM-Based Quantity Takeoff. Proceedings of the CI & CRC Joint Conference 2026.

Chapter 1. Introduction

This chapter lays the foundation for the study by providing an overview of its context, objectives, and significance. It begins with the Research Background and Rationale, highlighting the increasing applications of Generative AI, particularly Large Language Models (LLMs), in many industries. It’s also addressing skill gaps in BIM within the CM field. The chapter then presents the Statement of Research Aim and Objectives, outlining the study's primary goal of advancing preconstruction education by leveraging customized Generative AI chatbots. Following this, the Key Questions and Hypotheses detail the specific inquiries and assumptions that guide the research. The Research Scope defines the boundaries and focuses of the study, while the limitations address potential constraints and challenges that may affect the outcomes.

1.1. Research Background and Rationale

1.1.1. BIM-based QTO

The AEC industry has increasingly utilized BIM since the early 2000s as a transformative technology to facilitate the design and construction process (Ghaffarianhoseini et al., 2017; Volk et al., 2014). BIM integration could begin from the early design stage, during preconstruction services, or construction operations (Azhar, 2011). Recent software advancements have enabled BIM to handle more tasks than previously, such as speeding up the overall estimating process (S. Lee et al., 2015). In the construction industry, BIM models commonly serve as primary tools for visualization and constructability analysis, actively mitigating potential risks during construction (Olsen

& Taylor, 2017). Furthermore, the industry has already begun to use BIM beyond 3D modeling, particularly within larger firms. The multidimensional aspects of BIM can be extended to 7 dimensions: 4D for planning or scheduling, 5D for cost, 6D for sustainability, and 7D for facility management (Charef et al., 2018; Ying & Kamal, 2021).

Estimating plays a crucial role in every construction project, as it is instrumental in determining the budget throughout various phases, commencing from the early design stage and extending to the final project budget (Collins & Redden, 2022). An accurate, detailed estimate is pivotal for securing the bid at a specific project stage, particularly in traditional delivery methods. Additionally, alternative delivery methods such as Design-Build and CM at Risk necessitate preconstruction services, including estimates, during the early design phase and throughout the construction lifecycle. Accurately preparing a Bill of Quantities (BoQ) is crucial for obtaining a precise and comprehensive estimate (Dimitriou et al., 2018). This process of material quantification is mostly called Quantity Take-off (QTO) or Quantity Surveying (QS) (Hackett, 2010). Furthermore, the QTO task is predominantly linked with 2D construction drawings and specifications, making it labor and time-intensive, posing a substantial challenge for the industry (Hollberg et al., 2020).

A 2021 survey of 186 members of the American Society of Professional Estimators (ASPE) revealed that most professionals rely on 2D software to prepare the BoQ. Surprisingly, the survey also highlighted that most respondents do not use BIM widely for QTO tasks (Collins & Redden, 2022). However, there is significant potential to use BIM for QTO tasks, especially for simple building elements with basic geometry and fewer complications, making them easy to take off, such as concrete and steel (Olsen & Taylor, 2017). Recent studies show that awareness of BIM inclusion in the QTO process is increasing rapidly (Babatunde et al., 2018, 2020). Additionally, there is disagreement among professionals about what is beyond the 3 Dimensions of BIM, precisely the 5th Dimension, which is mainly related to cost (Charef et al., 2018). One of the industry's challenges in this transition is primarily the time required to generate the 3D model and the complexity of the software (Babatunde et al., 2019).

One of the key challenges in the industry's transition from 2D QTO to BIM-based QTO is understanding the information requirements necessary for BIM models to be sufficiently complete, quantifiable, and reliable for generating accurate BoQs (Liu et al., 2022a). These types of BIM functions have led to the introduction of standardized terms for BIM models based on the Level of Development (LOD). These levels range from LOD 100, which represents the schematic design, to LOD 500, which encompasses the as-built documentation for Facility Management (FM) purposes (Latiffi et al., 2015). BIM-based QTO in the early design stage could be very helpful to all stakeholders, as it can provide initial estimates even at low LOD. One of the benefits of engaging BIM-based QTO is to improve the reliability of estimation and constructability analysis (Choi et al., 2015).

It is essential to clarify the standard terms used in this study, including QTO and QS, which are often used synonymously to refer to tasks aimed at generating a BoQ. The quantity surveyor and estimator professions serve the same purpose and share many skills, tasks, and responsibilities. However, the profession of estimator is more widely recognized in the United States, represented by the ASPE and the Association for the Advancement of Cost Engineering (AACE). On the other hand, the Quantity Surveyor is more commonly used in other countries, such as the UK, where they are represented by the Royal Institution of Chartered Surveyors (RICS) (Hackett & Hicks, 2007).

According to the Bureau of Labor Statistics, Occupational Outlook Handbook (OOH) in 2023, "cost estimators collect and analyze data to assess the time, money, materials, and labor required to produce a product or provide a service." Typically, estimators must have a bachelor's degree in a related field, though experienced individuals from other occupations may qualify without one. In addition to essential qualities such as analytical, mathematical, and time management skills, most estimators undergo on-the-job training in software and techniques. This training may include BIM, Computer-Aided Design (CAD), or other estimating software. It's important to note that the employment outlook for cost estimators shows a projected decline of 3% in the future. This decline is primarily attributed to advancements in software development, which are expected to significantly enhance the efficiency and productivity of estimators (*Cost Estimators*, 2023).

1.1.2. Large Language Models and Generative Pre-Trained Transformers

LLMs have evolved significantly from early statistical language models to advanced architectures like transformers, which have revolutionized natural language processing (NLP) (Chukwuere, 2024). This evolution has been driven by the advent of deep learning, enabling models to achieve state-of-the-art performance in tasks such as language understanding and generation (Patil & Gudivada, 2024). The transition from task-specific to more generalized models has allowed LLMs to perform effectively across diverse domains (Patil & Gudivada, 2024). However, as LLMs approach the realm of artificial general intelligence (AGI), tracing their origins and understanding their development becomes crucial (Li et al., 2023). This includes addressing ethical concerns and the challenges posed by biases and ambiguities inherent in these models. Overall, the historical progression and principles underlying LLMs are essential for harnessing their full potential in various applications (Chukwuere, 2024).

Generative Pre-trained Transformers (GPTs) have revolutionized NLP, offering diverse applications across multiple domains. In digital marketing, GPTs enhance content creation, customer interactions, and social media marketing (Sharma & Sharma, 2023). The gaming industry utilizes GPTs for procedural content generation, mixed-initiative game design, gameplay, and user research (Yang et al., 2024). GPTs also impact business operations, website development, and conversational applications (Bhattacharjee, 2023). Their ability to generate coherent, contextually relevant text has transformed customer support, enabling personalized responses and tailored recommendations (Sharma & Sharma, 2023). Despite their potential, GPTs face challenges and limitations that require further research and development (Yenduri et al., 2024). As GPT technology continues to evolve, it promises to reshape various industries, improving efficiency and user experiences while presenting new opportunities for innovation and growth (Bhattacharjee, 2023; Yenduri et al., 2024).

NLP has emerged as a powerful tool in education, offering diverse applications to enhance teaching and learning processes. NLP techniques can be used for question answering, question construction, automated assessment, and error correction (Lan et al., 2024). These applications provide valuable insights into task difficulty, student performance, and individual differences (Allen et al., 2022). In STEM education, NLP tools have proven effective in evaluating higher-order cognitive functions and assessing transversal skills, supporting instructors in providing personalized feedback (Caratozzolo et al., 2022). The integration of NLP in educational technologies enables formative feedback for students and offers educators information about various aspects of the learning process. However, educational applications present unique challenges for NLP systems, requiring adaptations to address the specific needs of teachers and students (Allen et al., 2022). As NLP continues to advance, it holds significant potential for improving educational outcomes across various domains.

However, while LLMs and GPTs have revolutionized NLP and demonstrated broad applications across industries, their general-purpose nature often falls short of addressing the specialized needs of students in technical domains, such as BIM in construction education. Current educational applications of GPTs and NLP focus on tasks like question answering, automated assessments, and formative feedback, which, while valuable, lack the contextual depth required for BIM (Zhang et al., 2022), a field that demands proficiency in both theoretical concepts and practical skills such as 3D modeling and QTOs. It is also important to note that publicly available LLMs and GPTs often generate information without validation by authoritative or instructor-approved sources, which may limit their reliability for supporting technical learning and practice-based construction education.

1.1.3. Asynchronous learning

Asynchronous learning methods have gained prominence in higher education, particularly due to the COVID-19 pandemic (Soboń, 2022). These methods offer flexibility and independence to students, but their implementation varies across institutions (Kamaludin et al., 2023). Asynchronous Online Discussions (AODs) are widely used in higher education, but there is little consensus on best practices (Fehrman & Watson, 2021). While asynchronous learning can create a rich cognitive presence in military higher education (Soboń, 2022)It is often underutilized at the university level, primarily serving as a means of information transfer rather than facilitating teaching and instruction (Kamaludin et al., 2023).

Although asynchronous learning methods have demonstrated flexibility and resilience in higher education, particularly during crises like the COVID-19 pandemic and geopolitical conflicts, their application often focuses on information delivery rather than interactive teaching and instruction. This gap is especially pronounced in specialized and technical fields like BIM education, where hands-on, practical engagement is crucial for developing skills. While tools like Asynchronous Online Discussions (AODs) enhance cognitive presence, there is limited exploration of innovative asynchronous methods tailored to active learning in technical domains. This highlights the need for customized asynchronous learning tools, such as generative AI chatbots, that can provide contextualized support, simulate interactive learning environments, and bridge the gap between theoretical knowledge and practical application, addressing the specific challenges of BIM education.

1.2. Statement of Research Aim and Objectives

The central aim of this study is to support preconstruction education in construction management programs by leveraging customizable AI agents trained on instructor-approved knowledge bases and structured, interactive workflows for preconstruction tasks. The study focuses specifically on construction estimating and BIM-based QTO. To address this aim, the study is guided by three main objectives:

1. **Objective 1:** To investigate the current state of BIM-based QTO, with emphasis on its key benefits, challenges, and future opportunities in research and practice.
2. **Objective 2:** To develop a framework for a custom Generative AI chatbot tailored to estimating courses in CM education and evaluating its effectiveness as a virtual teaching assistant.
3. **Objective 3:** To design and develop a framework for asynchronous learning by leveraging custom chatbot dialogue trees and Generative AI responses as a primary instructional source for BIM education.

The overall goal of this study was to develop a framework, informed by case-based implementation and evaluation, for integrating customized AI agents into preconstruction education. This framework may be particularly useful for CM educators with limited computer programming experience who seek to incorporate AI-supported instructional tools into their courses. To achieve this goal and address the stated objectives, the study is guided by the following research questions:

1. **Research Question 1:** What is the current state of BIM-based QTO, particularly in terms of its key benefits, challenges, and future opportunities in research and practice?

2. **Research Question 2:** How can a custom Generative AI chatbot be developed for estimating courses in construction management education, and how effective is it in supporting student learning?
3. **Research Question 3:** How can a custom AI agent with a predesigned dialogue-tree architecture serve a central instructional role in asynchronous preconstruction education?

Together, these research questions provided a structured foundation for examining BIM-based QTO as a preconstruction practice, exploring the instructional potential of customized AI agents, and evaluating their use in asynchronous preconstruction learning environments. By aligning the research objectives with these questions, the study seeks to contribute to both CM education and the broader discussion on the practical integration of AI-supported learning tools in preconstruction education.

1.3. Research Scope

The scope of this dissertation centers on enhancing preconstruction education in CM through the integration of preconstruction education with customizable AI agents. The study focuses on three connected areas: first, examining the current state of BIM-based QTO by identifying its reported benefits, challenges, limitations, and future opportunities in research and practice; second, developing and evaluating a custom generative AI chatbot as a virtual teaching assistant to support students in estimating-related learning activities; and third, designing and testing an AI-supported asynchronous learning framework in which structured dialogue trees and generative AI responses guide students through BIM-related instructional tasks. The research is situated within CM education, with emphasis on estimating, BIM-based QTO workflows, and student learning experiences in the US. While the study considers broader implications for professional upskilling and future instructional applications, its empirical scope is limited to the selected educational contexts, AI platforms, deployment channels, instructional materials, and student populations examined during the study period.

1.4. Limitations of the Study

The study acknowledges the following limitations:

- The chatbot's performance is contingent on the quality and scope of the training dataset, which may limit its generalizability.
- Validation will be limited to a specific group of CM students, which may not fully represent the broader student population.
- The AI agents developed in this study were created using MCS and deployed through Microsoft Teams during the 2024–2025 timeframe. Therefore, the design, functionality, accessibility, and performance of the agents were influenced by the capabilities and limitations of these platforms at the time of development. As these technologies continue to evolve, future implementations may produce different results depending on changes in platform features, deployment options, and institutional technology environments.
- The effectiveness of the chatbot will be measured within a short-term educational setting, potentially excluding long-term impacts on professional skills.
- This dissertation is limited to construction management practices in the southeastern United States, with a primary focus on commercial construction projects in the U.S.

1.5. Statement of the Dissertation

This dissertation follows the manuscript-based dissertation format, designed to systematically address its overall aim through a cohesive progression of research objectives presented as publishable journal articles. The introductory chapter establishes the foundation by outlining the research problem, objectives, and significance, and by providing context for the study. Chapter 2 details the research methodology and aligns it with three distinct yet interrelated research questions. Chapters 3, 4, and 5 present these research questions as standalone journal papers, each comprising its own literature review, methodology, and results. These chapters are sequenced to ensure continuity and coherence in achieving the dissertation's overall aim while maintaining the structure of independent, publication-ready articles. The final chapters integrate the findings through a comprehensive discussion, followed by a conclusion chapter that summarizes contributions and provides recommendations for future research and practical applications.

Chapter 2. Research Methodology

This Chapter presents the research methodology used to address the three research questions guiding this dissertation, as illustrated in Figure 2.1. The chapter is organized to reflect the sequential development of the study, beginning with a systematic review that examines the current state, trends, benefits, and challenges of BIM-based QTO and related preconstruction technologies. Building on these findings, the second section describes the development and semester-based deployment of a custom AI agent as a virtual teaching assistant in estimating education, with a focus on evaluating its role in supporting students' learning and task completion over an extended instructional period. The third section then presents the design and testing of an AI agent serving as the primary instructional source for students in a BIM-based learning activity, emphasizing how structured dialogue trees and generative AI responses can support asynchronous learning. Together, these methodological sections provide a connected research design that moves from understanding existing knowledge and gaps to developing, deploying, and evaluating AI-supported instructional approaches in preconstruction and BIM education.

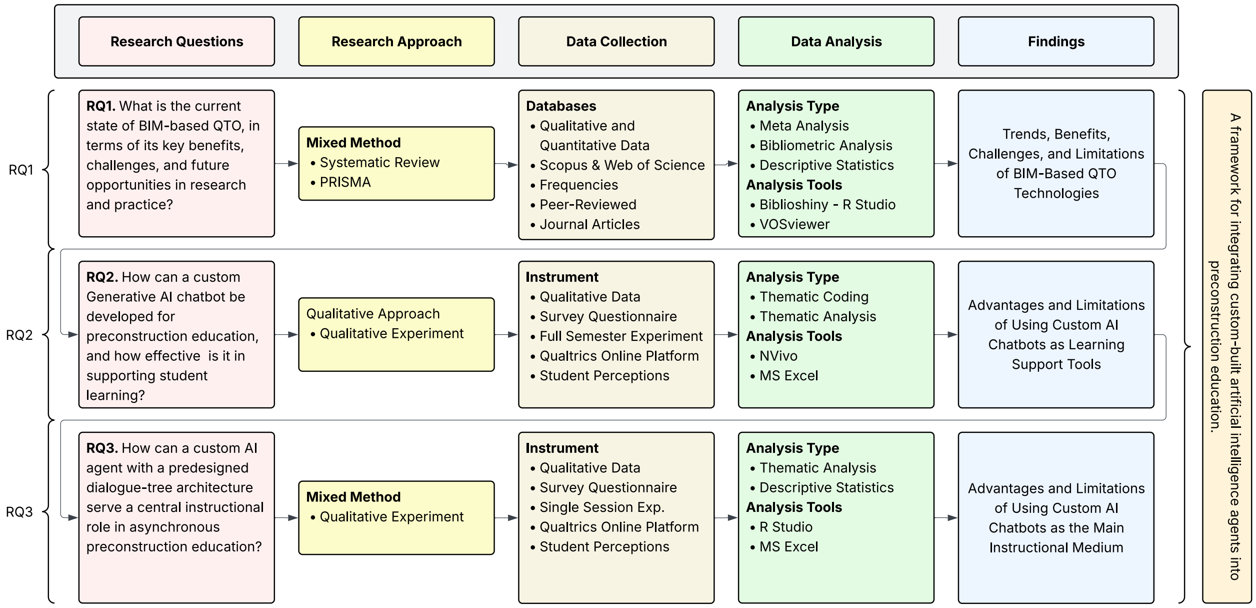

Figure 2.1. The Research Design Flow Diagram and Methodological Approach

2.1. RQ1. What is the current state of BIM-based QTO, particularly in terms of its key benefits, challenges, and future opportunities in research and practice?

2.1.1. Study Overview

This objective focuses on identifying the key benefits and challenges the construction industry faces in implementing BIM-based QTO technology. The study aims to uncover gaps in technology adoption, particularly those stemming from a skills deficit among professionals, alongside other contributing factors, all of which are discussed in detail. To achieve this, a systematic review of the literature was conducted, providing critical insights into the current state of BIM-based QTO. This review aims to identify the state of the art in leveraging BIM for material quantification in the construction industry.

To achieve this aim, the following research objectives have been developed to guide the review process:

- To provide an overview of the current state of research on BIM-based QTO and highlight key findings, methodologies, and trends.
- To investigate the benefits and the challenges of leveraging BIM in material quantification practices.
- To identify gaps and suggest directions for future research and developments in the field of BIM-based QTO.

2.1.2. Data Collection

This systematic literature review follows the guidelines of The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA). The PRISMA guidelines have been set to ensure more transparent, accurate, and complete reporting for this systematic review, thus providing precise evidence-based results through a scientometric analysis. Furthermore, it helps to connect each objective of this research to identify the current body of knowledge in this field. Additionally, it provides an agenda for future research opportunities based on their frequent occurrence in the literature, which could be hard to achieve by studying individual studies separately (Page et al., 2021).

This systematic review, with a global scope, identified all publications on BIM in the field of QTO/QS services for construction projects. The focus of the study was limited to publications in the engineering and building construction technology domains until 2024. However, this review was limited to peer-reviewed published journal articles only. The eligible publications were limited to English due to the researchers' language proficiency and to avoid missing information during translation. This review relied on two world-leading databases: Web of Science® and Scopus®. These two databases have contributions from around the world and publications related to the construction industry. Furthermore, both databases are repeatedly used in meta-analysis (Zhu & Liu, 2020). In this study, the latest search was conducted in December 2023, and the data were extracted from both databases.

2.1.3. Data Analysis

A bibliometric analysis was performed to provide a broader understanding of the included studies and to examine their main publication characteristics. The analysis was conducted using the Biblioshiny® package in RStudio®, which supported data processing, quantitative calculations, and the generation of selected visualizations through clustering algorithms such as Walktrap and Louvain (Aria & Cuccurullo, 2017). The records were imported from the selected databases in RIS format, merged into a single CSV file, and screened to remove irrelevant entries. The bibliometric analysis focused on identifying author keyword co-occurrence, temporal publication trends, regional distribution, and publication sources. In the subsequent systematic analysis, Biblioshiny® was also used to examine the extracted data, particularly the co-occurrence of methods, trends, benefits, and challenges.

2.2. RQ2. How can a custom Generative AI chatbot be developed for estimating courses in construction management education, and how effective is it in supporting student learning?

2.2.1. Study Overview

Building on the findings of RQ1, the systematic review highlighted that BIM-based quantity takeoff offers significant opportunities to improve estimating practices, but its adoption remains constrained by persistent skill gaps, limited graduate competencies, and the need for stronger training in preconstruction workflows. These challenges were evident not only in the literature but also in the broader discussion of professional readiness presented in Chapter 3. In response to this gap, RQ2 shifted the focus from identifying challenges to exploring a potential instructional intervention. Specifically, it examined whether a customized generative AI chatbot could be developed for construction estimating courses and whether such a tool could serve as a useful learning resource for students. This transition reflects the dissertation's progression from understanding the educational and professional needs associated with BIM-based QTO to investigating a technology-supported approach for addressing those needs within construction management education.

The aim of this study was to develop and evaluate a custom chatbot as a teaching assistant in an undergraduate construction estimating course to enhance student learning and engagement. The specific objectives of the study were to:

- To develop a custom chatbot integrated with course-specific data and resources.
- To deploy the chatbot to undergraduate students and facilitate its use throughout the course.
- To assess students' perceptions of the chatbot's value in learning construction estimating concepts.

Specific AI-related tools, including automatic speech recognition (ASR) (used at the front end of the research) and machine learning (used at the back end), which were fundamental to the process, will be highlighted. The proposed framework will provide STEM educators with a detailed method for developing their own custom chatbots, drawing on lessons learned from this first trial.

2.2.1.1. Study Design and Chatbot Development and Deployment

This study adopted a mixed-methods approach to evaluate the implementation and effectiveness of a custom-built chatbot. The study design encompassed three main phases: generating a course-specific dataset, building the chatbot, and deploying it to students.

2.2.1.2. Generating the dataset

The dataset used for the chatbot's training was collected from an extensive archive of class recordings from 11 previous course sections stored in Panopto, a video management platform. These recordings were transcribed automatically using Panopto's ASR feature, producing text with an accuracy of approximately 90–95%. The unedited transcripts served as the foundational dataset for the chatbot, reflecting the course's instructional content and style. Additionally, the chatbot was linked to the Bluebeam Revu software user guide, a critical resource for the course.

2.2.1.3. Building the Chatbot with Microsoft Copilot Studio

The custom-built chatbot was developed using MCS, selected for its user-friendly interface, seamless integration with Auburn University's technological ecosystem, and free access for students. Panopto-generated transcripts were uploaded directly into the platform without additional editing or cleaning. The Copilot platform's features, including automated data analysis and response generation, minimized the need for extensive coding or manual preprocessing, making it accessible to faculty without programming expertise.

Figure 2.2 shows a flowchart illustrating the structure of an AI-based learning system designed for students. At the top is the "Manager: Instructor," who oversees the system, supported by inputs such as transcripts of recorded lectures, trusted resources, and model instructions. These components feed into a central "Knowledge Database" that serves as the core repository of information. The database integrates with reasoning capabilities powered by "OpenAI" to generate answers. Student inputs are recognized through text, guided by prompts. Finally, the processed responses are delivered to the end users, who are students.

The chatbot was deployed through Microsoft Teams, which served as the primary access platform. Students were provided with a link to the chatbot via the course’s Canvas page. Its functionality was demonstrated at the beginning of the course and periodically highlighted during lectures to encourage engagement and adoption.

2.2.1.4. Deployment and Interaction

The chatbot was deployed across four course sections, involving 120 students, over two semesters. It functioned as a supplemental learning tool, enabling students to ask questions anonymously or seek assistance outside class hours. Faculty also modeled its use during lectures by posing questions and evaluating the chatbot’s responses in real time.

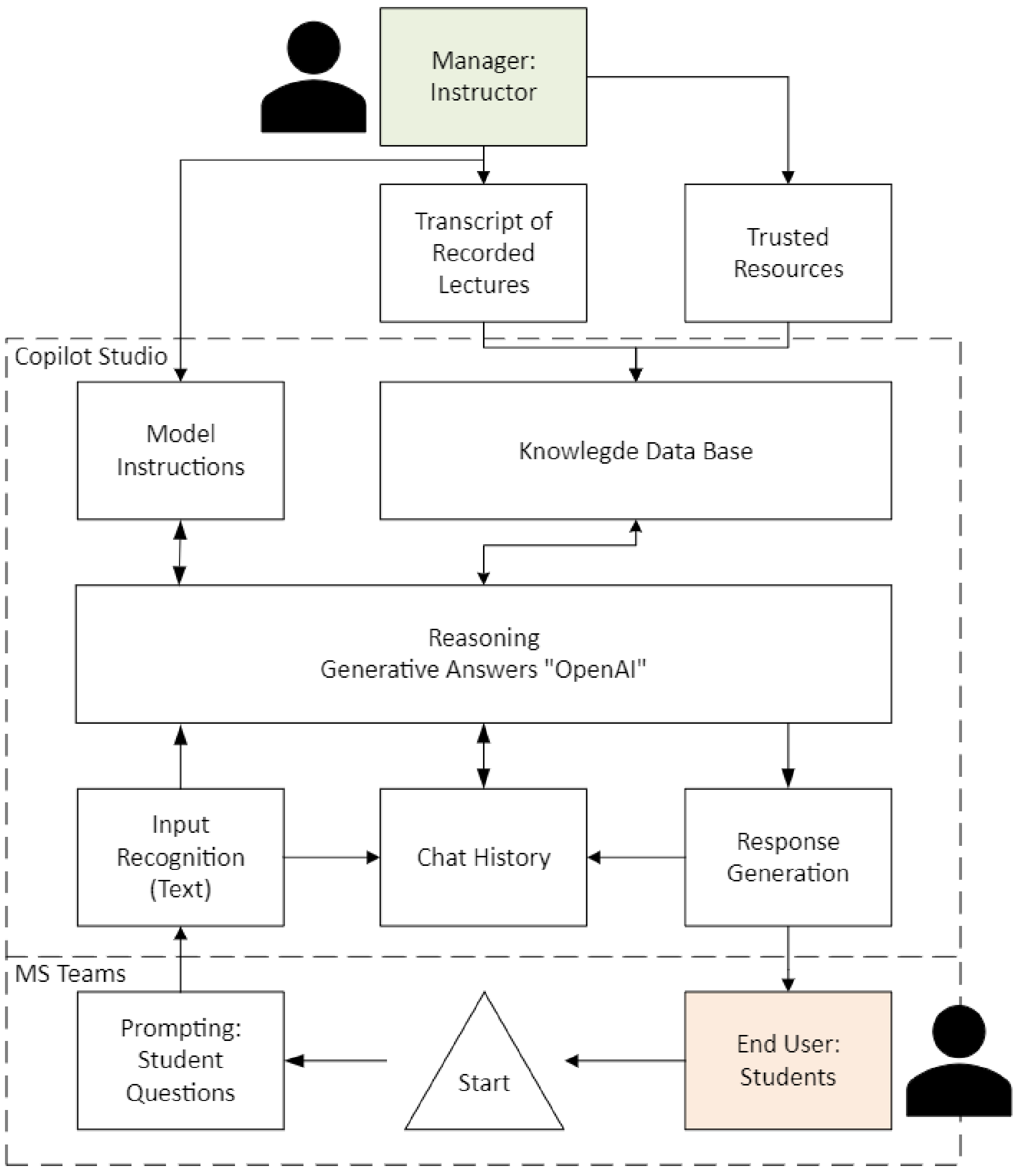

Figure 2.2. Framework for AI-Powered Student Learning Support System

2.2.2. Data Collection

Data for this study were collected through an online Qualtrics survey administered at the end of the semester after students had used the custom-built AI agent, DrCGPT, as a supplemental virtual teaching assistant in construction estimating courses. The agent was deployed across four course sections over two semesters, with approximately 120 students exposed to the tool through Microsoft Teams and Canvas. The survey was designed to capture students' perceptions of the agent's educational value, their prior experience with AI chatbots, their preferred sources of instructional support, and their interest in seeing similar AI agents implemented in other Building Science courses. Administering the survey at the end of the semester allowed students to reflect on their sustained interaction with the chatbot across multiple estimating and QTO topics. Participation was voluntary and anonymous to encourage honest feedback, and the instrument included both closed-ended and open-ended questions to support a multi-method understanding of student experiences.

Approval of the Institutional Review Board (IRB) was required for this study because it involved human subjects. Prior to any data collection, the study protocol was submitted to the Auburn University IRB for review and was approved with an exempt classification. All participant-facing materials, including the consent form, information letter, and survey questions, were reviewed by the IRB and are provided in Appendix 1.

2.2.3. Data Analysis

The survey data were analyzed using a multi-method approach that combined descriptive statistics with qualitative thematic and sentiment analysis. Responses were first exported from Qualtrics into Excel, and exclusion criteria were applied to remove incomplete or unreliable responses, including surveys completed in less than 60 seconds, unfinished submissions, and responses with more than half of the items unanswered. After this screening process, 102 valid responses were retained for analysis. Closed-ended questions were summarized using descriptive statistics to identify trends in students' prior AI use, help-seeking preferences, and perceptions of the chatbot's usefulness. Open-ended responses were analyzed through manual review and NVivo-assisted coding to identify recurring themes and sentiment categories, including positive, neutral, negative, and mixed perceptions. This analytical process provided both a broad quantitative overview of student responses and a deeper qualitative understanding of how students perceived the value, limitations, and potential future use of DrCGPT in CM education.

2.3. RQ3. How can a custom AI agent with a predesigned dialogue-tree architecture serve a central instructional role in asynchronous preconstruction education?

2.3.1. Study Overview

Building on the findings of RQ2, Chapter 4 demonstrated that the customized generative AI chatbot could be developed and implemented as a teaching assistant in a construction estimating course, with students reporting neutral-to-positive experiences when interacting with the tool. These findings suggested that AI agents may provide useful instructional support, particularly for answering questions, guiding students through estimating concepts, and supplementing course materials. Based on this initial implementation, Research Question 3 extended the investigation by shifting the AI agent's role from a supplemental teaching assistant to a more central instructional role. Specifically, the focus moved toward designing an interactive AI-supported workflow for asynchronous learning in BIM-based QTO tasks. This progression enabled the dissertation to examine whether generative AI could support students not only as an additional resource but also as a structured instructional medium, with broader implications for scalable construction education and future professional upskilling.

This study aims to design and develop a framework for asynchronous learning using custom chatbot dialogue trees and generative AI responses to enhance BIM education. The methodology for achieving this goal is outlined in the following phases:

2.3.1.1. Design and Development of Chatbot Dialogue Trees

The custom chatbot will be designed and trained on trusted instructor-approved data sources, such as the Revit Architecture user manual. This ensures that the chatbot's responses are accurate, relevant, and reliable. The chatbot will be tailored to interact with students throughout a four-day experiment, during which students will rely solely on the chatbot for learning BIM skills. In other words, their interaction with the chatbot will serve as the primary method for acquiring BIM knowledge during the experiment.

The chatbot's interactions will be guided by pre-designed, structured dialogue trees that provide step-by-step guidance for commonly taught BIM tasks. These dialogue trees will be based on materials from previous assignments that focus on teaching students the fundamentals of BIM modeling. Key components of the dialogue trees include:

- Task initiation prompts: Clear instructions to begin specific BIM tasks.
- Sequential steps: Detailed guidance aligned with BIM software workflows.
- Decision nodes: Branching paths based on user input, directing students to the next appropriate step or additional resources.

When the dialogue tree pathways are insufficient, the chatbot will leverage generative AI capabilities via Copilot Studio. This enables context-aware responses that supplement the structured dialogue trees, ensuring comprehensive support for students as they navigate BIM tasks.

2.3.1.2. Implementation of Asynchronous Learning Framework

The implementation phase will focus on deploying the chatbot on Microsoft Teams to ensure accessibility for students within their existing learning environment. A pilot deployment will be conducted with a sample population of 60 CM students to test the tool's usability and refine it based on feedback. The chatbot will guide students through specific BIM tasks, such as creating structural and architectural models. Learning modules aligned with BIM curriculum objectives will be provided, allowing students to engage asynchronously at their own pace.

2.3.2. Data Collection

A pre-survey questionnaire will be administered before the experiment to assess the students' baseline knowledge of BIM modeling. The experiment will span four class days during which students will learn BIM modeling exclusively through interactions with a customized chatbot. At the conclusion of the experiment, a post-survey questionnaire will be conducted to evaluate students' perceptions of the chatbot as a learning tool and to measure changes in their self-assessed knowledge and skill levels. This approach aims to capture both qualitative feedback on the learning experience and quantitative shifts in students' perceived competence in BIM.

Approval of the IRB was required for this study because it involved human subjects. Prior to any data collection, the study protocol was submitted to the Auburn University IRB for review and was approved with an exempt classification. All participant-facing materials, including the consent form, information letter, and survey questions, were reviewed by the IRB and are provided in Appendix 2.

2.3.3. Data Analysis

For data analysis, the experiment's results will be compared with historical data collected from five previous semesters in which traditional teaching methods were employed for the same assignment. Statistical methods, such as paired t-tests and ANOVA, will be used to compare performance outcomes, such as assignment grades, between the experimental and historical control groups. Additionally, the pre- and post-survey data will be analyzed to measure knowledge retention and skill acquisition within the experimental group. The analysis will provide insights into the effectiveness of the chatbot-based learning approach in enhancing BIM skills compared to traditional teaching practices.

Chapter 3. RQ1. What is the current state of BIM-based QTO, particularly in terms of its key benefits, challenges, and future opportunities in research and practice?

3.1. Introduction

3.1.1. General overview

The AEC industry has increasingly utilized BIM since the early 2000s as a transformative technology to facilitate the design and construction process (Ghaffarianhoseini et al., 2017; Volk et al., 2014). BIM integration could begin from the early design stage, during preconstruction services, or construction operations (Azhar, 2011). Recent software advancements have enabled BIM to handle more tasks than previously. In the construction industry, BIM models commonly serve as the primary tools for visualization and constructability analysis, actively mitigating potential risks during the construction phase (Olsen & Taylor, 2017). Furthermore, the industry has already begun to use BIM beyond a 3D modeling tool, particularly within larger firms. The multi-dimensional aspects of BIM can extend to seven dimensions: 4D to planning or scheduling, 5D to cost, 6D to sustainability, and 7D to facility management (Charef et al., 2018; Ying & Kamal, 2021).

Estimating plays a crucial role in every construction project, as it is instrumental in determining the budget throughout various phases, from the early design stage to the final project budget (Collins & Redden, 2022). An accurate, detailed estimate is pivotal for securing the bid at a specific project stage, particularly in traditional delivery methods.

Additionally, alternative delivery methods such as Design-Build and CM at Risk necessitate preconstruction services, including estimates, during the early design phase and throughout the construction lifecycle. Accurately preparing a Bill of Quantity (BoQ) is crucial for obtaining a precise and comprehensive estimate (Dimitriou et al., 2018). This process of material quantification is commonly referred to as Quantity Take-off (QTO) or Quantity Surveying (QS) (Hackett, 2010). Furthermore, the QTO task is predominantly linked to 2D construction drawings and specifications, making it labor- and time-intensive and posing a substantial challenge for the industry (Hollberg et al., 2020).

A 2021 survey of 186 members of the ASPE revealed that most professionals rely on 2D software to prepare the BoQ. The survey also highlighted that most respondents do not use BIM widely for QTO tasks (Collins & Redden, 2022). However, there is a significant potential for using BIM for QTO tasks, especially for simple building elements with basic geometry features with less complication, making them easy to take off, like concrete and steel (Olsen & Taylor, 2017). Recent studies showed that the awareness of BIM to be included in the QTO process is increasing rapidly (Babatunde et al., 2018, 2020). Additionally, there is disagreement among professionals about what is beyond the 3 Dimensions of BIM, precisely the 5^{th} Dimension, which is mainly related to cost (Charef et al., 2018). One of the industry's challenges in this transition is primarily the time required to generate the 3D model, and the software complexity (Babatunde et al., 2019).

One of the confusing aspects of the industry transition from 2D QTO to BIM-based QTO is the related information requirements on the BIM model to be quantifiable and complete to generate an accurate BoQ (Liu et al., 2022a). These types of BIM functions have led to the introduction of standardized terms for BIM models based on the LOD.

These levels range from LOD 100, which represents the schematic design, to LOD 500, which encompasses the as-built documentation for Facility Management (FM) purposes (Latiffi et al., 2015). BIM-based QTO in the early design stage could be very helpful to all stakeholders, as it can provide initial estimates even at low LOD. One of the benefits of engaging BIM-based QTO is improved reliability in estimation and constructability analysis (Choi et al., 2015).

It is essential to clarify the standard terms used in this review. QTO and QS are regarded as synonymous tasks aimed at generating a Bill of Quantities (BoQ). The quantity surveyor and estimator professions serve the same purpose and share many skills, tasks, and responsibilities. However, the profession of estimator is more widely recognized in the United States, represented by the ASPE and the AACE. On the other hand, the Quantity Surveyor is more commonly used in other countries, such as the UK, where they are represented by the RICS (Hackett & Hicks, 2007).

According to the Bureau of Labor Statistics, Occupational Outlook Handbook (OOH) in 2023, "cost estimators collect and analyze data to assess the time, money, materials, and labor required to produce a product or provide a service." Typically, estimators must have a bachelor's degree in a related field, though experienced individuals from other occupations may qualify without one. In addition to essential qualities such as analytical, mathematical, and time management skills, most estimators undergo on-the-job training in software and techniques. This training may include BIM, Computer-Aided Design (CAD), or other estimating software. It's important to note that the employment outlook for cost estimators shows a projected decline of 3% in the future. This decline is primarily attributed to advancements in software development, which are expected to significantly enhance the efficiency and productivity of estimators (*Cost Estimators*, 2023).

3.1.2. Originality of the Review

Several review articles on BIM in general have been published over the last two decades. Using the Scopus® Database in December 2023, 146 review articles have been published with "Building Information Modeling" (BIM) in their title (Figure 3.3). These articles covered various topics related to BIM, but not necessarily for material quantification. For instance, a systematic review article discovered the current BIM applications for existing buildings (Volk et al., 2014). Another article was about finding the Internet of Things (IoT) application and connection with BIM (Tang et al., 2019). Another search engine, namely Google Scholar, was utilized to retrieve more relevant review articles. For example, a systematic review assessed the professional view of the definition and scope of each BIM dimension (Charef et al., 2018). Another review article discussed the applications and the state of the art of BIM development in a specific country's construction industry (Page et al., 2021). Additionally, a review article explored the integration of BIM with digital twins (Zhu et al., 2020). However, no review article has been found addressing BIM in the context of QTO or QS.

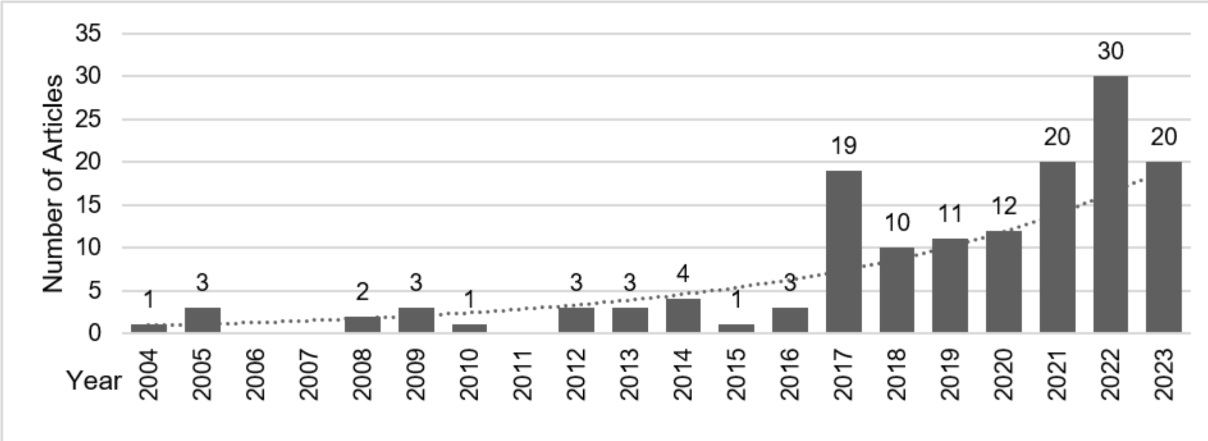

Figure 3.3. BIM-related Review Articles Production over Time in Scopus® Database

3.1.3. Aim, Objectives, and Structure

This review aims to identify the state of the art in leveraging BIM for material quantification in the construction industry. To achieve this aim, the following research objectives have been developed to guide the review process:

i. To provide an overview of the current state of research on BIM-based QTO and highlight key findings, methodologies, and trends.

ii. To investigate the benefits and the challenges of leveraging BIM in material quantification practices.

iii. To identify gaps and suggest directions for future research and developments in the field of BIM-based QTO.

This review article is divided into five sections. Section 2 provides a comprehensive overview of the research design and methodology used to develop this review. Section 3 presents the results of this review, highlighting the relevant findings and providing a scientometric analysis that answers the research questions. Additionally, it will identify the challenges, trends, and future opportunities for leveraging BIM into QTO. Section 4 provides a more in-depth discussion of the analysis and connects the variety of results, aiming to propose a conceptual model for BIM-based QTO implementation. Finally, section 5 provides conclusions and recommendations for future research opportunities and developments.

3.2. Methodology

3.2.1. PRISMA

This systematic literature review follows the guidelines of The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA). The PRISMA guidelines have been applied to ensure more transparent, accurate, and complete reporting in this systematic review, thereby providing precise, evidence-based results through a scientometric analysis. Furthermore, it helps to connect each objective of this research to identify the current body of knowledge in this field. Additionally, it provides an agenda for future research opportunities based on their frequent occurrence in the literature, which could be hard to achieve by studying individual studies separately (Page et al., 2021).

3.2.2. Scoping Review

This systematic review, with a global scope, identified all publications on BIM in the field of QTO/QS services for construction projects. The study focused on publications in the engineering and building construction technology domains throughout 2024. However, this review was limited to peer-reviewed published journal articles only. The eligible publications were limited to English due to the researchers' language proficiency and to avoid missing information during translation. This review relied on two world-leading databases: Web of Science® and Scopus®. These two databases have contributions from around the world and publications related to the construction industry. Furthermore, both databases are repeatedly used in meta-analysis (Zhu & Liu, 2020). In this study, the latest search was conducted in December 2023, and the data were extracted from both databases. Figure 3.4 shows the overall research design.

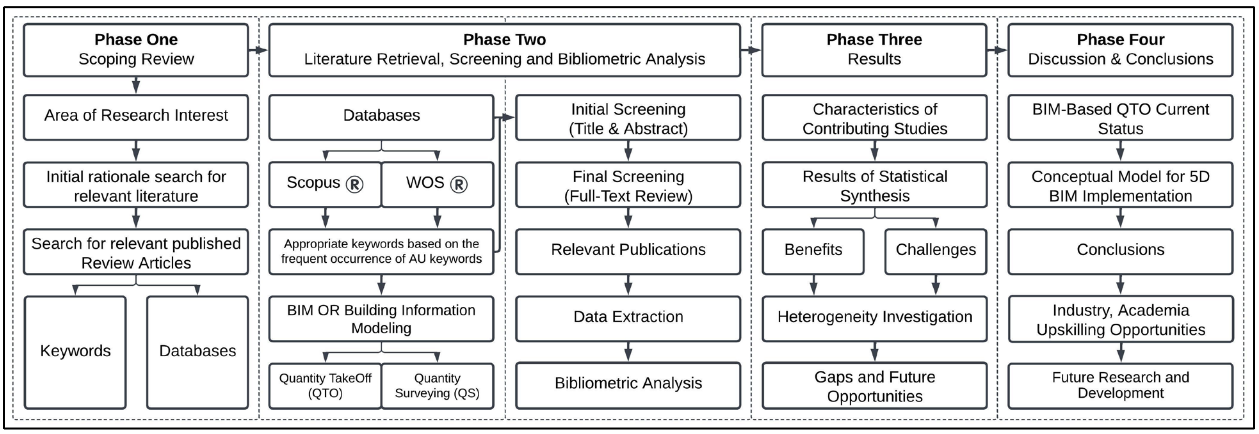

Figure 3.4. Research Design and Methodology

As an initial step, preliminary searches were conducted to identify and refine the study's keyword list. The initial set of keywords included relevant terms such as estimate, quantity take-off, quantity surveying, BoQ, BIM, 5D BIM, and material quantification. The initial literature retrieval was performed using the Scopus® Database, which returned 278 records. Subsequently, using the PageRank algorithm (Aria & Cuccurullo, 2017). The highest-ranking keywords were selected to further refine the keyword set, based solely on the author's keywords. Finally, a list of keywords was identified as highly relevant to the review's context. The final keywords that have been used in this review for literature retrieval from both databases were as follows: "(bim OR building AND information AND modeling) AND (qto OR quantity AND take AND off) OR (qs OR quantity AND surveying)". The queries were based on the search fields of the title, abstract, and authors' keywords.

The limits that have been applied to the search strategy of each database are described as follows: in the Scopus ® database, the subject area was chosen to be limited to Engineering, the language was limited to English, the publication type was limited to an article, and the end date was set to 2024. Based on these eligibility criteria, 76 articles were retrieved from the Scopus® database. On the other hand, the Web of Science® category was limited to Construction Building Technology, the language was limited to English, the publication type was limited to articles, and the end date was set to 2024. Based on these eligibility criteria, a total of 162 articles were returned from the Web of Science® Database. The total number of returned articles from both databases was 238, ranging from 1995 to 2025 (Figure 3.5). The full records were exported separately from each database as RIS files.

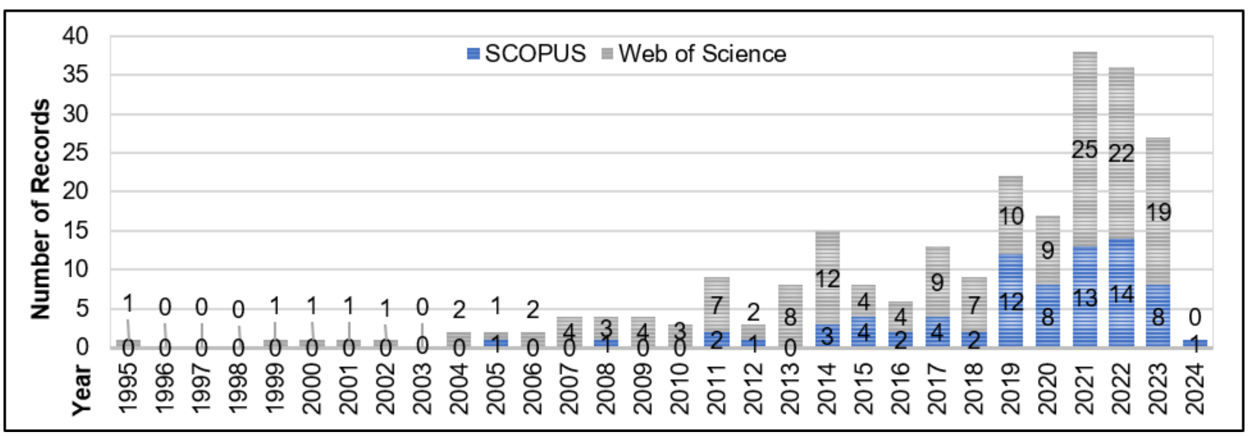

Figure 3.5. The number of records were returned from Scopus and WOS over time.

3.2.3. Screening Process

3.2.3.1. Initial Screening (Title and Abstract)

The screening process and data storage were managed using the Covidence® platform. Covidence® is an online platform that helps researchers conduct screening during a systematic literature review (*Covidence Product Updates and Bug Fixes*, 2023). Starting with duplicate removal, the Covidence platform identified 24 articles, which were subsequently removed and manually verified by the authors. The total number of articles then decreased from 238 to 214, which were ready for initial screening. The initial screening focused on how relevant the title and abstract of each record were to the research aim and objectives, considering the inclusion criteria based on the study characteristics: research method, population group, and outcomes, as shown in Figure 3.6. It's worth noting that an active machine learning tool, developed by EPPI-Centre®, was used to prioritize the initial screening. This tool continually re-orders the articles based on past screening behavior (*Covidence Product Updates and Bug Fixes*, 2023). A total of 139 records were irrelevant to the subject area, such as "How to develop a BIM workflow for landscape architecture: A practical approach." (Brückner et al., 2019) and "Excavation Safety Modeling Approach Using BIM and VPL." (Khan et al., 2019). Other articles were removed in this phase due to the irrelevance of the research theme, such as "As-built case studies for BIM as a conflict detection and documentation tool." (Abd & Khamees, 2017). Of the remaining records, 75 were eligible to proceed to the following screening phase, a full-text review.

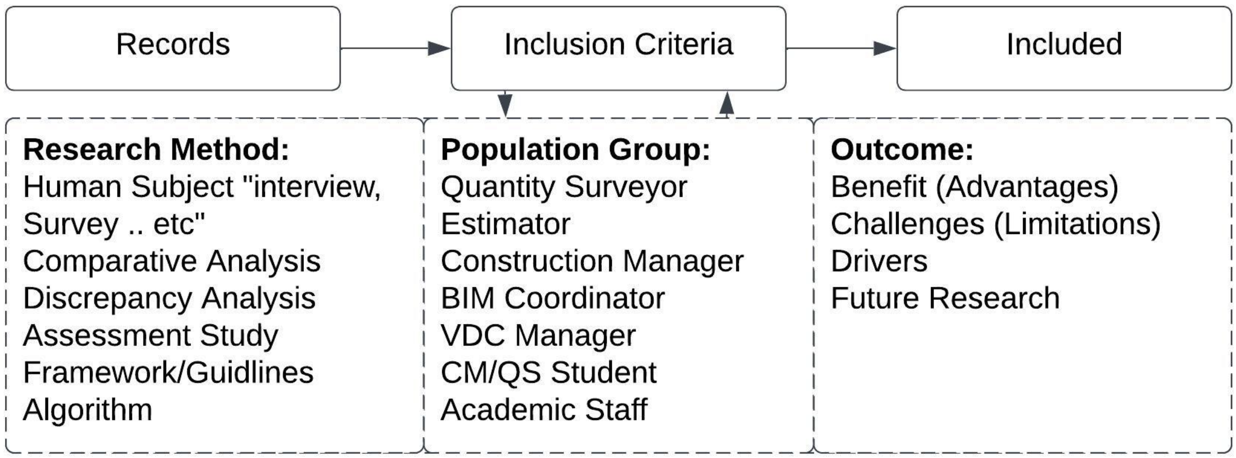

Figure 3.6. Inclusion Criteria for the Initial Screening (Title and Abstract)

3.2.3.2. Final Screening (Full Text Review)

The final screening was conducted on the remaining 75 articles. This screening process involves a comprehensive full-text review of each record. This step was crucial for conducting a detailed assessment of the relevant articles to determine which records fully meet the inclusion criteria. It was also vital for creating a data extraction plan. Furthermore, this phase was considered an essential step in defining the structure of the data categories by identifying the research theme for each record in the data extraction plan. A total of 23 articles were excluded due to their irrelevant focus in the study, such as “Bim Structural Project Applied in A Case Study: Interoperability Analyses, Reinforcement Detailing Drawings and Quantity Take-Off” (Sampaio & Gomes, 2021). The primary focus of this study is to analyze the degree of interoperability achieved throughout the development of the entire structural BIM process. However, no significant development or aspects were investigated regarding Bim-based QTO. Another example, “Scan-To-Bim Technique in Building Maintenance Projects: Practicing Quantity Take-Off” (Sing et al., 2022) was also excluded. The reason for exclusion was that the study's focus is more on the Scan-to-BIM process and object recognition than on material quantification using BIM. There were no significant developments in BIM-based QTO in this study. The following Figure 3.7 details the PRISMA flow diagram of this review.

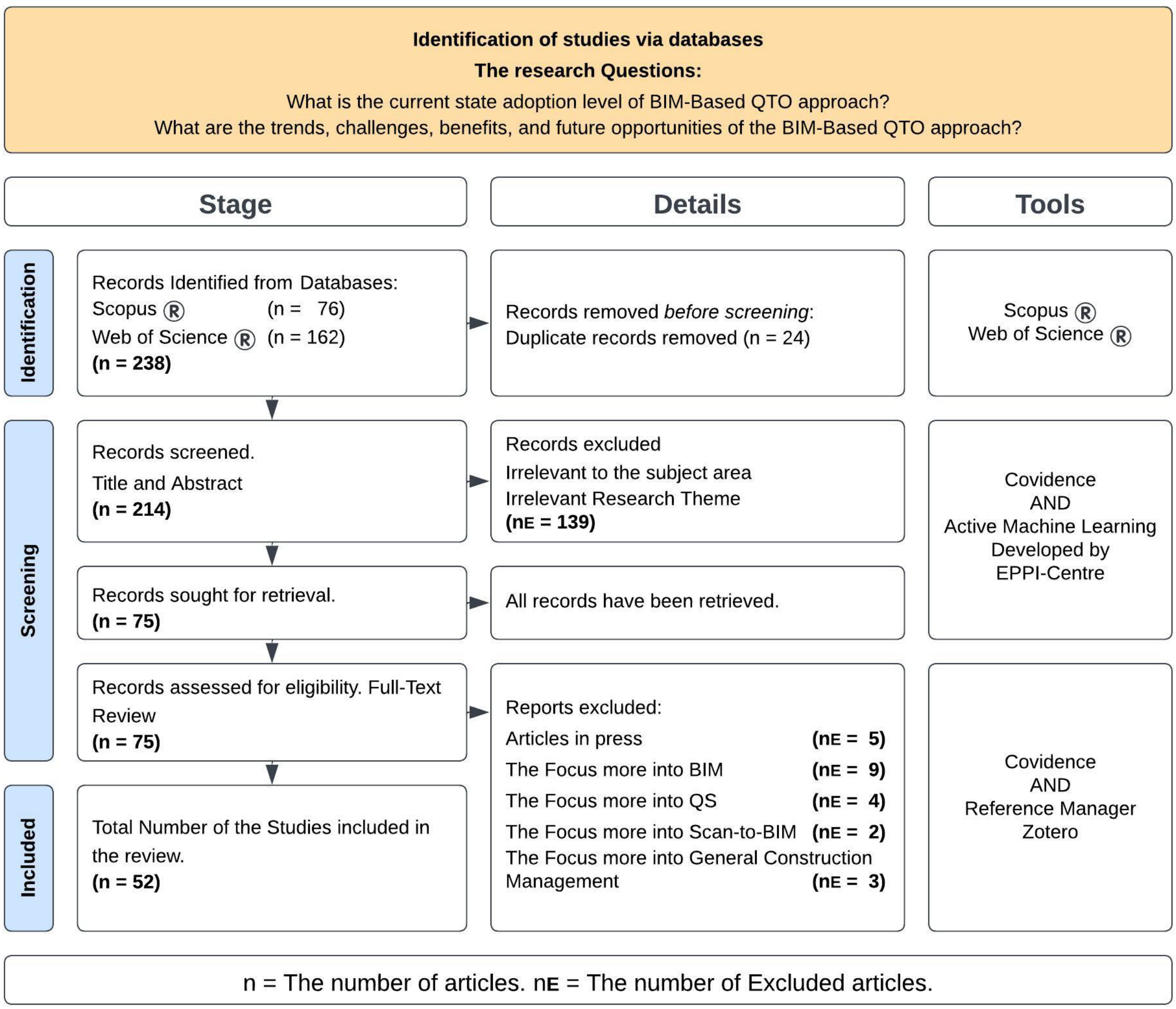

Figure 3.7. PRISMA Flow Diagram of the Systematic Review Process

3.2.4. Data Extraction

Data extraction was performed manually by the authors, using the reference manager software Zotero® and Microsoft Excel® for data storage. The information was primarily extracted from the abstract, keywords, methodology, results, and conclusions sections of each study, excluding the introduction and literature review sections, which typically reference studies beyond the scope of this review. This step also contributes to the bias management plan. The following (Table 3.1) provides the essential data extracted from the included studies, sorted by year of publication, to carry out the meta-analysis using the summary of findings table (Higgins & Green, 2008). Acronyms were included for a proper data presentation, and a legend below each table or figure will be provided, indicating the acronyms and their corresponding words.

Table 3.1. Summary of Findings from the Literature

No.	Citation	Author	Year	CN	Method	Population Group	Trends	Benefits Coded	Challenges Coded
1	(Jadid & Idrees, 2007)	Jadid et al.	2007	SA	CS	0	ALM	B01	0
2	(Matipa et al., 2008)	Matipa et al.	2008	NG	CS; SQ	23 QSs	LCC; UPS; RAR; CAP	B10; B03	C23; C14; C01
3	(Cho et al., 2011)	Cho et al.	2011	KR	AR; CS	0	SMM; CLS	B11; B01	0
4	(Monteiro & Martins, 2013)	Monteiro et al.	2013	PT	AS	0	MDM	0	C07; C02; C25; C04
5	(S. Wu et al., 2014)	Wu et al.	2014	UK	AR	4 QTO software	NRM; COD	B04; B14; B02; B06	C07; C04; C02; C08
6	(S.-K. Lee et al., 2014)	Lee et al.	2014	KR	CS	0	SRR	B25	C23
7	(Aibinu & Venkatesh, 2014)	Aibinu et al.	2014	AU	SQ; I	SQ: 40 Experts, I 2 Experts	LMT; CAP	B11; B10; B03	C19; C01; C10; C13; C15; C06; C24; C02; C07; C03
8	(Wong et al., 2015)	Wong et al.	2015	MY	SQ; I	15 professionals	CAP; IMP	B11; B14; B03; B16; B30	C12; C10
9	(Harrison & Thurnell, 2015)	Harrison et al.	2015	NG	I	5 QSs	IMP	B04; B08; B02; B03; B01; B07	C27; C02; C11 ; C14; C04; C18; C26; C05; C03; C28; C01
10	(Taihairan & Ismail, 2015)	Taihairan et al.	2015	MY	SQ; I	25 QSs and a government agency	IMP; CAP	B03; B13; B18; B05; B17; B08	C19; C16; C09; C15; C05
11	(S. Lee et al., 2015)	Lee et al.	2015	KR	CS	0	SRR	B02; B06; B05	C17; C08
12	(Choi et al., 2015)	Choi et al.	2015	KR	AS	0	LOD; EVM	B15; B03; B13	0
13	(Whang & Min, 2016)	Whang et al.	2016	UK	CS	0	IMP	B01; B03; B04; B05; B13	C03

No.	Citation	Author	Year	CN	Method	Population Group	Trends	Benefits Coded	Challenges Coded
14	(K. N. Ali et al., 2016)	Ali et al.	2016	MY	I; FG	I: 15 QSs, FG: 30 Experts	EDU; SMM	B01; B21	C01; C05; C21
15	(Kehily & Underwood, 2017)	Kehily et al.	2017	IE	AR	16 Experts	LCC	B09 ; B04; B12	C22; C09; C02; C01; C13
16	(Alrashed & Kantamaneni, 2018)	Alrashed et al.	2018	SA	SQ	365 Respondent	OCC	B20; B31; B16	0
17	(Babatunde et al., 2018)	Babatunde et al.	2018	NG	SQ	Academic staff: 27, Students:73	EDU; BEN	B02; B06; B12; B32; B01; B08; B11	C13; C12
18	(C. Wang et al., 2018)	Wang et al.	2018	CN	I	200 Professionals & QS students	EDU; VR	B07; B14; B01; B33	C10
19	(Mayouf et al., 2019)	Mayouf et al.	2019	UK	I	20 from academic and industry	LMT; IMP	B02; B03; B10	C19; C07; C04; C09; C08; C02; C18; C20; C08; C16
20	(B. Yang et al., 2019)	Yang et al.	2019	CN	AR	0	ALM; COD	B02	C07; C02; C17
21	(Kim et al., 2019)	Kim et al.	2019	KR	AR; AS;	0	QDC; IMO; CMO	B02	C08; C04; C17
22	(Babatunde & Ekundayo, 2019)	Babatunde et al.	2019	KR	SQ	10 students + 10academic staff	EDU	0	C15; C29; C11; C05; C01; C02; C16; C03; C04
23	(Santos et al., 2019)	Santos et al.	2019	BE	CS	0	LCA; LCC; IDM; MVD	0	C27
24	(Yii et al., 2019)	Yii et al.	2019	MY	SQ	292 QSs	IMP	B23; B07	0
25	(Narlawar et al., 2019)	Narlawar et al.	2019	IN	CS	0	TRM	B01; B13; B04; B02	0
26	(D'Amico et al., 2020)	D'amico et al.	2020	IT	AR	0	IMP	B01; B28; B24; B04; B11	0
27	(Abuaddous et al., 2020)	Abuaddous et al.	2020	JO	SQ	35 Respondent	VOD; RSK	B03; B13; B08; B09; B12	C11
28	(Babatunde et al., 2020)	Babatunde et al.	2020	NG	SQ	67 Professionals	LMT	0	C12
29	(Hollberg et al., 2020)	Hollberg et al.	2020	SE	CS	0	LCA	B10; B03; B17	C22
30	(Khamees et al., 2020)	Khamees et al.	2020	IQ	AR; CS	0	LCA	B02; B09; B05; B20; B16; B08; B01	C06
31	(Saka & Chan, 2020)	Saka et al.	2020	CN	DS	17 experts 9 countries	EDU; UPS	B02	C01; C05; C03
32	(Xin & Aziz, 2020)	Xin et al.	2020	MY	CS	5 Institutions	EDU	0	C01; C21
33	(Stride et al., 2020)	Stride et al.	2020	AU	I	8 Professionals	FMG; UPS; LCA	B09; B12	C24; C03; C01; C05
34	(Yousif et al., 2020)	Yousif et al.	2020	IQ	AR	0	Web	B07; B05; B06	C04; C22; C06; C02
35	(Ismail, Rooshdi, et al., 2021)	Ismail et al.	2021	MY	FG	11 Participants	RLY	B15; B29; B01; B07; B12	C01; C09; C06; C19
36	(Ismail, Yousof, et al., 2021)	Ismail et al.	2021	MY	SQ	150 QSs	RSK	B34; B26	C01; C13; C03; C02; C05; C15

No.	Citation	Author	Year	CN	Method	Population Group	Trends	Benefits Coded	Challenges Coded
37	(Hashim et al., 2021)	Hashim et al.	2021	MY	I	4 QSs	EDU; UPS; LOD	B07; B06; B18; B03	C01
38	(Okereke et al., 2021)	Okereke et al.	2021	NG	AR	0	RAR	B09; B17	C09; C04; C25; C01
39	(Olatunji et al., 2021)	Olatunji et al.	2021	AU	SQ	73 QSs	BEN; LMT	B06; B27; B08; B05; B14	C02; C14; C01
40	(Venter et al., 2021)	Venter et al.	2021	ZA	SQ	61 Professionals	LMT	B02	C02; C03; C16; C11; C13
41	(Azizi et al., 2021)	Azizi et al.	2021	MY	I	5 QSs	IMP; SMM	B06; B18; B04; B21; B24; B19	C12; C06
42	(Baldrich Aragó et al., 2021)	Arago et al.	2021	ES	CS	4CS	RAR; UPS	B01	C01; C05
43	(Ying & Kamal, 2021)	Ying et al.	2021	MY	I	20 QSs	RAR; UPS	B05; B19; B10	C20; C10; C02; C03
44	(Liu et al., 2022a)	Liu et al.	2022	SG	AR	0	SMM; COD; NRM;	B02; B16; B01; B05	C02; C08; C07; C17; C04
45	(Liu et al., 2022b)	Liu et al.	2022	SG	AR	0	DDD; UBD; QDC	0	C06; C02; C18; C26; C20
46	(Keung et al., 2022)	Keung et al.	2022	CN	SQ; I	15 QSs & Practitioners	LMT, Lean	B22; B23; B01; B02; B09	C12; C02; C01; C18; C07; C11; C03
47	(Sherafat et al., 2022)	Sherafat et al.	2022	US	AR; CS	0	RLY	0	C04; C14
48	(Zhan et al., 2022)	Zhan et al.	2022	MY	SQ	102 Experts	Lean	B22; B07; B15	C10; C15; C05; C01
49	(Keung et al., 2023)	Keung et al.	2023	CN	SQ; CS	60 Experts	EDU; UPS; CAP	0	C01; C21; C02
50	(Hosny et al., 2023)	Hosny et al.	2023	EG	SQ; CS	200 Experts	MTW	B20; B21; B19	C01
51	(Akanbi & Zhang, 2023)	Akanbi et al.	2023	US	CS	0	ALM	B10	C14
52	(Valinejadshoubi et al., 2024)	Valinejad-shoubi et al.	2024	CA	CS	0	IMP; ALM	B01; B06; B04; B15	C06

- **CN:** Country of the corresponding author. Country abbreviations based on the ISO3166 standard.
- **0:** No significant findings that meet the inclusion criteria.
- **Method:** FG: Focus Group. SQ: Survey Questionnaire. I: Interview. FW: Framework. CS: Case Study. MG: Modeling Guidelines. AS: Assessment study / Analytical study. AR: Action Research DS: Delphi study.
- **Trends:** EDU: Education. LCC: Life Cycle Costing. LCA: Life Cycle Assessment. CLC: Construction Life Cycle. UPS: Upskilling. RAR: Role and Responsibilities of the QS profession. RLY: 5D BIM Reliability. MTW: Material Waste. ALM: Algorithm. MDM: Modeling method. NRM: New Rules of Measurement. SRR: Semantic Reasoning Rules. IMP: 5D BIM implementation, stakeholders' relationship. CAP: Capability of BIM and Features and BIM Competencies. LOD: Level of Development. EVM: Earned Value Management. OCC: Overall Construction Cost. BEN: Benefits and Advantages. LMT: Limitations, Barriers, and Challenges. VR: Virtual Reality. SMM: Standard Measurement of Method. CLS: Model Classification. COD: Building Codes, Regulations. QDC: Quantity Discrepancy. IMO: Individually Modeled Object. CMO: Compositely Modeled Object. TRM: Time and Resource Management. VOD: Variation Orders. FMG: Facilities Management. RSK: Risk Management. DEX: Data Exchange. DDD: Data-Driven Decision. UBD: Unstructured BIM Data. PRP: Progress Payments. IDM: Information Delivery Manual. MVD: Model View Definition. WEB: Web-Based Platforms.
- **Population Group:** QSs: Quantity Surveyors. Experts: Construction Industry Experts and Professionals, including Estimators, Quantity Surveyors, Project Managers, etc. Academics: Professors and lecturers in construction management or quantity surveying programs. Students: Students from only construction management or quantity surveying programs. Respondents have not been specified in the article.

3.2.5. Bibliometric Analysis

A bibliometric analysis was conducted to gain a comprehensive understanding and examine the characteristics of the contributing studies. The analysis used the Biblioshiny® package in RStudio® to process the data for calculations and to generate some of the presented visuals using different clustering algorithms, including Walktrap and Louvain (Aria & Cuccurullo, 2017). The data, imported directly in RIS format from the databases, was then merged into a single CSV file and modified to exclude irrelevant records. The bibliometric analysis aimed to identify author keyword co-occurrence, temporal analysis, and regional analysis, and determine the sources of publications. In the subsequent systematic analysis, the Biblioshiny® package was used to analyze the extracted data, focusing on the co-occurrence of methods, trends, benefits, and challenges. The subsequent section will delve into the results and analysis approaches of the included records, conducted in alignment with each objective of this review. Each detailed analysis method will be presented in its subsection, followed directly by the corresponding results.

3.3. Results

3.3.1. Characteristics of Contributing Studies

Bibliometric analysis was used to provide quantitative and visual analyses of the characteristics of the contributing studies, including the categorization of research findings and methodologies. The research trends were identified through the research themes of each study, alongside the BIM-based QTO, and what makes each study unique and valuable to the body of knowledge. Additionally, this analysis will synthesize the included studies, providing a temporal and geographical analysis of the research that contributed to them.

3.3.1.1. Content Analysis

All 52 journal articles included in this review underwent methodological analysis. Figure 3.8 illustrates the distribution of the included studies by research method, noting that several studies employed a combination of quantitative, qualitative, and mixed methods to comprehensively validate their findings. The following methods were adopted from the “Research Methods for Construction” by Richard Fellows and Anita Liu, which was published in 2021 (Fellows & Liu, 2021). They include seven distinct methodologies comprising survey questionnaires, interviews, focus groups, case studies, action research, assessment studies, and Delphi studies.

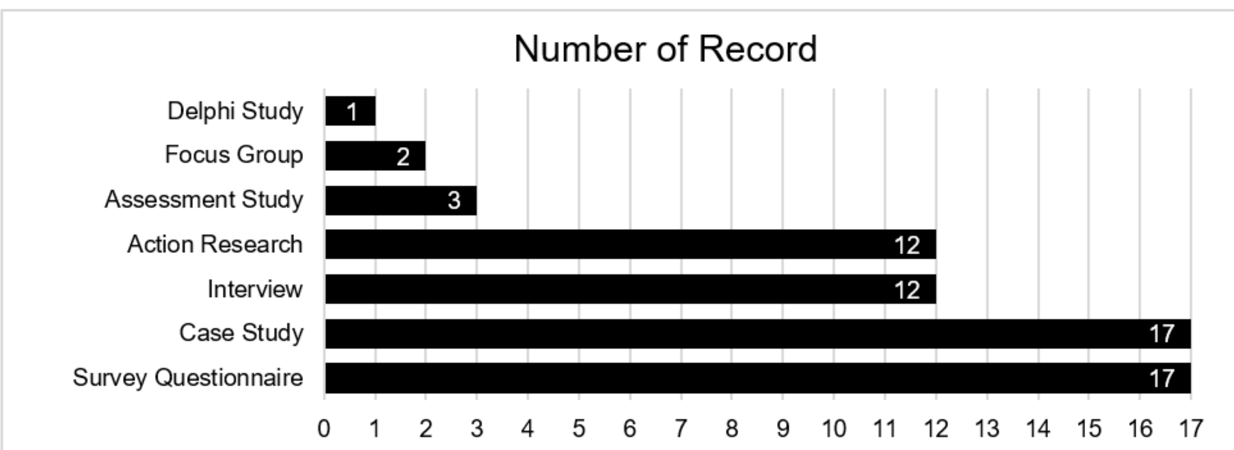

Figure 3.8. Frequently Used Methodologies on BIM-Based QTO Study Field

Questionnaire surveys and case study methods were the most frequently utilized methods in the research field of BIM-based QTO, with 17 occurrences each. Case studies served as illustrative studies for the application of new technology in the construction industry. Interviews and Action research were the second most frequent methods, with 12 records each. Action research studies primarily focus on active researcher participation in the research process, such as developing an implementation framework or algorithm and testing it through a case study and actual project data. This field of study has a strong connection to human-subject research, including survey questionnaires and interviews with professionals, experts, and faculty members.

3.3.1.2. Synthesis of Key Findings

All 52 eligible studies have addressed the Bim-based QTO alongside a specific subject area. Trends were identified based on the research subject area theme. The research trends of each study were identified based on the study's population and the major categories of challenges and benefits. These diverse trends enabled the study to provide a more comprehensive overview, relevant perspectives, and research interests, including 5D BIM implementation, education, upskilling, limitations, barriers, and challenges, which appeared to be the main trends in this field of study based on co-occurrence rank. Several trends were also addressed regarding BIM's capabilities, including its features, competencies, and life-cycle assessment (LCA). Figure 3.9, presented as a word cloud, shows the most frequent trends, illustrated alongside the BIM-based QTO. The larger the word, the more frequently the trend appears in the included studies.

Figure 3.9. Trend Frequency Word Cloud

3.3.1.3. Temporal Analysis

A temporal analysis was conducted to understand the evolution of trends within the body of knowledge. This analysis examined the year of publication alongside the concurrent trends present in the included studies. Figure 3.10 illustrates the six most prominent trends that are progressively aligning with industry needs. There is a notable surge in research related to 5D BIM implementation and stakeholder relationships, driven by the requirements of new technologies that demand a well-defined implementation approach. Furthermore, the educational aspect of research is on the rise in response to industry demand for BIM-competent graduates to address the shortage of trained professionals (K. N. Ali et al., 2016; Saka & Chan, 2020). The focus on professional training and upskilling for seasoned professionals, as well as on identifying limitations and barriers, would take a secondary position to the growth of research production over time. Upskilling is becoming increasingly critical for the industry and is recognized as a major barrier to the widespread adoption of the BIM-based approach (Babatunde & Ekundayo, 2019; Baldrich Aragó et al., 2021).

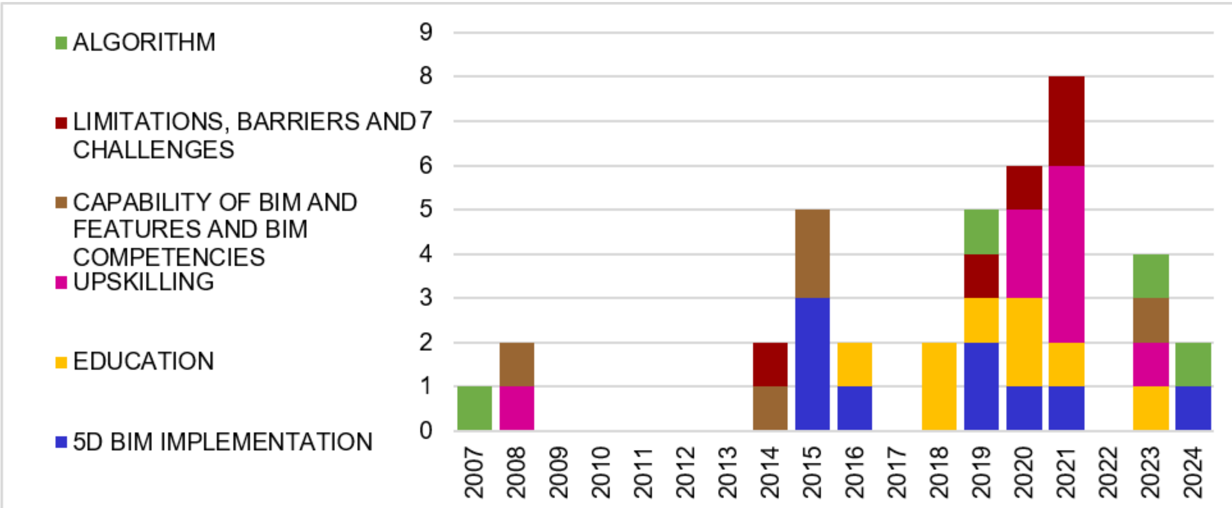

Figure 3.10. Trend Frequency over Time

3.3.1.4. Keywords Co-occurrence Network

Based on the search settings and inclusion criteria, it is anticipated that "Building Information Modeling" or "BIM" will be the most frequently used keyword by the authors in their publications. Figure 3.11 shows the co-occurrence network of the authors' keywords, generated using the Walktrap clustering algorithm from the Biblioshiny package in R Studio (Aria & Cuccurullo, 2017). There are strong connections between BIM, the QTO, and cost estimation keywords, reflecting the research focus of the included records. The results also indicate that the Industry Foundation Classes (IFC) have a weak connection with the other keywords. This raises concerns about the reliability of the IFC format for handling building materials and quantitative information in data transmission between various software applications. Additionally, it is pertinent to consider its impact on BIM interoperability across different software options.

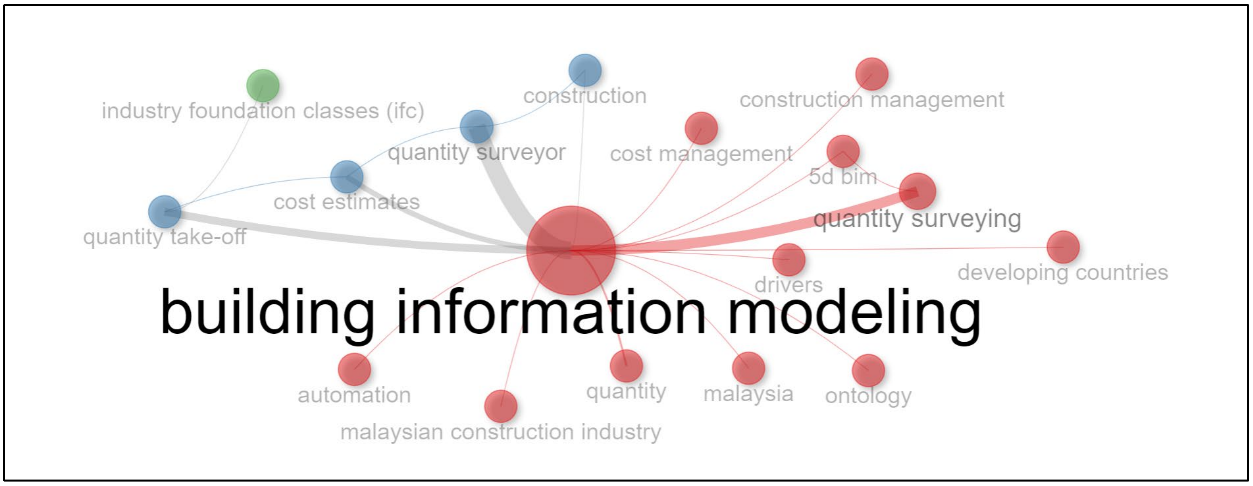

Figure 3.11. Authors' Keywords Co-occurrence Network

3.3.1.5. Geographical Distribution and Comparative Regional Analysis

The included studies were categorized by the country of the corresponding author (Figure 3.12). A total of 11 articles were published in Malaysia. South Korea, Nigeria, and China rank second in terms of publication numbers: six, five, and five, respectively. These numbers suggest that research progress in the field of BIM-based QTO in these countries is more advanced and is increasingly accepted among professionals and firms adopting the BIM-based QTO approach. It's worth noting that some of the studies from these countries started to explore the integration of sustainability and lean principles into the fifth dimension of BIM, which refers to cost (Ismail, Rooshdi, et al., 2021; Zhan et al., 2022). The objective of this review is to examine the global perspective on this field and facilitate the exchange of experiences to effectively address its challenges and benefits. The technological nature of this topic allows more flexibility in exploring international experiences. The international co-authorship rate in the included studies is 30.61%.

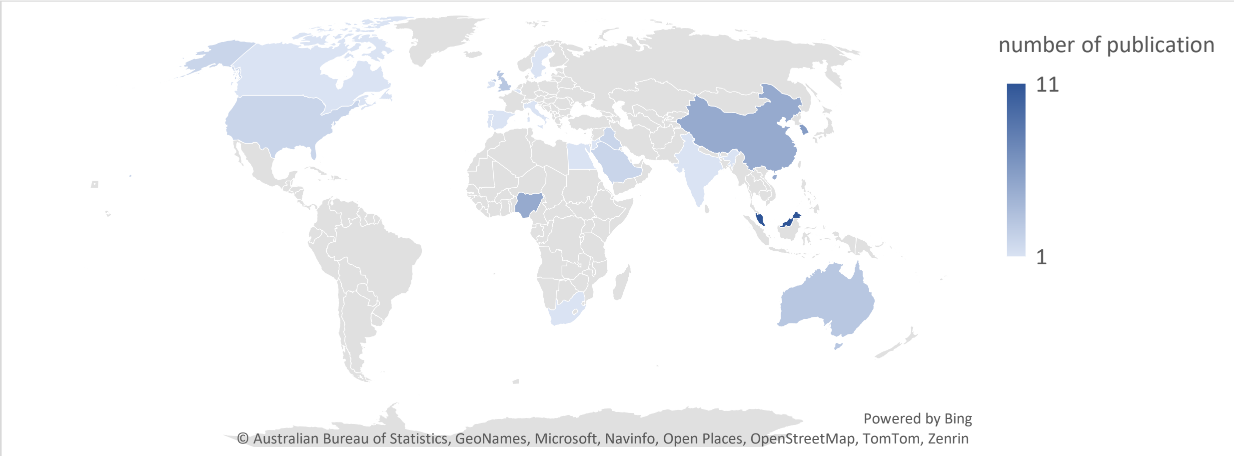

Figure 3.12. Global Map of the Corresponding Author's Country

3.3.1.6. The Source of Publications

Table 3.2 shows that the most frequent source on this topic is “Automation in Construction®”, which also has the highest local impact (H-index = 6) and contributes 13.4% to this field of study, with a total of 7 articles. The earliest publication was in this journal in 2007, and production started increasing by 2019. The second most frequent source of contributing journals is “Journal of Information Technology in Construction®,” with 5 articles and local impact on this topic (H-index = 3). Both sources' production on this topic over time has increased, reflecting the industry's growing demand for a successful transition. Several articles addressed that one of the BIM-based adoption challenges is the limited studies in this field, with corresponding recommendations of conducting more studies on this issue (Azizi et al., 2021; Babatunde et al., 2018, 2020; Keung et al., 2022; Wong et al., 2015).

Table 3.2. Sources' Production over Time

Journal / Year	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024	Total
Automation in Construction	1						1	1					1	1		1		1	7
Construction Innovation		1																	1
Journal of Asian Architecture and Building Engineering					1														1
Journal of Professional Issues in Engineering Education and Practice								1											1
Journal of Information Technology in Construction								1		1	1					1	1		5
Informes De La Construccion									1										1
International Journal of Sustainable Construction Engineering and Technology									1						3				4
International Journal of Construction Supply Chain Management									1										1
Journal of Computational Design and Engineering									1										1
Korean Society Journal of Civil Engineering									1										1
International Journal of Applied Engineering Research										1									1
Journal of Engineering, Design and Technology												1	2	1					4
Infrastructures Journal												1		1					2
Computer Applications in Engineering Education												1							1
Malaysian Construction Research Journal													1	1	1				3
International Journal of Innovative Technology and Exploring Engineering													1						1
Journal of Management in Engineering													1						1
Structural Engineering International													1						1
Architectural Engineering and Design Management														1					1
Civil Engineering Journal (Iran)														1					1
Engineering, Construction, and Architectural Management														1					1
European Transport - Trasporti Europei														1					1
Periodicals Of Engineering and Natural Sciences														1					1
Built Environment Project and Asset Management															1				1
Engineering Journal															1				1
Engineering Management in Production and Services															1				1
Journal of Building Engineering															1				1
Journal of Engineering and Technology for Industrial Applications															1				1
Advanced Engineering Informatics																1			1
Iranian Journal of Science and Technology - Transactions of Civil Engineering																1			1

Journal / Year	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024	Total
Scientia Iranica																❶			1
Journal of Architectural Engineering																	❶		1
International Journal of Construction Education and Research																	❶		1

3.3.1.7. Software utilization

Many software options for BIM, material quantification, and cost estimation have been offered by various companies. Based on the studies included, Figure 3.13 shows a word cloud of the most frequently mentioned software options. Autodesk products appear to be the leader in software capabilities and development for this topic, with a total of 10 products mentioned in the records. The most widely used software is Autodesk Revit, noted in 18 records, accounting for 15% of all other software options in the studies. The second-place position was shared by CostX and ArchiCAD. It's worth noting that some of these programs specialize in cost estimating, while others focus on BIM modeling, BIM model validation, and visualization.

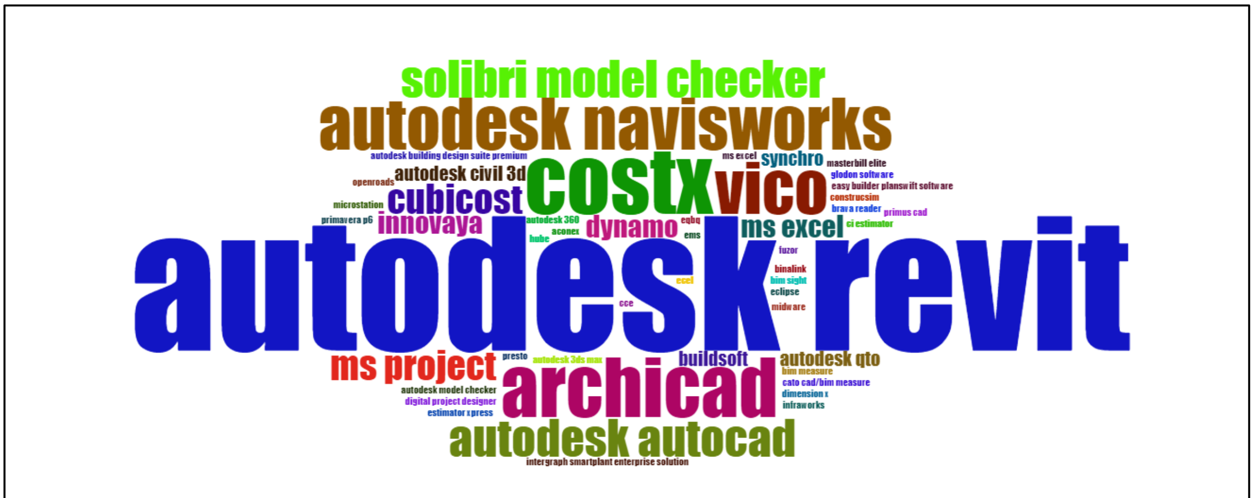

Figure 3.13. Software Options Frequency Word Cloud

3.3.2. Results of Statistical Synthesis of the Benefits and Challenges

The second objective of this review is to identify the benefits and challenges of BIM in the context of QTO tasks. Specifically, the third inclusion criterion requires that each article include at least one benefit or challenge, allowing for ranking each based on its frequency in the records. Additionally, it will clarify any inconsistencies across the individual studies, given the diverse nature of the studies and the varying population group backgrounds and countries.

The 52 studies included in this analysis underwent three rounds of coding to quantify each study's results. In the first round, relevant data regarding the benefits and challenges of the BIM-based QTO were extracted. To identify these benefits and challenges in each study's full text (excluding the introduction and literature review sections), a set of keywords—Benefits, Advantages, Features, Drivers, Challenges, Limitations, Barriers—was employed. These keywords were chosen to minimize bias risk and facilitate data extraction by highlighting them as the text is examined. In the second round, qualitative coding was performed to establish categories based on data interpretation (Fellows & Liu, 2021). This step was crucial for standardizing the extracted data across the studies, given that each used its own terminology. The categories were sorted as follows: cost, time, accuracy, management, skills, and software.

Each category corresponds to its own subcategories in a general way. For instance, the cost category is associated with the cost of technology implementation, return on investment, and project budget. The time category is related to the productivity of the material quantification process, change orders, early design estimates, and project schedules. The accuracy category discusses the margin of error, data reliability, and assumptions. The skills category concerns the professionals' data manipulation skills in the context of BIM for material quantification. The software category is related to data security, LOD, data complexity, and software capabilities. Lastly, the management category includes communications, collaborations, legal directions, regulations, cultures, conflicts, and multidisciplinary integrations. The third round involved matching the standardized categories and subcategories with the extracted data from the records. The subsequent sections delve into detailed analysis results, organized by benefits and challenges, and further categorized by specific categories.

3.3.2.1. BIM-Based QTO Benefits

Based on the coding and analysis of the included records, four categories of benefits were identified, each referring to a specific area of impact on the QTO process. Then, these categories were sorted by frequency of appearance in the records as follows: Management-related benefits, time-related benefits, accuracy-related benefits, and cost-related benefits. Figure 3.14 shows the frequency of each benefit over time, color-coded by category and sorted from highest to lowest.

CODE	BENEFITS / YEAR	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024	TOTALS
B01	Enhance the accuracy and completeness	1				1				1	2		2	1	2	2	2		1	15
B02	Productivity improvements								1	2			1	4	2	1	2			13
B03	Speed up the early estimates		1						1	4	1			1	2	1				11
B04	Ability to update simultaneously with design changes								1	1	1	1		1	1	1			1	8
B05	Reduce the manual errors									2	1				2	2	1			8
B06	Speed up overall estimating process								1	1			1		1	3			1	8
B07	Improve the readability of the project information									1			1	1	1	2	1			7
B08	Improve communication and collaboration									2			1		2	1				6
B09	Potential integration with the project LCC											1			3	1	1			6
B10	Reduce the intensive labor for QTO		1						1					1	1	1		1		6
B11	Easily provide alternatives					1			1	1			1		1					5
B12	Improve database management											1	1		2	1				5
B13	Improve risk management									2	1			1	1					5
B14	Improve the quality of decision making								1	1			1			1				4
B15	Improve the reliability of the cost estimates									1						1	1		1	4
B16	Reduce the construction time									1			1		1		1			4
B17	Enhance the future project estimates									1					1	1				3
B18	Facilitate the construction assemblies identification									1						2				3
B19	Reduce remeasurement process															2		1		3
B20	Reduce the construction cost												1		1			1		3
B21	Reduce the variability in cost estimates										1					1		1		3
B22	Ability to promote lean management																2			2
B23	Improve constructability analysis													1			1			2
B24	Improve resource utilization identification														1	1				2
B25	Ability to recognize work conditions automatically								1											1
B26	Conflict detection															1				1
B27	Facilitate multidisciplinary integration															1				1
B28	Improve cost and scope management														1					1
B29	Improve the sustainability of the cost estimates															1				1
B30	Minimize cost overruns									1										1
B31	Reduce material waste												1							1
B32	Reduce the loss of information												1							1
B33	Reduce the number of assumptions in QTO												1							1
B34	Reduce the pre-construction cost															1				1
BB1	**Management**					1			4	10	2	3	5	4	13	14	5		1	62
BB2	**Time**		1						3	8	1		3	5	6	5	3		1	36
BB3	**Accuracy**	1				1				4	4		4	1	4	8	4	2	2	35
BB4	**Cost**		1						1	1			2	1	3	2		2		13

Figure 3.14 BIM-Based QTO Benefits Frequency

The top five subcategories of benefits that frequently appeared in the records are enhanced accuracy and completeness, productivity improvements, faster early estimates, and the ability to update simultaneously with design changes. These benefits have a significant impact, with a 33% frequency among all the 34 identified benefits. The quantitative results indicate a consensus among the included studies that the utilization of BIM-Based QTO enhances the accuracy and completeness of estimates, with a 10% frequency ranking as the highest among all other benefits. Additionally, productivity improvement ranked second highest, with a frequency of 9%. The productivity gains from leveraging BIM-based QTO might be a contributing factor to the declining demand for the cost estimator profession (*Cost Estimators*, 2023).

3.3.2.2. BIM-Based QTO Challenges

Regarding challenges, four categories were identified based on the specific area of impact of BIM-based QTO adoption. These categories have been sorted by frequency of appearance in the records as follows: skills-related challenges, management-related challenges, software-related challenges, and cost-related challenges. The top five subcategories of challenges that frequently appeared on the records, with a frequency of nine or more, are limited BIM skills for estimators/quantity surveyors, lack of standard modeling techniques/approach, cultural challenges, professionals' resistance, risk of losing data through data exchange to different formats, and the cost of upskilling and training. These challenges have a significant impact, with a 41% frequency among all the 29 identified challenges. Figure 3.15 shows the frequency of each challenge over time, color-coded by category and sorted from most to least frequent.

The results indicate significant agreement on the lack of skills-related challenges, which is the highest frequency among all other categories at 32%. Furthermore, the most frequent subcategories are limited BIM skills for estimators/quantity surveyors and the lack of standard modeling techniques/approaches, with 19 and 17 records addressing these challenges, respectively. These two challenges have a significant impact, comparable to the mean frequency of all challenges (5.4), and a median of 5.

CODE	CHALLENGES / YEAR	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024	TOTALS
C01	Limited BIM skills for estimators/quantity surveyors		1						1	1	1	1		1	3	6	2	2		19
C02	Lack of standard modeling techniques/approach							1	2	1		1		3	1	4	3	1		17
C03	Cultural challenges and professionals' resistance								1	1	1			1	2	3	1			10
C04	Risk of losing data through data exchange to different formats							1	1	1				3	1	1	2			10
C05	The cost of upskilling and trainings									2	1			1	2	2	1			9
C06	Human errors								1						2	2	1		1	7
C07	Weak connection between SMM with BIM parameters							1	2					2			2			7
C08	Obstacles related to LOD								1	1				2			1			5
C09	Complex information and overloaded data									1		1		1		2				5
C10	Lack of awareness of BIM's capabilities								1	1			1			1	1			5
C11	Lack of legal directions and regulations									1				1	1	1	1			5
C12	Limited BIM-based QTO/QS research									1			1		1	1	1			5
C13	Low client's demands on using BIM for QTO								1			1	1			2				5
C14	Low interoperability between BIM model and estimation software		1							1						1	1	1		5
C15	The cost of the new technology and infrastructure								1	1				1		1	1			5
C16	Collaboration difficulties									1				2		1				4
C17	Difficult to combined miscellaneous work into BIM model									1				2			1			4
C18	Lack of a standard method for validating BIM model									1				1			2			4
C19	Relying on the designer BIM skills and competencies								1	1				1		1				4
C20	Advanced BIM related it skills													1		1	1			3
C21	Advanced topics typically are not covered in BIM education										1				1			1		3
C22	Lack of historical database											1			2					3
C23	Bim capabilities are limited		1						1											2
C24	Concerns about the integrity of the BIM 3d model								1						1					2
C25	Conflicts with other BIM features							1								1				2
C26	Inconsistent installation sequences									1							1			2
C27	Limited objects library and objects information declaration									1				1						2
C28	Increased client costs									1										1
C29	Poor internet connection													1						1
CC1	**Management**							2	5	5	1	1	1	9	5	10	8	1		48
CC2	**Skills**		1						4	5	3	1	1	4	8	13	6	3	1	50
CC3	**Software**		2					2	4	8		2		11	4	5	8	1		47
CC4	**Cost**								2	2		1	1	2		3	1			12

Figure 3.15 BIM-Based QTO Challenges Frequency

3.3.2.3. Results of Investigations into Heterogeneity

A comparative analysis of the benefits and challenges of leveraging the BIM-based QTO approach has been conducted. The first level of this analysis was based on the main categories. It has been found that two categories from the challenges and the corresponding categories from the benefits have potential inconsistencies. Table 3.3 shows the number of occurrences for each benefit and challenge in their respective categories.

Table 3.3. Temporal Analysis of Corresponding Challenges vs Benefits Categories

Category / Year	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**	**2021**	**2022**	**2023**	**2024**	**Total**
Cost Benefits		1						1	1			2	1	3	2		2		13
Cost Challenges								2	2		1	1	2		3	1			12
Management Benefits					1			4	10	2	3	5	4	13	14	5		1	62
Management Challenges							2	5	5	1	1	1	9	5	10	8	1		48

The first set includes the management-related categories (CC1 vs BB1). The data shows agreement across records that benefits are more prevalent than challenges in the cost-related categories. The challenges include several cost category items, such as the high cost of technology implementation (Babatunde & Ekundayo, 2019). Additionally, the cost of infrastructure that this technology needs could be a serious issue, especially for micro and small companies (Ismail, Yousof, et al., 2021; Sherafat et al., 2022). Furthermore, several studies have identified the low demand from clients to use the BIM approach for QTO tasks as a challenge, leading to slow adoption due to a lack of client financial support. They claim that there is a lack of knowledge among stakeholders, including clients, regarding how the completed BIM model could benefit them for facility management, Life Cycle Costing (LCC), and Life Cycle Assessments (LCA) (Kehily & Underwood, 2017; Venter et al., 2021).

The second set presents the management-related categories of the BIM-based QTO approach. The results show a significant development in this category, with high frequency agreement on both benefits and challenges, with a total of 62 and 48 co-occurrences in the included records, respectively, as shown in Figure 3.16, which shows that there are two waves of research production over time that have addressed these issues, around 2015 and 2021, respectively. The key benefit of this category is the ability of the BIM model to be updated simultaneously with design changes, reducing the time and resources needed to generate an estimate for any change order during the construction phase. Similarly, it applies to any design changes and addenda during the preconstruction phase. This capability enables the client to explore different design alternatives and their associated costs in a timely manner, with minimal effort (D'Amico et al., 2020; S. Wu et al., 2014). Additionally, these automated tasks that provide immediate feedback could significantly improve decision-making quality by avoiding wasted time and enabling design decisions based on early, updated estimates, also known as data-driven decision-making. (Nguyen et al., 2022; Okereke et al., 2021; S. Wu et al., 2014).

The second level of the comparative analysis was centered on the specific subcategories of challenges and their corresponding benefits, as illustrated in Figure 3.17. The initial set of challenges pertained to human errors, specifically those occurring between C06 and B05. BIM models, created by humans, are also susceptible to errors during data entry and geometry modeling (Liu et al., 2022b). These errors, if present, can have a serious impact on semantic information, thereby affecting the accuracy of automatic quantity schedules and leading to incorrect estimates. This raises concerns about the overall reliability and integrity of the BIM Model (Aibinu & Venkatesh, 2014;

Stride et al., 2020). Conversely, there is consensus on the potential to reduce human errors by leveraging the BIM-based QTO approach. Recent studies highlight improvements in the developed BIM tools for verifying the completeness and correctness of BIM models based on both geometric and semantic rules (Liu et al., 2022a). Visualizing building components in the BIM environment is also recognized as a means to enhance estimate accuracy (Olatunji et al., 2021).

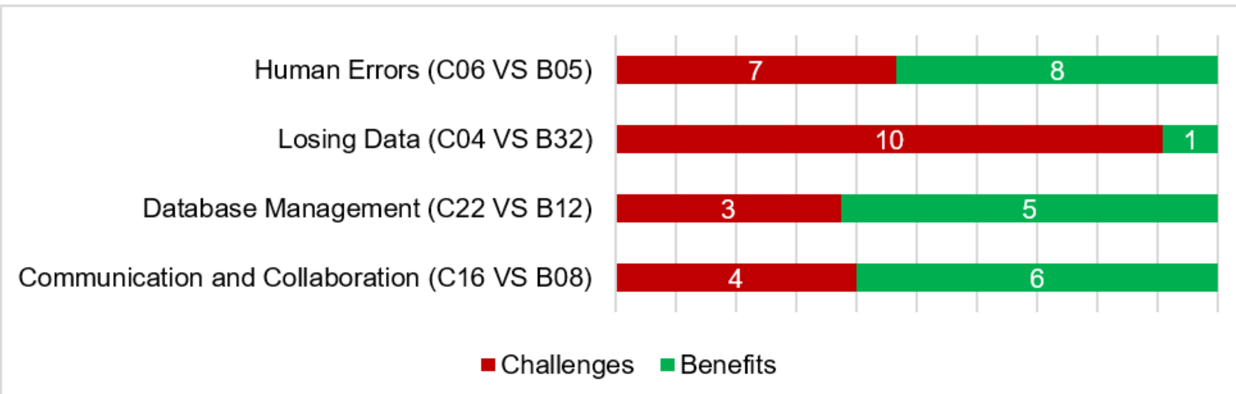

Figure 3.16. Comparative Directional Chart of Corresponding Challenges vs Benefits Subcategories

The results indicate that the risk of data loss could pose a critical challenge, preventing the industry's adoption. During certain phases, data may need to be transmitted and extracted into different formats, potentially leading to the loss of semantic data during the exchange formatting process. (Alrashed & Kantamaneni, 2018; Liu et al., 2022a). Additionally, various modeling methods and approaches may introduce the risk of unintended information errors. The International Foundation Class (IFC) format remains limited in its ability to incorporate the necessary information for the BIM-Based QTO approach. (Monteiro & Martins, 2013), raising concerns about the low interoperability between BIM models and estimation software (Babatunde et al., 2020; Harrison & Thurnell, 2015; Olatunji et al., 2021; Sherafat et al., 2022).

Database management elicits opposing opinions among researchers, depending on the context of its use. Most of the addressed challenges revolve around the lack of database history, which could prevent and complicate the utilization of BIM-based QTO in LCC and LCA applications. This is noteworthy, given the potential of these applications to not only enhance the effectiveness of 5D BIM during the preconstruction and construction phases but also to contribute significantly to post-construction utilization, particularly in facility management (Hollberg et al., 2020; Kehily & Underwood, 2017). Conversely, there are numerous benefits associated with improving databases through BIM. This improvement aims to reduce information loss by leveraging a reliable BIM database (Babatunde et al., 2018; Ismail, Rooshdi, et al., 2021). By employing a BIM-based QTO approach, the LCC database will correspondingly improve over time (Abuaddous et al., 2020). This enhancement also enables the storage of assets in digital formats with pertinent information, thereby serving as a significant factor in effective asset management.

The last set of inconsistency analysis focuses on the collaboration and communication aspects of using a BIM-based approach. The absence of collaboration among industry experts can pose challenges, as each firm develops its approach independently without standardized modeling techniques and a transparent information entry approach, resulting in incomplete experiences that may be suitable for one project but not for another (Babatunde & Ekundayo, 2019; Mayouf et al., 2019). Furthermore, due to the complexity of BIM software, inefficient exchange and sharing of information within the project team can create a poor communication environment (Taihairan & Ismail, 2015; Venter et al., 2021). On the positive side, this approach has the potential to enhance communication among the project team and designers by facilitating access to information for the entire project team (Babatunde et al., 2018; Harrison & Thurnell, 2015). This easy access to information can also keep other project stakeholders informed and aware of the project budget, thereby reducing information errors and providing early warnings for potential issues (Abuaddous et al., 2020; Taihairan & Ismail, 2015).

3.3.3. Gaps and Future Opportunities

This section is focused on addressing the third objective of this review, which aims to identify evidence-based research gaps related to the primary challenges, inconsistencies, and less frequently discussed benefits. Additionally, future recommendations and a research agenda proposal will be presented based on the records' suggestions.

3.3.3.1. Gap Analysis

This review has assessed the challenges and benefits of leveraging the BIM-Based QTO approach to identify gaps in research and development. These gaps were sorted into three categories based on the research focus area as follows: professional skills, software development, and the translation of standards and codes into BIM cost-related data.

Challenges associated with professional skills were identified as the foremost barrier to the widespread adoption of BIM in material quantification practices. Despite 19 included studies recognizing this challenge, none have specifically delved into formulating solutions or investing efforts to address this concern for experienced construction professionals, entry-level quantity surveyors, and estimators. Additionally, there is a lack of investigations aimed at upskilling seasoned employees to acquire the essential competencies required to align with the emerging BIM-based QTO approach currently available in the market.

The software development gaps can be classified into two closely interlinked categories: Application Programming Interface (API) development and Modeling and Data Entry Strategies. The first category includes gaps that are closely tied to the development of software tools, primarily aimed at software developers. This is intended to address the deficiency of user-friendly interfaces across various BIM software options, particularly in costing and material quantification tools. The second category of gaps targets CM experts with knowledge of QTO and estimating practices. Additionally, there are no significant developments in the modeling standards, frameworks, and rules to establish best practices. This gap aims to systematically standardize and streamline processes across projects, addressing the current lack of uniformity in the industry.

The translation procedure of standards and codes into BIM cost-related data represents a significant gap that researchers are working to address. While a few studies have addressed this topic and proposed NLP approaches and other frameworks to resolve the issue, these solutions are not yet mature enough for experimentation on real-world projects or practical implementation. It is recognized that the gap between NLP in computer science and its applications in construction is gradually narrowing over time (Chung et al., 2023). Therefore, initiating experimental research through case studies is essential to demonstrate the efficiency of their actual implementation.

3.3.3.2. Future Research Agenda Proposal

The adoption of the BIM-based QTO approach still faces numerous challenges and limitations in its implementation within quantity surveying firms and construction firms that perform in-house QTO. Adopting the BIM approach is crucial for the long-term survival of these firms (Wong et al., 2015). Four studies highlight the limited research on this topic as a significant challenge, emphasizing the need for further exploration through related searches (Azizi et al., 2021; Babatunde et al., 2018, 2020; Keung et al., 2022). The recommendations from the included studies have been analyzed and categorized by the area of interest within the research topic of BIM-based QTO. Table 3.4 identifies future research opportunities in BIM-based QTO research and development.

Table 3.4. Future Research Agenda Proposal

Citations	Years	Category – Subcategory
-	-	**Construction Management Related Research Opportunities**
(Aibinu & Venkatesh, 2014; Mayouf et al., 2019; Stride et al., 2020)	2014; 2019; 2020;	Enhancing collaboration between industry and academia stands as a beneficial strategy for advancing practical research based on real-world case studies, thus improving the efficacy and generalizability of research outcomes.
(Kim et al., 2019; Liu et al., 2022a)	2019; 2022;	Conducting experiments to identify the key advantages and obstacles related to material quantification within interior building components and the semantic information of unmodeled elements
(Kim et al., 2019)	2019	Establishing criteria for BIM validation, including the precision and completeness of material quantities.
(Babatunde et al., 2018; Stride et al., 2020)	2018; 2020;	Investigating the challenges and benefits of 5D BIM in various countries facilitates the dissemination of a broad spectrum of industry experiences.
(Liu et al., 2022b)	2022	Investigating the role of 5D BIM in Data-Driven Decisions (DDD)
(Choi et al., 2015)	2015	Expanding the scope of 5D BIM research to other building elements, such as the framing, steel, and concrete

Citations	Years	Category – Subcategory
-	-	**Collaboration and Communication-Related Research Opportunities**
(Ismail, Yousof, et al., 2021)	2021	Investigate the relationship between stakeholder awareness of 5D BIM capabilities and adoption levels.
(Keung et al., 2022)	2022	Engage subcontractors, manufacturers, and vendors in the investigation related to 5D BIM.
(Harrison & Thurnell, 2015)	2015	Identify development areas that could enhance 4D and 5D BIM, as well as overall interoperability and collaboration among project teams.
(Azizi et al., 2021)	2021	Investigate the impact of other construction industry roles on 5D BIM.
(Hashim et al., 2021)	2021	Further investigation of the reasons why contractors are not implementing BIM in their practices
(Keung et al., 2023)	2023	Address real-life construction problems and complex engineering topics in the context of 5D BIM.
(Sherafat et al., 2022)	2022	Study the impact of the BIM-based QTO approach on the construction workforce.
-	-	**Databases and Algorithm-Related Research Opportunities**
(Hollberg et al., 2020)	2020	Establishing LCA databases for long-term perspective applications
(Zhan et al., 2022)	2022	Integrating interactive lean tools into 5D BIM applications
(S. Lee et al., 2015; Monteiro & Martins, 2013)	2013; 2015;	Developing ontologies for all aspects of construction work
(Cho et al., 2011)	2011	Establishing an Online Analytical Processing (OLAP) system connected to 5D BIM data
(Liu et al., 2022a)	2022	Developing efficient algorithms that automate data extraction using NLP and Machine Learning to create a human-free knowledge model
-	-	**Standards, codes, and regulations: Related Research Opportunities**
(Nguyen et al., 2022)	2022	Developing standards for modeling techniques, approaches, and data entry methods
(B. Yang et al., 2019)	2019	Implementing effective methods to translate conventional rules into compliance for use in 5D BIM
-	-	**Academia, Upskilling, and Training Related Research Opportunities**
(Mayouf et al., 2019)	2019	Conduct more research to enhance the effective teaching of advanced BIM in higher education institutions and colleges, mainly focusing on QTO.
(Harrison & Thurnell, 2015; Saka & Chan,	2015; 2020;	Identify the essential BIM skills for future professionals to utilize 5D BIM effectively.

Citations	Years	Category – Subcategory
2020; Taihairan & Ismail, 2015)		
(K. N. Ali et al., 2016)	2016	Address curriculum development impact that aimed at integrating BIM into teaching practices for estimating and quantity surveying.
(Ying & Kamal, 2021)	2021	Investigate the impact of 5D BIM on the roles of estimators and quantity surveyors.
(C. Wang et al., 2018)	2018	Explore the use of Virtual Reality (VR) and Augmented Reality (AR) for facilitating simulation training and education, particularly in the context of estimating and quantity surveying.
-	-	**Software Developer's Future Opportunities**
(Liu et al., 2022b)	2022	Developing the software interface to enhance user-friendliness for QS professionals and estimators by incorporating specialized tools and components tailored for QTO.
(S. Wu et al., 2014)	2014	Developing streamlined data exchange formats capable of handling BIM Data to minimize data loss
(Nguyen et al., 2022)	2022	Developing an Object Information Declaration System and copyright considerations
(Kehily & Underwood, 2017)	2017	Enhancing IFC and COBie to ensure the capability of handling 5D BIM information
(Santos et al., 2019)	2019	Development of BIM tools related to LCA and LCC

3.4. Discussion

The implementation of the BIM-based QTO approach is still in its early stages (Ismail et al., 2021), and the industry faces numerous challenges and obstacles that are interconnected across various aspects in a consecutive hierarchy. The existing literature has contributed to the body of knowledge using diverse methodologies, with survey questionnaires and case studies being the most employed data collection techniques. These methods have effectively gathered expert feedback on technology development in the field of implementation, helping identify numerous benefits and challenges associated with BIM-based QTO. However, this section examines the results more closely, subjecting them to causal analyses that lead to the implementation model for BIM-based QTO.

The results shown in Figure 3.9 highlight the predominant trends identified in the related literature: Education, Upskilling, Limitations, Barriers, and Challenges. This suggests a strong relationship between the lack of BIM-based QTO implementation and these identified trends. Additionally, Figure 3.10 illustrates the temporal analysis of these trends, revealing a continuous increase over time, emphasizing the sustained demand for these topics. Among the various trends, upskilling and education emerge as the most prominent, with the highest cumulative occurrence. Even though 19 studies have recognized this challenge, none have focused specifically on formulating solutions or on investing effort to address the concerns of experienced construction professionals. This observation is closely linked to the primary and recurrent challenges hindering the industry's adoption and full implementation of BIM-based QTO. These challenges are attributed to professionals lacking the necessary skills and to high expectations for graduates' competencies (K. N. Ali et al., 2016; Hashim et al., 2021; Keung et al., 2023).

By focusing on the most prevalent benefits and challenges, it becomes evident that the researchers expressed interest in incorporating BIM into estimating and material quantification practices as early as 2007. They sought to explore the challenges and benefits associated with this innovative approach. The trend gained popularity in 2014, when the topic began to attract more attention among researchers, who began gathering insights from industry professionals about their experiences with BIM-based QTO in their work. Table 3.5 illustrates the evolving perspective, highlighting the top 5 benefits and the top 5 challenges from 2007 through the end of 2023.

Table 3.5. Top 5 benefits and challenges from 2007 through the end of 2023

Benefits / Challenges	**Year**	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024	**Total**
Enhance the accuracy and completeness.	B01	1				1				1	2		2	1	2	2	2		1	15
Productivity improvements.	B02								1	2			1	4	2	1	2			13
Speed up the early estimates.	B03		1						1	4	1			1	2	1				11
Ability to update simultaneously with design changes.	B04								1	1	1	1		1	1	1			1	8
Reduce the manual errors.	B05									2	1				2	2	1			8
Limited BIM skills for estimators/quantity surveyors.	C01		1						1	1	1	1		1	3	6	2	2		19
Lack of standard modeling techniques/approach.	C02							1	2	1		1		3	1	4	3	1		17
Cultural challenges and professionals' resistance.	C03								1	1	1			1	2	3	1			10
Risk of losing data through data exchange to different formats.	C04							1	1	1				3	1	1	2			10
The cost of upskilling and training.	C05									2	1			1	2	2	1			9

Initially, the focus was more on the benefits, but after 2019, with increased adoption by industry professionals, the challenges began to grow, mainly related to professionals' ability to keep pace with this revolutionary shift. Skill-related challenges were compounded by the absence of standardized modeling techniques and approaches, leading professionals to adopt a project-by-project method. As of the close of 2023, a significant shift was observed: attention to benefits decreased, and more challenges emerged in response to industry demands.

3.5. Implications of the Results for Practice

However, the targeted population for this topic, those who are directly engaging in these issues, comprises seasoned professionals in preconstruction management, primarily Estimators and Quantity Surveyors. (Stride et al., 2020). Additionally, CM and quantity surveying students from higher education institutions also play a significant role in this adoption (K. N. Ali et al., 2016; Mayouf et al., 2019). Each of these two population groups is involved in distinct experiences to maintain and enhance their skills. Based on the main findings of this meta-analysis of the existing literature, this research proposes a conceptual model for BIM-based QTO implementation (Figure 3.17) that integrates academia, industry, and professional training agencies to effectively manage their contributions and achieve a fully sustainable engagement.

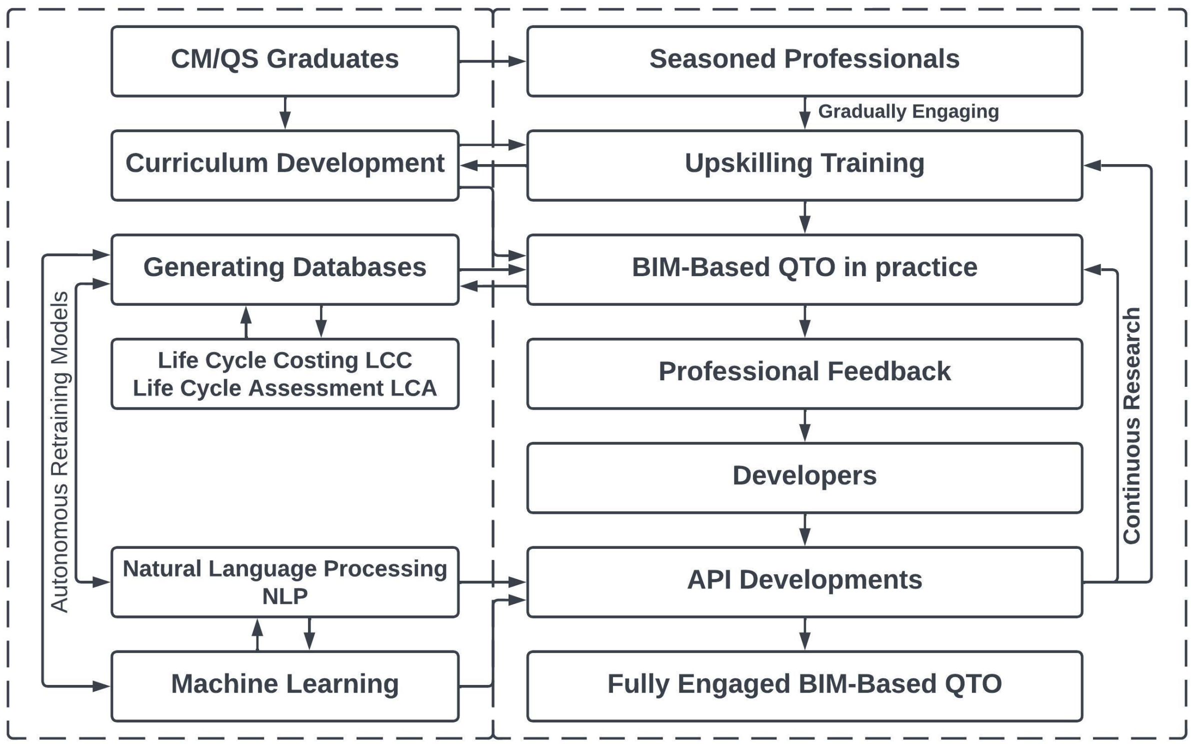

Figure 3.17. Conceptual Model for BIM-Based QTO Implementation

The model begins by targeting two specific population groups: Seasoned Professionals and CM/QS Students. It then establishes connections between these groups and their respective skill sets to gain a comprehensive understanding of material quantification using BIM. The process starts with Seasoned Professionals undergoing upskilling training, gradually immersing themselves in BIM practices. This gradual engagement is crucial for overcoming cultural resistance, a challenge identified in various studies (Babatunde & Ekundayo, 2019; Keung et al., 2022). On the other hand, CM/QS students enhance their BIM skills throughout their learning journey, following an updated curriculum aimed at adopting BIM for QTO. However, these curriculum developments may not be sufficient at the time to produce graduates with full BIM competencies for the industry. Consequently, entry-level employees, as is customary, may require additional advanced BIM training, which could be facilitated by seasoned professionals or training agencies.

Once the professional begins using the available tools on the market, more detailed feedback on the API can be collected through the research process, including publications on software development and improvement approaches based on the experiences of various experts. This step has the potential to contribute to solving issues related to software complexity and the lack of collaboration among industry experts (Babatunde & Ekundayo, 2019). The developments in these APIs would, in turn, be integrated into Upskilling training to further improve it. The fundamental concept of connecting professionals in a continuous loop of development alongside other experts, developers, researchers, and academia will gradually enhance the adoption of this approach (Mayouf et al., 2019). The goal is to establish a robust set of APIs and approaches, ultimately integrating 5D BIM seamlessly into the QTO and estimating processes.

Using BIM-based QTO, the opportunity to build a database would help avoid discarding data once the project is completed. Creating a historical database based on project specifications would enable the development of object family libraries that can be retained in-house for future use. These libraries can then be utilized to streamline the quantification process for future projects. The database's historical records can also contribute to LCC and LCA, providing reliable data for various stakeholders (Kehily &

Underwood, 2017; Santos et al., 2019; Stride et al., 2020). This information becomes valuable for applications such as facility management on the owner's side and sustainability considerations for the design and construction teams. This sustainable advancement loop remains live and is continually updated with each additional project, leading to outcomes that benefit all parties involved.

NLP would play a significant role in API development. NLP's contribution lies in facilitating the translation of project information into 5D BIM data, providing rich semantic information that can be utilized for material quantifications and other BIM features (Liu et al., 2022a). Additionally, it is closely linked to the Standard Method of Measurement (SMM) utilization in the context of BIM-based QTO (B. Yang et al., 2019). This facilitation involves a live link with machine learning models, referencing both pre-trained models and historical databases generated through the utilization of BIM-based QTO over time (Hollberg et al., 2020). The training model sequence can autonomously retrain itself, enhancing its contributions to API systems over time.

3.6. Conclusions

This paper explores the benefits, challenges, and future opportunities of the BIM-Based QTO approach through a bibliometric analysis of relevant publications. The study employed the PRISMA method to identify relevant literature, initially screening 238 journal articles and selecting 52 articles from Scopus® and Web of Science® databases based on inclusion criteria. The selected articles underwent a comprehensive review to formulate a conceptual implementation model for BIM-Based QTO. Using the Heterogeneity method to investigate the statistical synthesis of the included studies, the study identified critical gaps in skills-related aspects, software functionality, data entry strategies, and translation procedures for standards and codes.

The primary findings suggest that current trends in BIM-based QTO implementation techniques and professional upskilling are widespread. The most significant challenge in adopting this approach is the limited professional skills in BIM. Furthermore, the BIM-based QTO approach has been shown to improve the productivity, accuracy, and completeness of cost-estimating tasks. BIM databases can potentially benefit 5D BIM practices, API developments, LCC, and LCA. NLP is closely associated with the 5D BIM revolution.

Future research opportunities have been identified to address research gaps across several areas of interest associated with the BIM-based QTO approach. These areas include construction management, collaboration and communication, software development, databases, algorithms, academic research opportunities, and upskilling training for seasoned professionals. Subsequently, a conceptual model for BIM-based QTO implementation has been developed, aligning with the proposed future research objectives, and is intended to combine the contributions of existing literature into a unified framework. The aim of this model is to achieve comprehensive, sustainable integration with the BIM-based QTO approach.

Although numerous review articles have been published about BIM, they vary in their focus. Some examine the level of agreement across the different dimensions of BIM in the existing literature, including the fifth dimension, which is related to cost (Charef et al., 2018). The agreement level drops in higher dimensions, suggesting limited BIM implementation in specific fields. Other reviews highlight the application of IoT in conjunction with BIM (Tang et al., 2019) or the use of digital twin technology (Bortolini et al., 2022). The concept of digital twins is widely used in facility management and maintenance applications. In this context, the quantity of materials plays a crucial role, especially in maintenance and life-cycle assessments. Additionally, some reviews examine the level of BIM adoption within the industry (Tanko et al., 2022). They highlight various aspects of BIM applications, including BIM-based QTO, which has significant potential for implementation in the industry. This systematic review examines the current state of BIM-based QTO use among quantity surveyors and estimators. The review identifies the main benefits of this approach as enhancing the completeness, accuracy, and productivity of the QTO task. However, the review also highlights challenges, such as the need to develop solutions and invest effort to address the skill-set concerns of experienced construction professionals, entry-level quantity surveyors, and estimators.

The major contribution of this review is to offer a comprehensive understanding of the benefits and challenges of the BIM-based QTO approach. This was achieved by transforming the qualitative findings from 52 relevant journal articles into a standardized format. It is important to note that this review focused specifically on journal articles closely related to BIM-based QTO. A more extensive review is recommended to include conference papers that were excluded due to their scope. This broader scope would facilitate a more comprehensive identification of BIM-based QTO benefits and challenges and allow additional experts' experience to be incorporated.

The findings from the systematic literature review presented in this Chapter provided a foundation for understanding the current state of BIM-based QTO and its role in construction estimating. The review highlighted several recurring challenges, including the need to strengthen construction management graduate competencies, support professional upskilling, and improve educational approaches related to preconstruction topics such as traditional QTO and BIM-based QTO. Building on these findings and the first research objective, Chapter 4 shifts the focus from identifying these challenges to exploring a potential instructional response. Specifically, the chapter presents the development and implementation of a customized generative AI agent as a teaching assistant designed to support students in a construction estimating course, with an emphasis on QTO-related learning and construction management education.

Chapter 4. RQ2. How can a custom Generative AI Agent be developed for estimating courses in construction management education, and how effective is it in supporting student learning?

4.1. Introduction

Estimating is an essential topic in construction management curricula, forming the foundation for cost prediction, resource planning, and informed project decision-making. As a core competency in the field, estimating is traditionally taught through a range of pedagogical approaches, from hands-on exercises using hard-copy drawings, scales, and manual calculations to more advanced computer-based instruction supported by specialized software. Prior research has explored diverse strategies for enhancing estimating education, including immersive experiential activities, structured hands-on learning, and the integration of BIM to improve students' conceptual understanding and measurement accuracy (Besiktepe et al., 2024). For example, Collins and Redden (2021) demonstrated that engaging students in field-based estimating tasks significantly improved their confidence and understanding of course learning objectives. Their exercise, based on Kolb's Experiential Learning Theory (ELT), revealed measurable learning gains and highlighted the pedagogical value of incorporating real-world scenarios into the classroom. Beyond physical hands-on tasks, immersive digital technologies such as Virtual Reality (VR), Augmented Reality (AR), and Mixed Reality (MR) have also been adopted to simulate construction environments, improving student engagement and spatial comprehension (Alizadehsalehi et al., 2019; P. Wang et al., 2018). These technologies support learning in areas such as safety training, design visualization, and equipment operation.

At the onset of the COVID-19 pandemic, many educational institutions shifted to remote learning using video conferencing platforms such as Zoom, Microsoft Teams, and others. These platforms enabled instructors to record and store lectures either locally, on the platform itself, or on cloud-based services like Panopto, YouTube, OneDrive, Box, and Dropbox (Jacques et al., 2021; Yanai et al., 2022). Even after the return to in-person classes, these recorded lectures continued to serve as valuable resources for both students and educators (Rehatschek, 2019).

During the same period, advances in AI, particularly generative chatbots, have rapidly introduced new possibilities for instructional support (Abbasnejad et al., 2023). In parallel with these trends, recent advances in AI, particularly LLMs, offer new opportunities for enhancing construction education in scalable and accessible ways (Grassini, 2023). Tools like OpenAI's ChatGPT have rapidly gained traction in academic settings by providing instant, conversational support tailored to learner needs (Huang et al., 2024). These AI systems can assist students with clarifying complex topics, navigating software tools, and reinforcing technical skills, all without the need for physical infrastructure or real-time instructor intervention. However, most off-the-shelf chatbots are designed for general use and lack the contextual nuance, professional judgment, and industry-informed reasoning that experienced faculty bring to the classroom (Dongbo et al., 2023). Despite this potential, there remains limited research on how generative AI can be effectively adapted to support domain-specific learning (Khennouche et al., 2024), particularly those involving software-based estimating and QTO practices.

The expansion of AI technologies is exponential, with ChatGPT amassing over a million subscribers within a week of its release (Baidoo-anu & Ansah, 2023). This surge in AI adoption has impacted various sectors, including education, where it is being explored for its potential to personalize learning (Alasadi & Baiz, 2023; Pesovski et al., 2024), provide instant academic assistance, and streamline administrative tasks. Generative AI, including tools like ChatGPT, is able to support learning by overcoming language barriers, generating adaptive learning materials, and assisting with assessment questions (Huang et al., 2024). These tools are being used in educational settings to provide clarifications, assist with homework, offer feedback, and support language practice (Khennouche et al., 2024).

Despite the growing interest in AI in education, there is a notable research gap concerning the specific application of generative AI for learning support in construction management education (Collins et al., 2024). While AI has been researched for various purposes in construction, including project management (Ivanova et al., 2023), risk mitigation, and information management (Pan & Zhang, 2021; C. Wu et al., 2022). There is limited research on the use of AI chatbots to directly support students in this discipline (Qadir, 2023). While AI-based chatbots have been explored in general education contexts (Khennouche et al., 2024)Their application in addressing the unique challenges of construction management remains largely unexplored. Optimizing conversational flow in this context could enhance dialogue and improve chatbot effectiveness across educational topics.

This study introduces a custom generative AI agent designed as a virtual teaching assistant for undergraduate construction management students enrolled in estimating courses. The research proposes a framework for developing and deploying AI agents tailored to support domain-specific learning, contributing to both construction education and the broader field of educational technology. By detailing the agent's design, integration, and evaluation, the study provides a practical model for implementing AI-enhanced learning in technical disciplines where accuracy, context, and real-time support are critical.

4.2. Literature Review

4.2.1. Large Language Models and Generative Pre-Trained Transformers

LLMs have evolved significantly from early statistical language models to advanced architectures like transformers, which have revolutionized NLP (Chukwuere, 2024). This evolution has been driven by the advent of deep learning, enabling models to achieve state-of-the-art performance in tasks such as language understanding and generation (Patil & Gudivada, 2024). The transition from task-specific to more generalized models has allowed LLMs to perform effectively across diverse domains (Patil & Gudivada, 2024). However, as LLMs approach the realm of artificial general intelligence (AGI), tracing their origins and understanding their development becomes crucial (Li et al., 2023). This includes addressing ethical concerns and the challenges posed by biases and ambiguities inherent in these models. Overall, the historical progression and principles underlying LLMs are essential for harnessing their full potential in various applications (Chukwuere, 2024).

GPTs have revolutionized NLP, offering diverse applications across multiple domains. In digital marketing, GPTs enhance content creation, customer interactions, and social media marketing (Kumar Sharma & Sharma, 2023). The gaming industry utilizes GPTs for procedural content generation, mixed-initiative game design, gameplay, and user research (D. Yang et al., 2024). GPTs also impact business operations, website development, and conversational applications (Bhattacharjee, 2023). Their ability to generate coherent, contextually relevant text has transformed customer support, enabling personalized responses and tailored recommendations (Kumar Sharma & Sharma, 2023). Despite their potential, GPTs face challenges and limitations that require further research and development (Yenduri et al., 2024). As GPT technology continues to evolve, it promises to reshape various industries, improving efficiency and user experiences while presenting new opportunities for innovation and growth (Bhattacharjee, 2023; Yenduri et al., 2024).

NLP has emerged as a powerful tool in education, offering diverse applications to enhance teaching and learning processes. NLP techniques can be used for question answering, question construction, automated assessment, and error correction (Lan et al., 2024). These applications provide valuable insights into task difficulty, student performance, and individual differences (Allen et al., 2022). In STEM education, NLP tools have proven effective in evaluating higher-order cognitive functions and assessing transversal skills, supporting instructors in providing personalized feedback (Caratozzolo et al., 2022). The integration of NLP into educational technologies enables formative feedback for students and provides educators with insights into various aspects of the learning process. However, educational applications present unique challenges for NLP systems, requiring adaptations to address the specific needs of teachers and students (Allen et al., 2022). As NLP continues to advance, it holds significant potential for improving educational outcomes across various domains.

4.2.2. Custom AI Agents

In recent years, many AI-driven tools have been developed to perform specialized tasks tailored to the needs of end users in higher education. For example, Scopus AI® offers a novel way to search the Scopus database, enabling researchers to efficiently discover relevant literature in their areas of study (Aguilera-Cora et al., 2024). Similarly, Elicit® is an AI-powered academic search tool that helps researchers find relevant articles for their work (Kung, 2023). Additionally, Lucidchart® allows users to create mind maps and diagrams, and it has incorporated generative AI to automatically transform text descriptions into diagrams, simplifying the creation process (Faulkner & Contributor, 2018). These samples of AI-powered tools exemplify the growing trend of specialized AI applications that facilitate human-computer interactions in education and academic settings.

In education and training, platforms like LinkedIn Learning have integrated AI chatbots to enhance the learning experience (Spirgi & Tronsberg, 2022). Their chatbot assists learners by providing on-demand answers to course-specific questions. This feature is integrated alongside video content, allowing learners to ask questions relevant to the topic they are watching. Similarly, tools like ChatGPT have proven invaluable for programmers, aiding in writing and debugging code, diagnosing issues, and improving or optimizing code efficiency (Kuhail et al., 2024). For instance, GitHub's Copilot in Visual

Studio Code leverages generative AI to assist developers in coding tasks (Denny et al., 2023).

Software developers have also adopted AI to streamline workflows in the Architecture, Engineering, and Construction (AEC) industries. Procore® introduced Procore Copilot, an advanced AI-powered search tool that simplifies access to project information, including RFIs, submittals, specifications, drawings, and documents (*Procore Copilot*, 2025). This tool automates routine tasks, reduces manual workloads, and delivers insights, allowing construction professionals to focus on high-value activities. Similarly, Togal.AI® uses AI to automate QTO processes (*The Ultimate AI Companion for Estimators | Togal.AI*, 2025). It detects plan lines from PDF drawings, identifies room boundaries to generate plan geometry, and calculates material quantities. Togal.AI has also integrated a generative AI chatbot to help users navigate plans and execute QTO tasks more effectively.

4.2.3. Generative AI in Education

GPTs, like OpenAI's ChatGPT, Microsoft Copilot, and Google Gemini, are increasingly revolutionizing higher education by enhancing learning experiences and supporting academic initiatives. They offer personalized tutoring, assist with course design, and create diverse educational content, contributing to dynamic, interactive learning environments. For example, GPT can facilitate critical thinking and provide tailored assessments, such as multiple-choice quizzes or open-ended case studies, aligning with individual student needs (Faisal et al., 2024; Ningsih & Lahby, 2024). In specialized disciplines like chemistry and computer networking, GPT aids students in tackling complex problems, fostering better engagement and comprehension (Ardyansyah et al., 2024; Soto et al., 2024). Moreover, GPT supports professional development and course alignment, helping educators design content that complements faculty competencies (Kumar et al., 2024). These tools have demonstrated significant potential to enrich educational experiences, enabling educators and learners to explore innovative pedagogical approaches.

Despite its benefits, integrating GPT into higher education presents challenges that warrant careful consideration. Ethical concerns regarding data privacy, security, and model biases are prevalent, emphasizing the need for transparent guidelines and user training (Grassini, 2023). Additionally, over-reliance on GPT could hinder critical thinking and academic integrity, with risks of misinformation and reduced student engagement in independent problem-solving (Grassini, 2023; Rożek, 2024). Resistance from educators, stemming from concerns about fraudulent use, further complicates adoption (Phongsatha, 2024). Addressing these issues requires a balanced approach, incorporating ethical use, ongoing monitoring, and AI literacy programs to ensure GPT enhances education without undermining its core values (Huang et al., 2024). As such, continuous refinement and optimization of GPT models remain crucial for sustaining their reliability and educational relevance (Moussa, 2024).

4.2.4. AI Chatbots in Domain-Specific

Several researchers have begun developing customized AI agents for specific tasks within the construction industry. For example, Zheng and Fischer (2023) introduced BIMS-GPT, an AI-driven agent designed to read and retrieve data from BIM models. This system enables users to query BIM datasets using natural language, facilitating intuitive access to building-specific information. The authors reported that BIMS-GPT achieved 99.5% accuracy in classifying user queries, demonstrating its potential to enhance data retrieval efficiency in BIM-based workflows.

Similarly, to improve risk identification in tunnel projects, (Isah & Kim, 2025) developed an intelligent question-answering system that integrates a tunnel risk knowledge graph (TRisKG) with a generative pretrained transformer (GPT) model. The system, known as QASTRisk, addresses two key challenges in risk management: the unstructured nature of historical risk data and the heavy reliance on manual expertise, which is often time-consuming and error-prone. By leveraging AI-based techniques, QASTRisk enables rapid, intuitive risk identification at the early stages of tunnel projects, aiding decision-making to prevent safety incidents, project delays, and cost overruns. This work highlights the growing role of AI-driven solutions in automating complex construction management tasks and enhancing project efficiency.

In summary, the literature highlights the growing potential of generative AI, particularly LLMs, in educational settings, including specialized areas like construction management. The use of AI-driven tools, such as GPTs and custom agents, has shown promise in supporting learning experiences and addressing domain-specific tasks within the construction industry. While studies suggest that AI can benefit education by offering personalized learning and automating certain processes, challenges remain, including inaccuracies, irrelevant responses, and effective integration. These findings underscore the need to tailor AI technologies to meet the specific requirements of both educators and students, particularly in technical fields such as construction management.

4.3. Custom AI Agent Development

4.3.1. Background on Construction Estimating Course

The Construction Estimating course is a core requirement for junior-level Building Science students at Auburn University and provides foundational and advanced instruction in construction estimating across CSI Divisions 1–33. Delivered as a single, integrated class covering both QTO and cost estimating, the course is structured around a single comprehensive project spanning the entire semester. Although the project itself varies each term, the curriculum, weekly schedule, and instructional approach remain consistent. This continuity allows students to progressively build their skills in a stable learning environment while applying concepts to a real-world project. Instruction emphasizes hands-on, computer-based methods, and students use multiple software applications, with Bluebeam Revu® serving as the primary tool for QTOs and ProEst® by Autodesk supporting the development of full estimates across multiple trade packages. Each class includes a lab component where students work at their own pace with direct guidance from the instructor, and the semester concludes with a bid-day simulation that reinforces practical, industry-relevant decision-making. To support learning outside of class time, all sessions are recorded via Zoom and shared with students.

Throughout the semester, students commonly ask questions related to navigating the software platforms and understanding the technical nuances of performing QTO and developing trade-specific estimates. Typical inquiries include identifying the most appropriate Bluebeam functions for certain take-offs, determining how to display and organize quantities, and selecting accurate line items within the ProEst database. To address these challenges, the course follows a structured instructional model: the instructor begins with a lecture introducing the topic, demonstrates the step-by-step take-off or estimating workflow, and then transitions into an open lab session where students apply the material independently while receiving timely support. This approach helps ensure that students gain confidence using professional estimating tools and develop the practical competencies required for commercial construction projects.

4.3.2. Selection of Agent Development Platform

Based on the comparison outlined in Table 4.6, Copilot Studio was selected as the platform for this study on AI-supported learning due to its alignment with several key criteria relevant to educational settings. The platform offers customization options that allow educators to adapt the agent to specific instructional content and includes basic dialogue tree support for managing structured interactions. Additionally, it is compatible with existing university systems and offers a low-code environment, helping reduce technical barriers to implementation. Copilot Studio also allows for the sharing of customized agents and is available to students at no cost. These combined features made it a practical choice for exploring the potential of AI-driven tools to support learning in a university context.

Table 4.6. Comparison of Custom AI Agent Platforms for Educational Use

Criteria	Copilot Studio	ChatGPT	Google Gemini	Meta AI
Ability to customize agents using specific instructional content	✓	✓	✗	✗
Ability to share customized agents with other users	✓	✓	N/A	N/A
Free access for students	✓	✓	✓	✓
Integration with existing university ecosystems (e.g., Microsoft, LMS)	✓	✗	✗	✗
Low-code environment (minimal programming skills required)	✓	✓	N/A	N/A
Conversation management with dialogue tree or flowchart support	✓	✗	✗	✗

Copilot Studio is a user-friendly, low-code platform that lets users build AI agents and agent flows without extensive programming experience. One of its key strengths is its ability to connect to external data sources via prebuilt or custom plugins, giving users the flexibility to develop and manage a wide range of workflows. This capability enables agents to provide responses and actions tailored to the user's needs. Copilot Studio enables individuals from various backgrounds to design and deploy agents that can support tasks such as customer service, sales assistance, and employee support across multiple channels, including websites, mobile apps, and Microsoft Teams. Users can also create agent flows to automate repetitive processes and link different services, with flows that can be triggered by specific events (iaanw, 2025).

4.3.3. AI Agent Design and Knowledge Base Creation

This study aimed to leverage Zoom-recorded lectures by transcribing the lecture content to create a course-specific knowledge base. This knowledge base was then used to support a generative AI agent via Retrieval-Augmented Generation (RAG). The agent was developed using MCS, a low-code platform, making it accessible to educators without programming expertise. Behavioral scripting, including programmatic prompting and trigger phrase activation, was employed to tailor the agent's responses to course-specific topics, such as construction estimating, which often requires extensive use of software tools.

The AI agent's knowledge base was derived from Panopto® recordings of a previous course section. These recordings were automatically transcribed using Panopto's built-in automatic ASR system, which provides an estimated accuracy of 90–95% (Panopto, 2024). The transcripts were used in their unedited form to preserve the instructional flow, terminology, and explanations commonly provided during the course. To further support student learning, the agent was also linked to the official Bluebeam Revu® user guide, as this software is the primary tool used to teach QTO procedures in the class (see Figure 4.18).

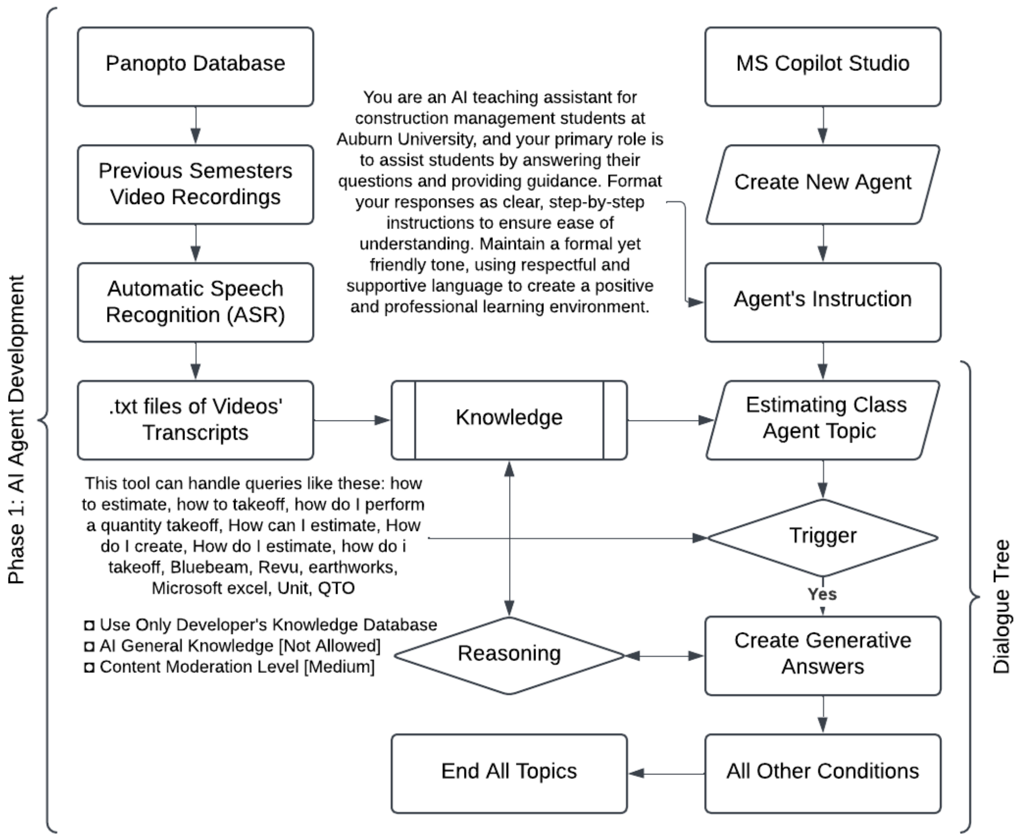

Figure 4.18. AI Agent Development Framework

A new AI agent was created within CS specifically for the estimating course, and instructions were provided on how to respond to end-user queries in their natural language. This eliminated the need for manual coding to tailor the agent's behavioral script to course-specific content. The instructions stated: *"You are an AI teaching assistant for construction management students at Auburn University, and your primary role is to assist students by answering their questions and providing guidance. Format your responses as clear, step-by-step instructions to ensure ease of understanding. Maintain a formal yet friendly tone, using respectful and supportive language to create a positive and professional learning environment."*

4.3.4. Instructional Topics and Trigger Phrases

An "Agent Topic" was created within Copilot Studio to manage the conversational flow between the agent and the students. By default, the system employs natural language understanding (NLU) to interpret user queries and trigger relevant phrases or nodes within the defined topic. For this implementation, a new topic titled "Estimating Class" was created with trigger phrases such as "how to estimate," "how to take off," "how do I perform a quantity takeoff," "how can I estimate," "Bluebeam," "Revu," "earthworks," "Microsoft Excel," "unit," "ProEst," and "QTO." Once triggered, the conversation would proceed to the primary AI-driven node, “Generative Answers,” which retrieves information from a predefined data source. To ensure reliability, the AI was restricted from using its general knowledge and was limited to responses based solely on the uploaded transcripts and Bluebeam’s user support page. This restriction was intended to maintain accuracy by ensuring that answers remained directly relevant to the course content. The dialogue structure continuously cycles through this process unless the user enters a blank query or triggers a different topic. Figure 4.19 shows the structured dialogue tree for the estimating question.

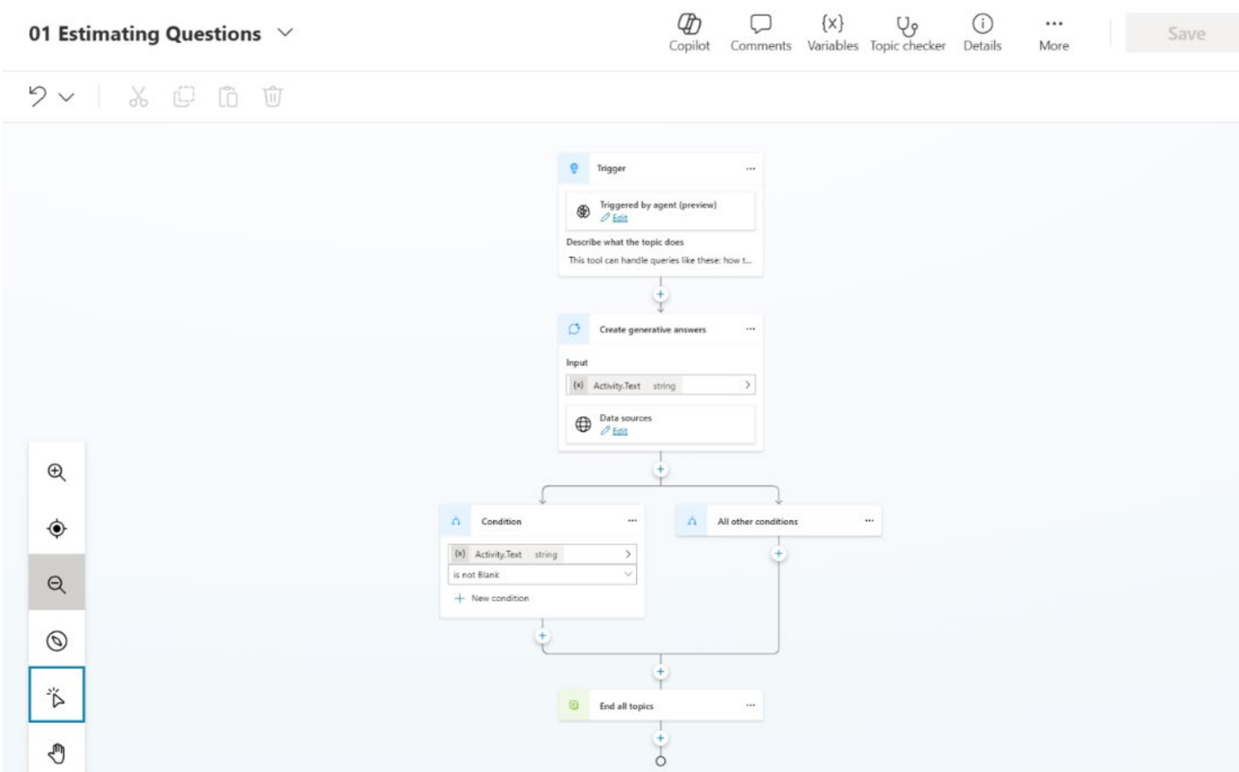

Figure 4.19. Topic Dialogue Tree showing the generative answers node

4.3.5. Deployment and Student Interaction

The Agent was deployed over two semesters across four sections of a construction estimating course, engaging a total of 120 students, 60 during the Summer 2024 semester and 60 during the Fall 2024 semester. At the beginning of each semester, researchers introduced the study to students and presented Figure 4.20 to illustrate the database's process and reliability, which supports the Agent's responses. Students accessed the Agent via Microsoft Teams through a link provided on the course's Canvas page. The AI Agent's user interface was user-friendly, and the students were familiar with and had experience using Microsoft Teams prior to this study, as shown in Figure 4.21. The authors demonstrated their functionality during the semester's class meetings and encouraged engagement by modeling real-time usage. Serving as a supplemental learning tool, the agent enabled students to ask questions anonymously and seek assistance outside class hours.

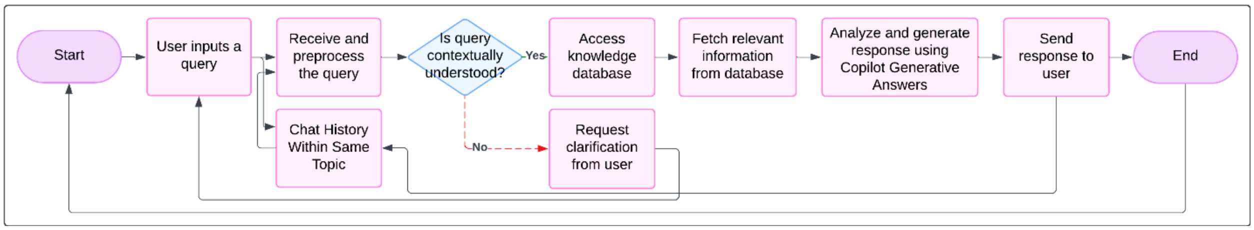

Figure 4.20. Framework for AI-Powered Student Learning Support System

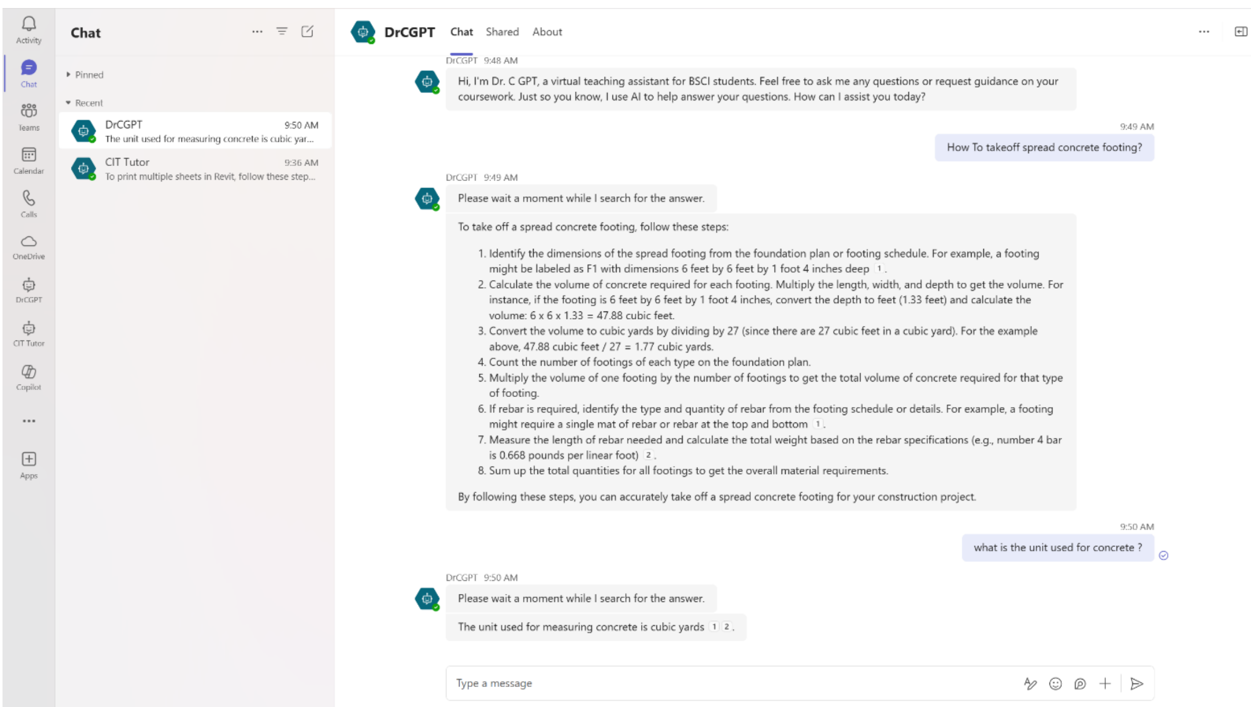

Figure 4.21. User Interface of AI Agent “DrCGPT” in Microsoft Teams Environment

4.4. Methodology

4.4.1. Research Aim and Objectives

The primary research question guiding this study was: “Would a custom-built generative AI agent, as a virtual teaching assistant, be valuable to undergraduate students in a construction estimating course?” Accordingly, the aim of this study is to evaluate students’ perceptions, prior experiences, and preferences regarding the use of a custom AI-powered chatbot (DrCGPT) to understand its educational value and identify opportunities for broader implementation across the construction management curriculum. The research also explores the development of an AI agent capable of answering course-related questions by mimicking the instructor’s responses. By incorporating previous lecture recordings into the agent’s knowledge database, the system can deliver consistent, on-demand support and provide students with guidance like what they would receive in a traditional classroom setting.

To carry out the research aim and answer the primary research question, this study followed a structured six-step research design, as illustrated in Figure 4.22. The process began with defining the research aim and research question, which centered on evaluating the educational value of a custom-built generative AI agent (DrCGPT) in a construction estimating course. In Step 2, the AI agent's knowledge base was established by selecting course-specific estimating and QTO materials verified by the instructor for accuracy and alignment with the learning objectives, including the transcript of old lectures. Step 3 involved selecting an appropriate low-code AI development platform and determining a secure, accessible deployment method for student use. Step 4 defined the data types required to assess students' perceptions, prior experiences, and preferences, including both quantitative survey items and qualitative open-ended responses. In Step 5, survey instruments were developed to capture student feedback and measure the perceived value of the AI agent. Finally, Step 6 outlined the data analysis procedures, including descriptive statistics for quantitative data and thematic analysis of qualitative responses, to provide deeper insight into student experiences.

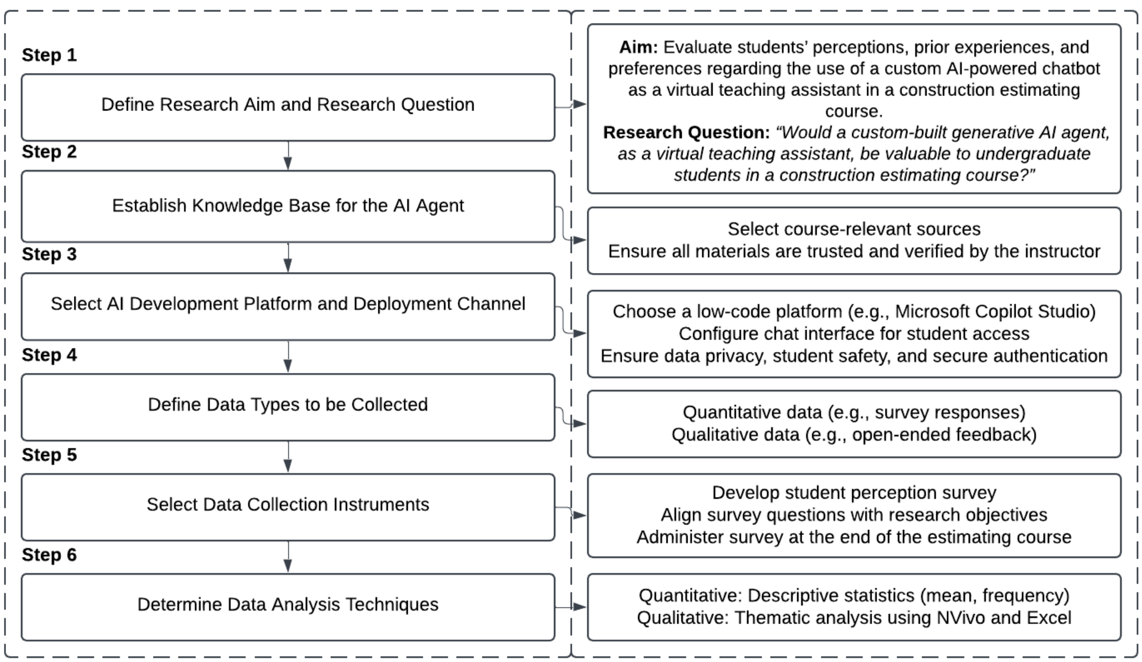

Figure 4.22. Structured Research Design for Developing and Evaluating a Custom Generative AI Agent in Construction Education

4.4.2. Data Collection

Data for this study were collected through an online survey administered using Qualtrics at the end of the semester, after students had consistent exposure to the DrCGPT chatbot across multiple course topics. The survey was distributed to four sections of an undergraduate construction estimating course, totaling approximately 120 students who participated in the semester-long experiment. By administering the survey at the end of the course, students were able to reflect on their sustained interactions with the chatbot and offer informed perspectives on its value as a virtual teaching assistant. Qualtrics was selected for its secure administration, flexibility in question design, and ability to capture both quantitative and qualitative data suitable for mixed-methods analysis. Participation was voluntary, and students responded anonymously to encourage honest feedback about their experiences and preferences.

The rationale for the survey questions was to evaluate the core components of the research aim: perceived value, prior experience, usage preferences, and the potential to scale similar tools across the curriculum (Table 4.7). Q1 gathered open-ended reflections on whether the chatbot supported learning in QTO and estimating, directly addressing the study's primary research question on perceived educational value. Q2 assessed students' preferred methods for seeking help, enabling comparisons between AI assistance and traditional support sources such as instructors or peers. Q3 examined students' prior exposure to chatbots like ChatGPT, providing context on how familiarity with AI tools may influence adoption and comfort levels. Q4 explored whether students had encountered chatbot-enabled instruction in other courses, thereby contextualizing DrCGPT within broader academic experiences. Finally, Q5 invited students to identify other Building Science courses where a similar chatbot might be beneficial, offering insight into perceived scalability and potential instructional impact beyond the estimating course. Together, these questions provided a structured means of understanding students' perceptions, needs, and expectations as the construction management field increasingly integrates generative AI technologies.

Table 4.7. Summary of Survey Questions and Their Types Used to Evaluate DrCGPT Chatbot Integration in Construction Estimating Course

Code	Survey Question	Question Type
Q1	Please describe your opinion regarding whether or not the DrCGPT Chatbot was a valuable resource to you for learning the quantity takeoff and estimating practices taught in this course.	Open-ended
Q2	If you had a question about something we were working on in this specific course, would you prefer to: - Select Choice	Closed-ended
Q3	Have you previously utilized a Chatbot, such as ChatGPT, to answer course-specific questions?	Closed-ended
Q4	Are there any previous or current courses that you have taken where a Chatbot, such as DrCGPT, was utilized? If so, please describe.	Open-ended
Q5	Would you like to see Chatbots similar to Dr. CGPT be developed for your other BSCI classes? If so, please list them below and describe why you feel a Chatbot would be valuable in that course.	Open-ended

4.4.3. Data Analysis

A mixed-methods analytical approach was adopted to interpret the survey data, combining quantitative summaries with in-depth qualitative exploration. Closed-ended items were examined using descriptive statistics to capture overall trends in students' preferences, prior chatbot experience, and patterns of support-seeking behavior. These quantitative indicators provided a foundational understanding of how students interacted with DrCGPT and how their experiences aligned with the study's broader aim of evaluating the chatbot's perceived educational value. Qualitative responses were then analyzed using thematic coding to uncover deeper insights into students' reflections, expectations, and recommendations. NVivo software supported this process by enabling both manual coding and machine-learning-based auto-coding, allowing efficient pattern detection while retaining researcher oversight to ensure accuracy.

Open-ended comments were categorized into sentiment-informed thematic groups, such as positive, neutral, negative, and mixed perceptions, to capture the range and nuance of students' experiences with the AI agent. This layered approach also enabled the identification of emergent themes related to instructional usefulness, comparison with traditional sources of support, perceived reliability of the chatbot, and interest in expanding similar tools across other BSCI courses. The integration of machine-assisted coding with manual review strengthened the credibility of the findings while providing a comprehensive understanding of how students perceived the value, limitations, and broader applicability of DrCGPT within the construction management curriculum.

4.5. Results

The survey responses were exported from Qualtrics in Excel format. Exclusion criteria were applied to ensure data validity and reliability. Responses were excluded if the completion time was deemed unrealistic (less than 60 seconds, n=4), if the participant did not complete the survey (left before finishing, n=4), or if more than 50% of the questions were left unanswered (4 or more empty responses, n=4). After exclusions, 102 valid responses were retained, representing 85% of the total population sample.

4.5.1. Q1: Perceived Usefulness and Sentiment Analysis

To analyze students' perceptions of the DrCGPT chatbot, sentiment analysis was conducted on open-ended responses collected from the survey questionnaire. The analysis focused specifically on qualitative feedback to the question: "Q1: Please describe your opinion regarding whether or not the DrCGPT Chatbot was a valuable resource to you for learning the QTO and estimating practices taught in this course." Responses were reviewed and manually categorized into three sentiment groups: "positive, neutral, or negative," based on the overall tone and language used by the students. Positive responses included expressions of satisfaction, usefulness, or engagement; neutral responses conveyed indifference or mixed feelings without strong emotion; and negative responses reflected frustration, lack of clarity, or ineffectiveness. Only responses that directly addressed opinions about the AI agent were included in this analysis. Ambiguous or off-topic comments were excluded to maintain the focus on the research objective.

The survey results indicate that most students held a neutral view regarding the AI agent's usefulness, with 58.42% (n=59) selecting a neutral response. These responses included comments such as, "*It was helpful when I remembered to use it,*" reflecting moderate engagement with the tool. A smaller proportion, 33.66% (n=34), expressed a positive opinion, suggesting the agent was a valuable resource for learning QTO and estimating practices, illustrated by remarks like, "*I found DrCGPT to be a valuable resource for easily obtaining help in this course.*" Only 3.96% (n=4) reported negative experiences, citing issues such as the specificity required in prompting (e.g., "*I think it was helpful but sometimes frustrating because of how specific the prompts had to be*"). An additional 3.96% (n=4) provided mixed feedback, highlighting opportunities to further refine the agent's adaptability to different learning preferences (Table 4.8).

Table 4.8. Student Sentiment Toward AI Agent Usefulness

Answer	Number of Responses
Positive	34 (33.66%)
Neutral	59 (58.42%)
Negative	4 (3.96%)
Mixed	4 (3.96%)

4.5.2. Q2: Help-Seeking Behavior and Preferences

The survey results for Q2, presented in Table 4.9, indicate that most students (41%) preferred to ask the instructor directly when they had a question about the course content. A considerable portion (35%) stated that their preference depended on the nature of the question, suggesting that different types of inquiries may require different sources of support. Additionally, 21% of students opted to ask a classmate, while only 3% preferred using the AI agent for assistance. Notably, just 1% of respondents indicated a preference for utilizing another external data source, such as a Google search.

Table 4.9. Q2: Student Preferences for Seeking Help

Answer	Number of Responses
Ask the instructor directly	42 (41.18%)
Ask one of my classmates	35 (34.31%)
It depends on the question	21 (20.59%)
Ask the DrCGPT Chatbot	3 (2.94%)
I would utilize another source of data, such as Google	1 (0.98%)

4.5.3. Q3: Prior AI Chatbot Experience

In response to the close-ended survey question, “Q3: Have you utilized a Chatbot such as ChatGPT previously to answer course-specific questions?” the data collected provided insight into the students’ prior experience with AI-driven tools for academic support. Most students (84%) reported having previously used a chatbot, such as ChatGPT, to address course-related inquiries. In contrast, a smaller number of respondents (16%) reported not having used such AI-powered tools in an educational context prior to this course. These results provide a clear indication of the overall student familiarity with AI chatbots as academic resources before the integration of DrCGPT into the course.

4.5.4. Q4: Exposure to Educational AI Chatbots

In response to the open-ended question “Q4: Are there any previous or current courses that you have taken where a Chatbot such as DrCGPT was utilized? If so, please describe,” a total of 27 out of 102 respondents reported that they had been encouraged to use general-purpose AI chatbots, such as ChatGPT, in other courses. These courses included subjects like communications, construction information technology, and construction safety. However, while these students acknowledged using AI tools in their academic experiences, none of the respondents mentioned using a chatbot specifically developed and customized for a particular course.

4.5.5. Q5: Interest in Chatbot Integration in Other Courses

To further examine student interest in expanding the use of customized AI-driven learning tools, sentiment analysis was conducted on 83 out of 102 responses (response rate: 81.37%) to the open-ended question: “Q5: Would you like to see Chatbots like DrCGPT be developed for your other BSCI classes? If so, please list them below and describe why you feel a Chatbot would be valuable in that course.” The responses were analyzed using the Auto Code Sentiment feature in NVivo, which categorized them as positive, neutral, negative, or mixed based on overall sentiment. Positive responses (22.89%) demonstrated interest in expanding chatbot use, often citing course complexity, the need for additional academic support, or time-saving benefits. Neutral responses (77.11%) were either vague or non-committal, indicating no strong opinion on the further adoption of chatbots. NVivo did not identify any responses as negative or mixed. The distribution of sentiments is summarized in Table 4.10.

Table 4.10. Student Interest in Expanding Chatbot Use to Other BSCI Courses

Answer	Number of Responses
Positive	19 (22.89%)
Neutral	64 (77.11%)
Negative	0 (0.00%)
Mixed	0 (0.00%)

To further explore student interest in AI-driven learning support, respondents were asked to list specific courses where they would like to see a custom AI agent implemented. The results reveal varying levels of demand across different subjects. The highest interest was observed in the Structures course (10 responses), likely due to its complexity and the need for chatbot support to understand theoretical concepts and perform calculations. The Construction Information Technology (CIT) course received 5 responses, indicating a demand for assistance with technology-related topics and software applications. Both Scheduling and All Courses garnered (4 responses), reflecting moderate interest in chatbots for planning tasks or as a universal educational tool. The Safety course received (3 responses), suggesting potential value in chatbot integration for learning safety protocols and regulatory compliance. In contrast, the MEP

(Mechanical, Electrical, and Plumbing) course received only one response, possibly due to its specialized nature or fewer perceived challenges.

4.6. Discussion

4.6.1. Insights from AI Agent Development and Deployment

While the current findings indicate that the DrCGPT AI Agent has the potential to be a valuable educational tool, the results also highlight several areas for improvement and refinement. First, addressing student feedback is crucial to enhancing the AI agent's effectiveness. Some students reported that the chatbot lacked clarity or did not fully meet their learning needs. These challenges may stem from the limitations of current AI technologies, which, although capable of providing general support, may struggle with the nuanced and complex nature of certain course content. To address these issues, future developments should focus on improving the chatbot's ability to understand and respond to specific queries related to course material, potentially through more advanced NLP techniques.

In addition, the low preference for the AI agent as a primary source of help (3%) suggests that students may still prefer traditional forms of support, such as interacting with instructors or classmates. This preference may be attributed to the social and contextual aspects of learning, which AI agents, in their current form, may not fully replicate. As such, future iterations of the AI agent should aim to complement, rather than replace, existing support channels. One potential approach is to integrate the AI agent into a broader educational ecosystem that includes instructor feedback, peer collaboration, and other learning tools. This integration could help students feel more comfortable using the chatbot and encourage its adoption as a supplementary resource.

Another consideration for future development is the potential to increase the personalization of the AI agent. The results showed that students expressed interest in expanding the use of AI chatbots across other courses, suggesting that AI agents could be more effective if designed to meet the unique needs of different subjects. Customizing the agent for specific courses or topics, such as Structures or Construction Information Technology, could increase its relevance and usefulness to students. This would involve not only refining the chatbot's knowledge base but also incorporating feedback from both students and instructors to ensure that the AI agent evolves in a way that best supports learning objectives.

Finally, while the DrCGPT chatbot has shown potential, its role in education will likely continue to evolve as AI technologies advance. As AI agents become more sophisticated, they may be able to provide more personalized learning experiences, adapting to students' individual needs in real time. Future versions of the DrCGPT chatbot could incorporate features such as voice interaction, real-time data analysis, and seamless integration with other digital tools, further enhancing its ability to support students in their learning journeys. Moreover, as AI becomes more integrated into educational practices, it may become an indispensable tool for both students and instructors, offering a dynamic and scalable way to enhance teaching and learning outcomes.

4.6.2. Discussion of the Student Feedback and Educational Impact

The results of this study highlight students' mixed perceptions regarding the usefulness of the DrCGPT AI agent. Sentiment analysis of students’ open-ended feedback revealed that while 33.66% of respondents expressed a positive view of the AI agent, 3.96% reported a negative experience. The positive responses pointed to the chatbot's ability to assist with learning the course content, indicating that it was seen as a helpful resource for some students. However, the negative responses suggest that there are areas where the AI agent did not meet students' expectations or provide the desired level of support. These results indicate that while AI agents have the potential to serve as valuable educational tools, their effectiveness may vary depending on students' individual learning needs and preferences.

Regarding seeking help with course-related questions, the survey results showed that most students (41%) preferred to ask the instructor directly. This preference for instructor-led support was followed by a smaller proportion (35%) who chose to seek help depending on the nature of the question. Only a small number of students (3%) expressed a preference for the AI agent, suggesting that, despite the chatbot’s perceived value to some, it is not yet a preferred choice over more traditional support channels such as the instructor or classmates. This finding underscores the importance of understanding the context in which students find AI agents most useful and highlights the need for AI systems to be integrated into educational practices in ways that complement existing support structures.

The data also indicated that a significant majority of students (84%) had prior experience using general-purpose chatbots like ChatGPT for academic purposes. This familiarity may have influenced students’ perceptions of the DrCGPT chatbot, shaping their expectations and engagement with the tool. However, the limited exposure to course-specific chatbots, as indicated by the open-ended responses, suggests that many students have not yet encountered a chatbot specifically designed to support learning in their field of study. This highlights an opportunity to further explore how custom-designed AI agents, tailored to the specifics of a course or subject, can complement traditional teaching methods.

Lastly, students showed considerable interest in expanding the use of custom AI chatbots to other construction management courses. The positive responses to this idea suggest growing acceptance of AI-driven learning tools, particularly in subjects perceived as complex or requiring additional support. The Structures course received the most responses, indicating that students value AI assistance for understanding theoretical concepts and performing calculations. This interest in broader chatbot implementation points to a potential direction for future course design, where AI tools could play a more significant role in supporting students across different disciplines.

4.7. Conclusions

This study examined the value of a custom-built generative AI agent, DrCGPT, designed to support undergraduate students in a construction estimating course by leveraging transcribed lecture content through RAG within a low-code MCS environment. The results demonstrate that a course-specific AI tutor can enhance the learning experience and provide consistent, on-demand support without requiring instructors to possess advanced programming skills. Overall, student feedback indicated that 92.08% of participants reported a neutral-to-positive experience with interactions with the chatbot.

However, help-seeking preferences showed that human interaction remains the dominant choice: 41% preferred consulting the instructor and 34.31% preferred asking classmates, indicating that students continue to rely on interpersonal support even when AI assistance is available. 84% of the students had previously used general-purpose chatbots, but not customized agents tied to course material, highlighting a gap and an opportunity for discipline-specific AI tutors. Students also expressed interest in seeing similar customized chatbots developed for other courses, including Structures, Construction Information Technology, Safety, Scheduling, and MEP.

Although the findings are promising, this study was limited to a single course at a single university and was conducted in a live instructional environment where students still had regular access to the instructor. Future research should explore the performance and effectiveness of AI agents as standalone instructional tools, particularly in asynchronous learning settings. Expanding and refining the knowledge base, improving response accuracy, and integrating ethical and responsible AI considerations will be critical steps toward enhancing the educational value of customized generative AI tutors. Further studies should also investigate broader curriculum-level adoption and how student perceptions evolve as AI agents become more prevalent and more deeply embedded in everyday academic workflows.

This chapter presented the development and implementation of a customized generative AI agent as a teaching assistant in a construction estimating course. The findings suggested that students generally perceived the AI agent as a useful learning support tool, with neutral-to-positive feedback regarding its role in assisting with estimating and QTO-related tasks. Building on these results, Chapter 5 extends the investigation by examining whether a customized AI agent can support learning in a more central instructional role. Rather than positioning the agent solely as a supplemental resource, this next phase explores its use as a primary instructional resource, similar to how students may engage with recorded lectures, online tutorials, or other asynchronous learning materials. In this way, Chapter 5 builds on the outcomes of Chapter 4 by further examining the potential of interactive AI-based instruction for supporting BIM-based QTO learning in construction management education.

Chapter 5. RQ3. How can a custom AI agent with a predesigned dialogue-tree architecture serve a central instructional role in asynchronous preconstruction education?

5.1. Introduction

The rapid advancement of AI has led to the emergence of custom-built conversational agents designed to address domain-specific needs by integrating NLP and machine learning (ML). Unlike general-purpose systems, custom AI chatbots are tailored to deliver context-aware, personalized, and task-oriented interactions, enabling more efficient user support and decision-making processes. These systems provide real-time assistance, reduce reliance on human intervention, and enhance user experience across various applications (Hakim et al., 2024). Within educational contexts, such capabilities present significant opportunities to support learning environments by offering responsive and adaptive instructional assistance (Swetha et al., 2025).

BIM has the potential to transform QTO practices by improving accuracy, efficiency, and interdisciplinary collaboration within the AEC industry (Alathamneh et al., 2024). Despite these advancements, the integration of BIM-based QTO into construction education remains inconsistent and often insufficient. Many academic programs lack standardized curricula that adequately address BIM competencies required for QTO, resulting in fragmented learning outcomes and limited preparedness among graduates (Keung et al., 2023; Xin & Aziz, 2020). Existing instructional approaches frequently emphasize basic modeling and visualization rather than advanced QTO workflows, data validation, and automation techniques demanded by industry practice (N. Lee et al., 2019). Furthermore, students encounter cognitive challenges when transitioning from traditional 2D representations to 3D BIM environments, which affects their ability to perform accurate takeoffs and limits engagement with digital workflows (F. Yang, Akanbi, et al., 2024). These issues are compounded by limited access to industry-grade software and insufficient exposure to hands-on learning environments, ultimately restricting the development of practical BIM skills (F. Yang, Akanbi, et al., 2024).

From an industry perspective, the demand for professionals proficient in BIM-based QTO continues to grow, yet a significant skills gap persists (Marchiori et al., 2023). Employers consistently report that graduates lack domain-specific competencies such as advanced modeling, data extraction, and verification techniques necessary for reliable QTO outputs (Saka & Chan, 2020). While efforts such as upskilling initiatives, curriculum reform, and integration of emerging technologies have been proposed to bridge this gap, their implementation remains limited and uneven across institutions (Alathamneh et al., 2024; F. Yang, Zhang, et al., 2024). Therefore, a critical gap exists in developing and evaluating structured, scalable instructional approaches that effectively align BIM-based QTO education with industry requirements. This gap underscores the need for research on innovative pedagogical frameworks that systematically enhance student competency and better prepare graduates for evolving digital construction practices.

In this context, AI agents have emerged as promising tools for learning support in educational environments. Current implementations predominantly position these systems as intelligent teaching assistants capable of answering student questions, providing immediate feedback, and personalizing learning experiences (Basu et al., 2025). Notable examples, such as AI-driven teaching assistants deployed in large-scale courses, demonstrate the potential of these systems to handle high volumes of student inquiries and enhance engagement through adaptive interactions. Furthermore, AI agents have been integrated into various domains, including language learning and intelligent tutoring systems (ITS), where they support instructional delivery, monitor learner progress, and tailor content to individual needs (Moulieswaran & Kumar, 2023). These capabilities make AI agents particularly valuable in asynchronous settings, where access to immediate support is often limited.

However, despite their growing adoption, AI agents are not yet widely utilized as primary instructional tools. The existing literature consistently characterizes these systems as supplementary technologies that augment rather than replace human instructors. Key limitations, including concerns regarding response accuracy, lack of pedagogical reasoning, ethical considerations such as data privacy and algorithmic bias, and the necessity of human oversight, continue to constrain their role in autonomous instruction. Moreover, most implementations rely on hybrid models that incorporate human-in-the-loop mechanisms, predefined instructional pathways, or instructor validation processes. Consequently, educators remain central to curriculum design, content verification, and assessment.

Given these considerations, there is a need to explore structured and controlled approaches to integrating AI as a more central component of instruction, particularly in asynchronous learning environments. This study addresses this gap by evaluating a custom-built AI system designed with a dialogue-tree architecture in a construction education context, specifically in BIM-based QTO. By embedding instructional logic and domain-specific knowledge into system design, the research aims to assess whether this approach enables custom-built AI agents to act effectively and accurately as the primary instructional methods for learning construction management-related topics.

5.2. Literature Review

5.2.1. Artificial Intelligence in Construction Education

AI has emerged as a transformative force in construction education, reshaping both instructional approaches and student learning experiences. Recent studies demonstrate that AI-powered tools can significantly enhance efficiency and accuracy in construction-related tasks, particularly in estimating and project management. For instance, tools like Togal.AI have been shown to improve task completion speed, accuracy, and team coordination among undergraduate students, highlighting the potential of AI to augment practical learning outcomes (Zhao et al., 2025). In parallel, the integration of AI with BIM has enabled automation of workflows, optimization of design processes, and improved project management capabilities, aligning educational practices with evolving industry demands (Camargo et al., 2025; Kutá & Faltejsek, 2025). Furthermore, AI-driven platforms such as ChatGPT and Hypar have been utilized to foster collaborative learning environments, supporting the development of critical thinking, teamwork, and problem-solving skills among construction management students (Camargo et al., 2025). These advancements suggest that AI is contributing to the enhancement of technical competencies and the development of essential professional skills.

Despite these promising developments, the integration of AI into construction education remains largely supportive rather than transformative. The existing literature emphasizes the need for a structured curriculum development, including dedicated AI modules and hands-on training opportunities, to better prepare students for industry applications (Elhouar & Nguyen, 2025; Rivera et al., 2024). However, challenges persist, particularly regarding faculty readiness, as many educators report limited technical expertise and uncertainty about how to effectively incorporate AI into their teaching practices (Cheng et al., 2025). Additional concerns include the risk of over-reliance on AI tools, which may hinder the development of fundamental skills and critical thinking, as well as ethical and infrastructural barriers to AI adoption (Woźniak & Nowobilski, 2025). While future directions highlight the importance of expanding AI education and strengthening academia–industry collaboration (Z. Ali et al., 2025; Baduge et al., 2022). A critical gap remains in the literature: most studies position AI as a supplementary tool rather than exploring its potential as a primary instructional method.

5.2.2. AI Agents as Learning Tools

AI agents have emerged as transformative learning tools, enabling personalized, adaptive, and interactive educational experiences. A substantial body of literature highlights their ability to tailor instructional content to individual learner profiles, dynamically adjust learning pathways, and provide real-time feedback to enhance student engagement and knowledge retention (Karmakar & Das, 2024; Sunitha et al., 2023). These systems leverage advancements in NLP and LLMs to facilitate meaningful dialogue, enabling learners to interact with AI agents that mimic human tutoring. Such interactions support pedagogical strategies including task decomposition, guided problem-solving, and reflective learning practices, ultimately contributing to deeper cognitive engagement (Jiang et al., 2024; Triberti et al., 2024). Additionally, AI agents play a significant role in supporting educators by automating administrative and assessment-related tasks, generating instructional materials, and offering data-driven insights into student performance, thereby enabling more informed teaching strategies (Ul Rehman, 2025). Their capacity to enhance accessibility through adaptive interfaces, speech recognition, and assistive technologies further promotes inclusive learning environments for diverse student populations (Aydoğan & Kaptanlar, 2026).

From a technological perspective, AI agents are underpinned by advanced computational frameworks such as reinforcement learning, which enables adaptive decision-making in dynamic learning environments, and explainable AI (XAI), which enhances transparency and trust in AI-driven educational systems (Masayuki & Tomoyuki, 2022; Munjal & Lamba, 2024). Emerging integrations with augmented reality (AR) further enhance their capabilities by creating immersive, interactive learning environments that improve engagement and knowledge retention (Fallah et al., 2025). Despite these advancements, the literature consistently identifies ethical and practical challenges, including concerns related to data privacy, algorithmic bias, implementation costs, and the need for technical expertise (Hortal et al., 2025). Existing studies predominantly position AI agents as assistive technologies rather than as central teaching mechanisms and provide limited empirical evidence of their effectiveness in fully replacing or restructuring traditional instructional approaches.

5.2.3. Asynchronous Learning and AI-Enhanced Pedagogies

Asynchronous learning has emerged as a flexible and learner-centered instructional approach that accommodates diverse student needs by enabling access to educational content independent of time and location constraints (Chopra & Chitranshi, 2022). Additionally, asynchronous environments promote collaborative and reflective learning through discussion forums and peer interactions, which often lead to more thoughtful engagement compared to synchronous settings (Brown et al., 2025). Despite these advantages, challenges such as delayed feedback and reduced interaction immediacy can hinder learner engagement and progression. To address these limitations, researchers have proposed integrating structured instructional design elements, such as metadata tagging and clearly defined learning objectives, to enhance content delivery and maintain student motivation in asynchronous contexts (Abhisheka & Chatterjee, 2019).

The integration of AI-enhanced pedagogies into asynchronous learning environments has introduced new opportunities for personalization, engagement, and scalability. AI-driven systems enable adaptive learning pathways, real-time feedback, and intelligent tutoring, thereby supporting individualized learning experiences and improving student outcomes (Al Nabhani et al., 2026; Kakhkharova & Tuychieva, 2024). Furthermore, AI facilitates collaborative knowledge construction and shared cognition through interactive tools that position learners as active participants in the learning process (Chawaremera, 2025; Sidorkin, 2026). It also enhances self-regulated learning by providing continuous feedback and data-driven insights, empowering students to take greater control of their learning trajectories (Xu & Zheng, 2025). Despite the growing body of research highlighting the complementary strengths of asynchronous learning and AI, existing studies predominantly position AI as a supplementary tool rather than a primary instructional mechanism. Consequently, there is a clear research gap in evaluating the effectiveness of fully AI-driven asynchronous learning environments.

5.2.4. Research Gap and Synthesis

Although prior research emphasizes the expanding role of AI in education and calls for stronger alignment between academia and industry (Z. Ali et al., 2025). A significant gap persists in how AI is positioned within instructional frameworks. Existing studies consistently frame AI agents as supplementary or assistive tools that enhance engagement, personalization, and instructional support, rather than as primary teaching mechanisms. Similarly, in the context of asynchronous learning, the integration of AI has largely been explored as a complementary enhancement, with limited empirical investigation of fully AI-driven learning environments in which AI systems serve as the central instructional agent. This limitation is further compounded in domain-specific areas such as BIM-based QTO, where current educational approaches lack structured, scalable pedagogical models that effectively align with industry demands and digital workflows. Consequently, there is a clear need for research that moves beyond assistive applications of AI to evaluate its effectiveness as a primary instructional system in asynchronous learning environments.

5.3. Research Objectives

This study aimed to investigate the feasibility and instructional effectiveness of a custom-built AI agent as the primary instructional method for asynchronous BIM-based QTO through experimentation. The research included two primary objectives: (1) to develop a structured framework for designing AI agents as primary instructional tools, and (2) to assess students' perceptions of the effectiveness of a custom AI agent when used as the primary mode of instruction.

Unlike general-purpose AI systems that provide open-ended assistance and may generate incomplete or misaligned responses, the tested agent embedded instructional logic, sequencing, and constraints into its design to ensure accountable, reliable guidance. The research evaluated whether learners with limited prior BIM-based QTO experience could independently complete technical tasks through an AI-guided interactive session, and how the accuracy and consistency of AI-driven guidance influenced learner confidence and adoption intent.

5.4. Custom AI Agent Development

5.4.1. Development Platform Selection

Based on the comparison outlined in Table 5.11, MCS was selected as the platform for this study on AI-supported learning due to its alignment with several key criteria relevant to educational settings. The platform offers customization options that allow educators to adapt the agent to specific instructional content and includes basic dialogue tree support for managing structured interactions. In addition, it is compatible with existing university systems and provides a low-code environment, potentially reducing implementation-related technical barriers. MCS also allows for the sharing of customized agents and is available to students at no cost. These combined features made it a practical choice for exploring the potential of AI-driven tools to support learning in a university context.

Table 5.11. Comparison of Custom AI Agent Platforms for Educational Use

Criteria	**MCS**	**ChatGPT**	**Google Gemini**	**Meta AI**
Ability to customize agents using specific instructional content	✓	✓	✗	✗
Ability to share customized agents with other users	✓	✓	N/A	N/A
Free access for students	✓	✓	✓	✓
Integration with existing university ecosystems (e.g., Microsoft, LMS)	✓	✗	✗	✗
Low-code environment (minimal programming skills required)	✓	✓	N/A	N/A
Conversation management with dialogue tree or flowchart support	✓	✗	✗	✗

MCS is a user-friendly, low-code platform that enables the creation of AI agents and agent flows, making sophisticated automation accessible to users without extensive technical expertise. A key feature of MCS is its ability to integrate with external data sources via prebuilt or custom plugins, enabling the creation and management of complex workflows. This ensures agents can deliver powerful, intuitive user experiences. With its low-code interface, MCS democratizes AI by enabling individuals from diverse backgrounds to design and deploy agents that handle tasks such as customer support, sales assistance, and employee services across multiple channels, including websites, mobile apps, and Microsoft Teams. Users can create agent flows to automate repetitive tasks and integrate different services, with flows that can be triggered by events (iaanw, 2025).

5.4.2. Building the Agent in Microsoft Copilot Studio

The AI agent was developed within the low-code environment of MCS and was named “Revit Tutor,” with a user-facing description defined as “A virtual teaching assistant for students in the construction management program, specializing in Revit Architecture software.” The agent used the GPT-4.1 LLM, the default configuration recommended by MCS for conversational agents. To ensure consistent, pedagogically aligned responses, the agent’s behavior was guided by structured natural-language instructions covering multiple dimensions, including core responsibilities, response guidelines, communication style, student engagement strategies, and escalation protocol limitations. Additionally, the agent was connected to a curated and restricted knowledge base verified by the researcher, ensuring that all responses remained within the defined instructional scope of BIM-based QTO. This knowledge base served as the sole reference for the agent and included a transcript of a recorded lecture that represented the traditional instructional approach (instructor demonstration followed by a class exercise), as well as supporting materials such as Autodesk Assemble help documentation, troubleshooting resources, and Revit Architecture and Structure content.

5.4.3. Dialogue Tree Architecture Design

The dialogue tree architecture was designed as a structured, rule-based instructional workflow embedded within the custom AI agent developed in MCS. The process begins with user input, where a student initiates interaction by expressing intent to learn Autodesk Assemble. This triggers the agent topic through intent recognition, activating a guided dialogue sequence tailored to the learning objective (see Figure 5.23). Unlike open-ended AI systems, the agent operates through a predefined dialogue tree that integrates instructional logic, adaptive questioning, and conditional branching. The system evaluates whether prerequisite conditions, such as uploading a Revit model, are met and, if not, dynamically provides step-by-step guidance to complete those tasks. This ensures that learners progress through a validated instructional pathway rather than receiving unstructured or potentially incomplete responses.

Furthermore, the architecture incorporates progress tracking and decision checkpoints to maintain instructional accountability and continuity. The agent stores user responses as variables and uses conditional logic to verify task completion before advancing to subsequent steps, such as opening Assemble, navigating the interface, and selecting takeoff categories (e.g., rebar, structural steel, concrete). This scaffolded approach allows the agent to simulate an instructor-led experience within an asynchronous environment, ensuring that students remain aligned with the intended learning sequence. The dialogue tree also supports adaptive intervention, such as providing orientation guidance when users indicate unfamiliarity with the interface, and concludes with a validation step confirming task completion. Overall, this architecture demonstrates how a custom AI agent can operate structured pedagogy through a dialogue-driven system, positioning it as a primary instructional tool rather than merely a supplementary aid.

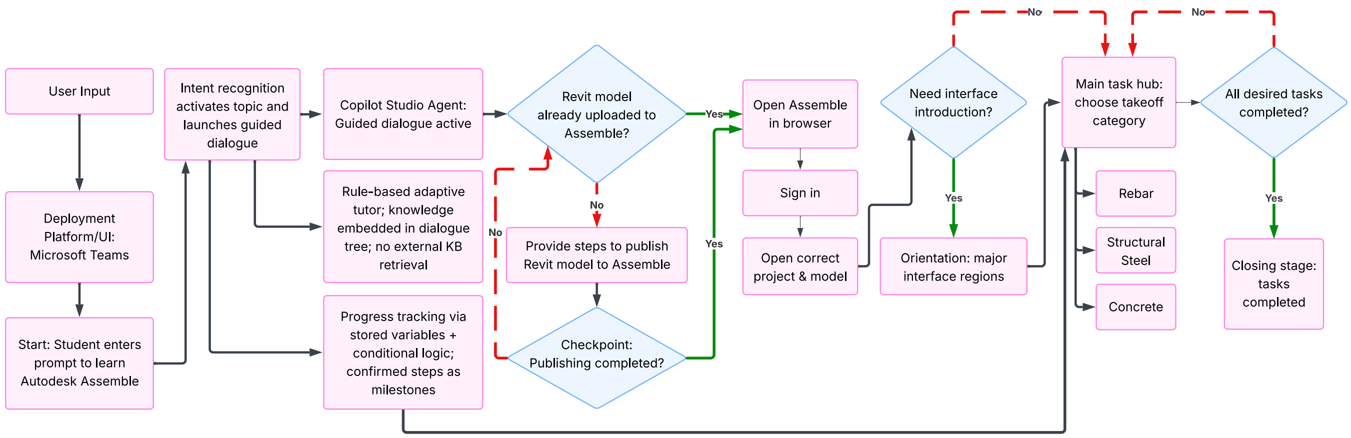

Figure 5.23. Dialogue-tree architecture of the AI agent illustrating guided workflow and conditional logic for BIM-based QTO learning in Autodesk Assemble.

5.4.4. The AI Agent Deployment Channel

The AI agent's deployment channel was implemented via Microsoft Teams, ensuring alignment with both the development environment and the institution's existing communication and security infrastructure. This integration enabled a cohesive ecosystem in which data management, course delivery, and student interactions were maintained on a unified, secure platform. Although access to the chatbot required authentication via university accounts, student anonymity was preserved because no personal identifiable information was collected or stored. Figure 5.24 presents the user interface and a representative example of student chatbot interaction. The AI agent was deployed as a text-based chatbot within Teams.

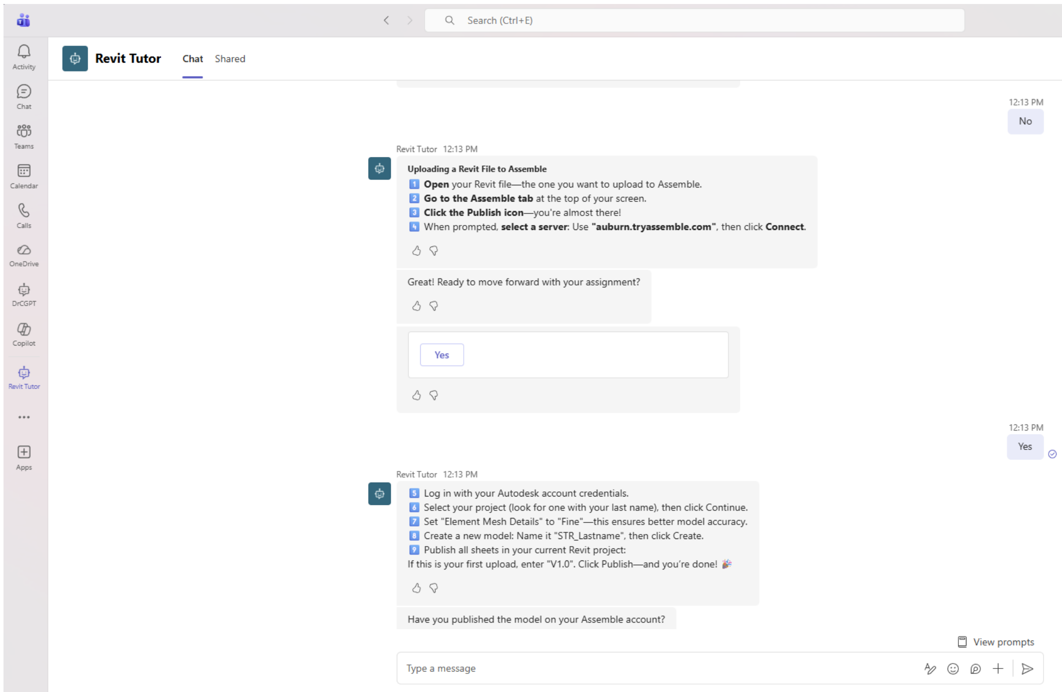

Figure 5.24. The AI agent in Microsoft Teams guides the upload of a Revit model to Assemble through step-by-step prompts.

5.5. Methodology

5.5.1. Experimental Design and Classroom Implementation

The experiment was conducted across eight sections of a senior-level undergraduate course titled ‘Construction Information Technology II’, offered over two consecutive academic semesters. In total, the study involved 114 students enrolled in the course during the Spring and Fall 2025 terms. This course introduces construction management students to emerging digital tools and workflows used in the industry, with particular emphasis on BIM applications. One of the primary technologies covered in the course is Autodesk Assemble, which students use for BIM-based QTO and analyzing construction model data. The experiment took place in the students' regular classroom setting, allowing the activity to be embedded naturally within the course structure.

The researcher introduced the custom AI learning agent and provided students with an overview of its purpose and functionality at the beginning of each session. The installation and access process was demonstrated through Microsoft Teams to ensure that all participants could successfully launch the agent before beginning the exercise. To standardize the starting point for all participants, the researcher instructed students to initiate their interaction with a predefined prompt. Each student was asked to type the phrase, "I want to learn Assemble," which activated the AI agent and initiated the guided learning sequence. Once triggered, the AI agent delivered structured, interactive, step-by-step instructions designed to teach students how to recognize and interpret specific symbols relevant to BIM-based workflows.

5.5.2. Post-Experiment Survey Instrument

The experimental activity was designed to last up to 60 minutes, although completion time varied among participants. Immediately after completing the activity, students were asked to complete an anonymous online questionnaire administered through the Qualtrics platform. Each student interacted with the AI agent independently on their own device and completed the survey individually. The post-experiment questionnaire served as the primary instrument to assess students' perceptions of the AI agent and its instructional effectiveness in supporting BIM-based QTO tasks in Autodesk Assemble. The survey collected both quantitative and qualitative data related to the agent's effectiveness, accuracy, clarity of guidance, usability, instructional quality, and overall usefulness as a learning tool

The survey instrument used a mixed-methods design, comprising Likert-type items, multiple-choice questions with categorical responses, and open-ended prompts (see Figure 5.25). This combination enabled the study to collect structured numerical data suitable for statistical analysis while also capturing richer qualitative feedback on students' experiences. The survey items were organized around three primary thematic areas: (1) students' prior exposure to Autodesk Assemble and their baseline familiarity with BIM-based QTO workflows, (2) perceptions of the AI agent's instructional quality, including the usefulness and accuracy of its responses, and (3) students' overall learning outcomes, satisfaction, and willingness to adopt AI-supported learning tools in the future. Table 5.12 summarizes the survey structure by grouping the questions according to their respective evaluation dimensions.

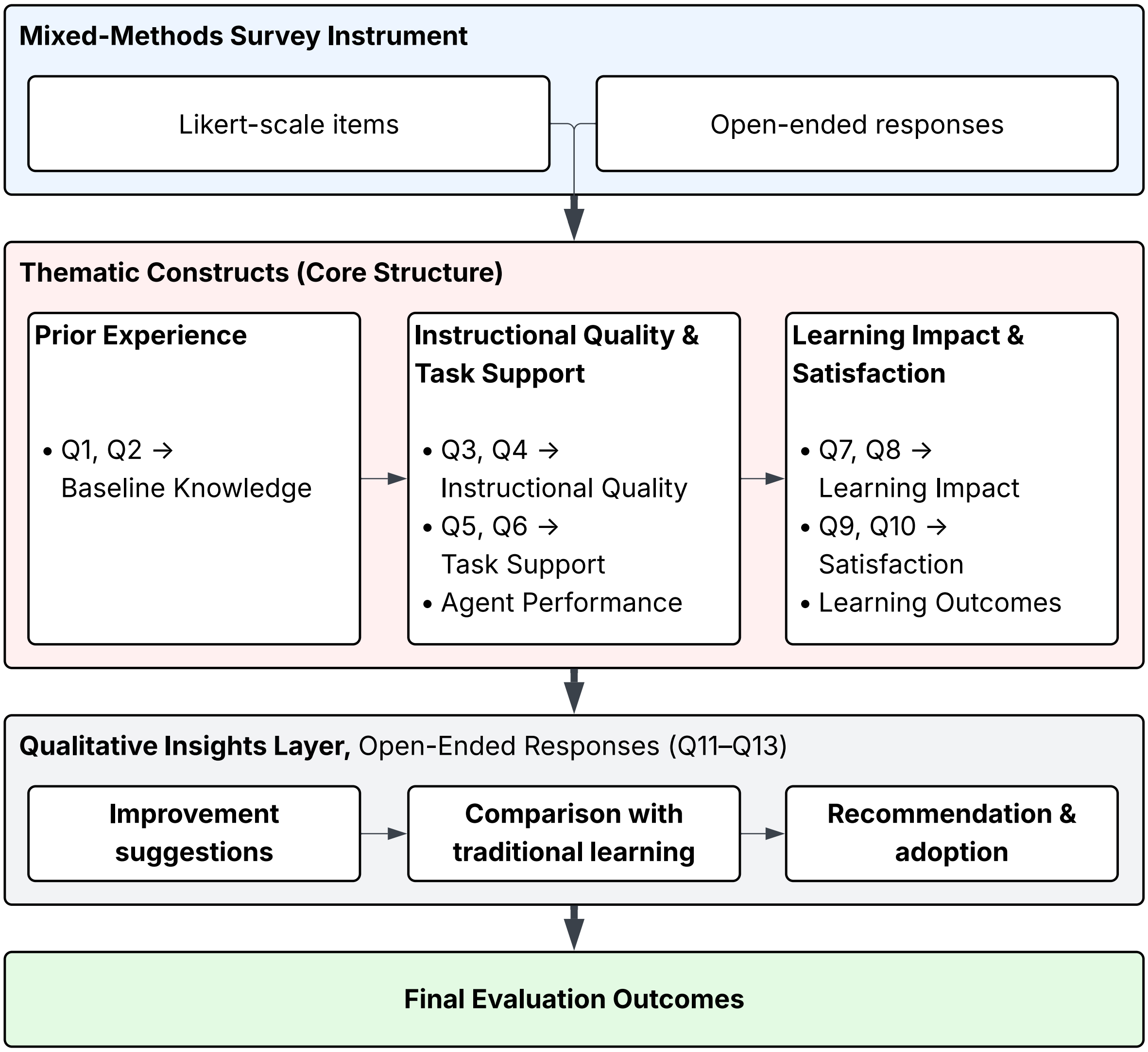

Figure 5.25. Mixed-methods survey design and thematic structure

Table 5.12. Post-experiment questionnaire design

N.	Question	Construct	Scale	MIN	MAX
Q1	Have you used Autodesk Assemble before this course?	Prior Experience	3-point	No, this is my first time.	Yes, I have used it extensively.
Q2	Before using the chatbot, how would you rate your familiarity with Autodesk Assemble?	Prior Experience	5-point	Not familiar at all	Extremely familiar
Q3	How useful was the chatbot in explaining Autodesk Assemble concepts?	Instructional Quality	5-point	Not at all useful	Extremely useful
Q4	Did the chatbot provide accurate and relevant responses to your questions?	Instructional Quality	5-point	Never	Always
Q5	Did the chatbot help you complete tasks within Autodesk Assemble (e.g., model navigation, data extraction, quantity takeoff)?	Task Support	3-point	No, I still struggled with the tasks.	Yes, it was very helpful.
Q6	How often did you need additional help from the instructor after interacting with the chatbot?	Task Support	5-point	Never	Always
Q7	After using the chatbot, how would you rate your confidence in using Autodesk Assemble?	Learning Impact	5-point	Not confident at all	Completely confident
Q8	Compared to traditional learning (e.g., lectures, manuals, YouTube), how effective was the chatbot in helping you understand Autodesk Assemble?	Learning Impact	5-point	Much less effective	Extremely effective
Q9	Would you prefer to use the chatbot again in future learning?	Satisfaction	3-point	No, I would rather use traditional methods	Yes, definitely
Q10	How satisfied are you with the chatbot experience?	Satisfaction	5-point	Extremely dissatisfied	Extremely satisfied
Q11	In what ways could the chatbot be improved to better assist learning Autodesk Assemble?	Instructional Quality	(Open-ended text response)		
Q12	How did your experience with the chatbot compare to traditional learning methods (e.g., instructor-led, textbooks, online tutorials)?	Learning Impact	(Open-ended text response)		
Q13	Would you recommend using an AI chatbot to other students learning Autodesk Assemble? Why or why not?	Satisfaction	(Open-ended text response)		

The questionnaire included 13 items designed to capture students' background, perceptions, and experiences with the AI-supported learning activity. The first two questions (Q1–Q2) established participants' prior exposure to Autodesk Assemble and familiarity with BIM-based QTO, providing context for interpreting later responses. Questions Q3–Q8 focused on evaluating the AI agent's instructional performance, including clarity, response accuracy, support in completing tasks, and its role in reducing reliance on the instructor. Questions Q9–Q10 examined broader learning outcomes, such as satisfaction and willingness to use the AI tool in future learning. The survey concluded with three open-ended questions (Q11–Q13) to capture qualitative insights on challenges, benefits, and suggestions for improvement. Different response scales were used: selected items employed a three-point scale for experience and frequency, while perception-based items used a five-point Likert scale, with higher values indicating more positive evaluations.

5.6. Results

5.6.1. Internal Consistency

An internal consistency analysis was conducted to examine both baseline experience items and post-intervention perception measures. For prior experience with Autodesk Assemble, Spearman's rank-order correlation and Cronbach's alpha were computed because the data were ordinal. The two baseline items, capturing prior usage and self-reported familiarity, showed a positive association ($\rho = 0.644$, $p < 0.001$), as illustrated in Figure 5.26, along with acceptable reliability ($\alpha = 0.728$), with confidence intervals ranging from 0.61 to 0.83 and corrected item–total correlations of 0.67. A second analysis evaluated relationships among perception-based items (Q3, Q4, Q5, Q7, Q8, Q9, and Q10) that represent instructional quality, task support, learning impact, and satisfaction. The Spearman correlation matrix in Figure 5.27 showed moderate associations, with coefficients ranging from 0.22 to 0.61. The strongest relationships were observed between Q3 and Q10 (0.61), Q8 and Q10 (0.55), and Q3 and Q8 (0.53), while other pairwise correlations remained within a similar moderate range.

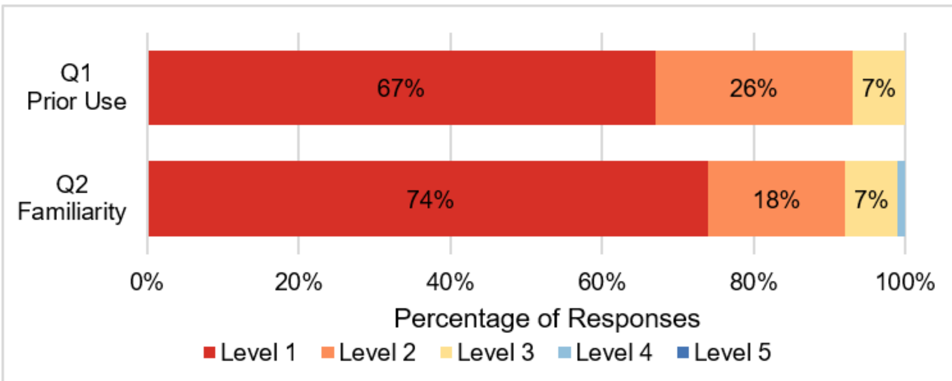

Figure 5.26. Response distribution for Q1 (Prior Use) and Q2 (Familiarity)

5.6.2. Prior Experience

All participants were senior-level undergraduate students enrolled in a Construction Information Technology course within a Construction Management program. Prior to the experiment, most reported limited exposure to BIM-based QTO. In response to Q1, the majority indicated little to no prior experience with Autodesk Assemble (Figure 5.27). On a five-point Likert scale, the mean score was 1.4, well below the midpoint of 3, reflecting low familiarity across the cohort. This baseline is important for interpreting the results, as it indicates that participants entered the activity with minimal prior knowledge. As such, the dataset represents a population suitable for evaluating the effectiveness of the AI-assisted learning approach, since the instructional intervention was introduced to students without substantial prior experience in BIM-based QTO workflows.

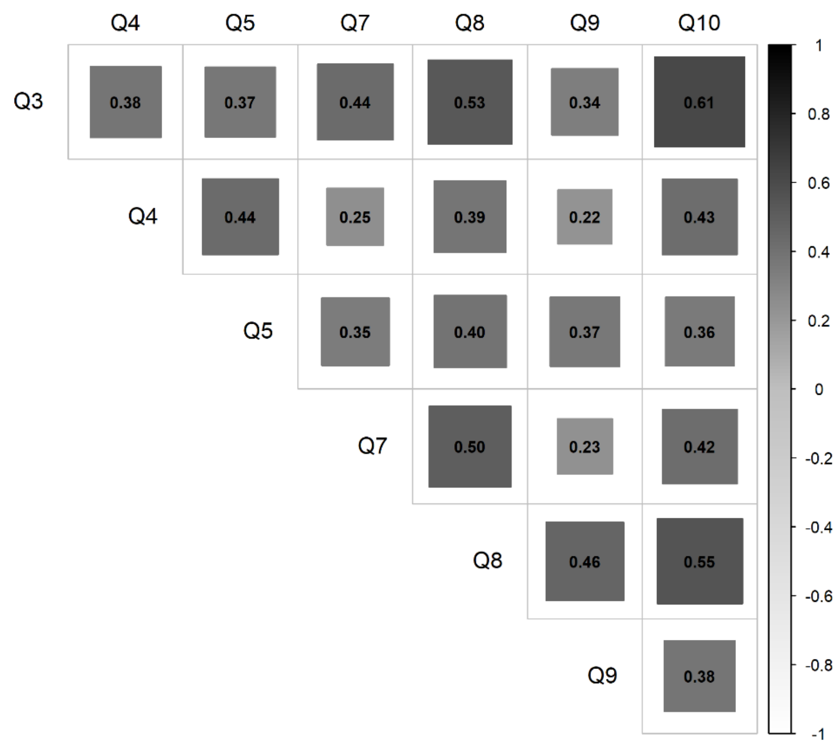

Figure 5.27. Spearman correlation matrix of survey items representing students' perceptions, with correlation coefficients displayed within each cell.

This baseline finding was further supported by Q2, which assessed self-reported familiarity with Autodesk Assemble prior to interacting with the agent. Responses again reflected limited prior exposure, with a mean score of 1.39 on a five-point scale, and most students selected the lowest familiarity levels. The consistency between Q1 and Q2 indicates alignment between reported experience and perceived familiarity, suggesting reliable baseline measures. This agreement strengthens the dataset by confirming that participants had minimal prior knowledge before the intervention.

5.6.3. Instructional Quality

Students' perceptions of the chatbot's usefulness in explaining Autodesk Assemble concepts were evaluated using a five-point Likert scale Q3. Overall, participants reported high levels of perceived usefulness, with a mean score of 4.11 (SD = 0.72). The median and mode were both 4, indicating that the most common response was "useful." Nearly half of the participants (53%) selected a rating of 4, while 30% rated the chatbot as very useful (5). Only a small proportion of responses fell below the midpoint of the scale: 16% selected 3, and 2% selected 2, with no respondents selecting the lowest rating (Figure 5.28). These results suggest that most students perceived the chatbot as an effective instructional method for explaining Autodesk Assemble concepts during the learning activity.

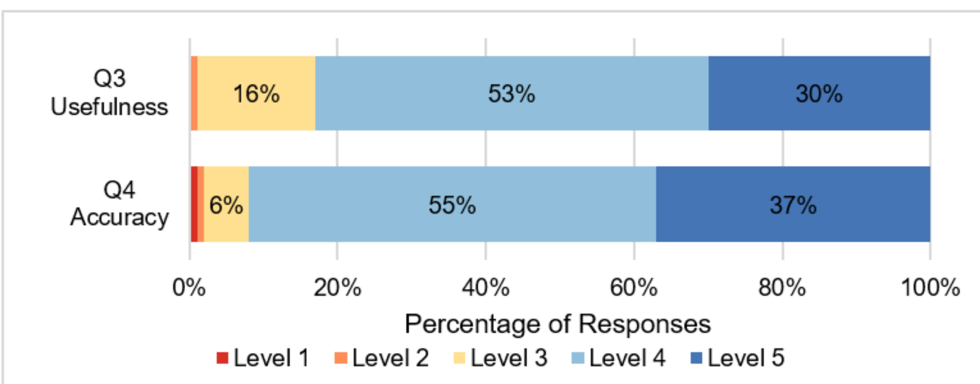

Figure 5.28. Response distribution for Q3 (Usefulness) and Q4 (Accuracy).

Students' perceptions of the accuracy and relevance of the chatbot's responses were evaluated using a five-point Likert scale Q4. Overall, participants reported high satisfaction with the chatbot's responses, with a mean score of 4.26 (SD = 0.69). The media and mode were both 4, indicating that the most common response was that the chatbot provided accurate and relevant information. More than half of the respondents (55%) rated the chatbot at 4. In comparison, 37% selected the highest rating of 5, suggesting that most students perceived the chatbot as highly reliable in answering their questions. Only a small proportion of participants provided ratings below the midpoint (Figure 5.28). These findings indicate that students generally perceived the chatbot as a trustworthy and relevant source of instructional methods for understanding the topic.

5.6.4. Task Support

Participants were asked in Q5 to evaluate whether the chatbot assisted them in completing tasks in Autodesk Assemble, including model navigation, data extraction, and QTO. Overall, students reported strong positive perceptions of the chatbot's ability to support task completion, with a mean score of 2.82 (SD = 0.41) on a three-point scale. The median and mode were both 3, indicating that the most frequent response was the highest rating available on the scale. A large majority of participants (82%) selected the highest rating (3), suggesting that the chatbot effectively supported students in performing practical tasks within the software environment. Approximately 17% of respondents indicated moderate support (rating of 2), while only one participant (0.9%) reported that the chatbot did not help with task completion (Figure 5.29). These findings suggest that the chatbot was a useful instructional tool.

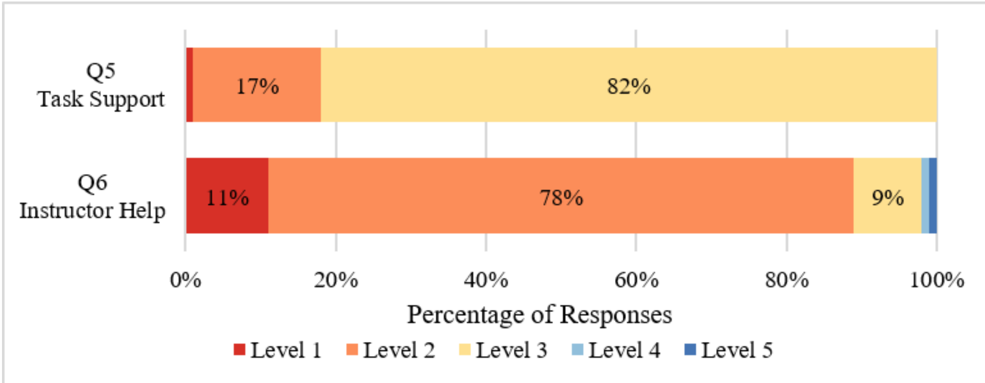

Figure 5.29. Response distribution for Q5 (Task Support) and Q6 (Instructor Help)

Participants were asked Q6 to report how frequently they required additional help from the instructor after interacting with the chatbot during the learning activity. Overall, the responses indicate a relatively low reliance on instructor assistance, with a mean score of 2.05 (SD = 0.62) on a five-point scale. The median and mode were both 2, suggesting that most students required only occasional instructor support after consulting the chatbot. A large majority of participants (78%) selected a rating of 2, while 11% reported rarely needing additional help (rating of 1). Only a small proportion of students indicated moderate or frequent need for instructor intervention, with 9% selecting 3, and fewer than 3% selecting 4 or 5. These findings suggest that the chatbot was generally effective in addressing students' questions and reducing the need for direct instructor assistance.

5.6.5. Learning Impact

Students were asked in Q7 to evaluate their level of confidence in using Autodesk Assemble after completing the learning activity supported by the chatbot. The results indicate a moderate increase in perceived confidence, with a mean score of 3.14 (SD =

0.78) on a five-point Likert scale. The median and mode were both 3, indicating that the most common response reflected a moderate level of confidence. Nearly half of the participants (53%) selected a rating of 3, while 26% reported higher confidence with a rating of 4, and 4% selected the highest rating of 5. A smaller proportion of students reported lower confidence levels, with 16% selecting 2 and 2% selecting 1 (Figure 5.30). Overall, these findings suggest that the chatbot-supported learning activity improved students' confidence in navigating and using Autodesk Assemble, although most students still reported developing rather than fully mastering it.

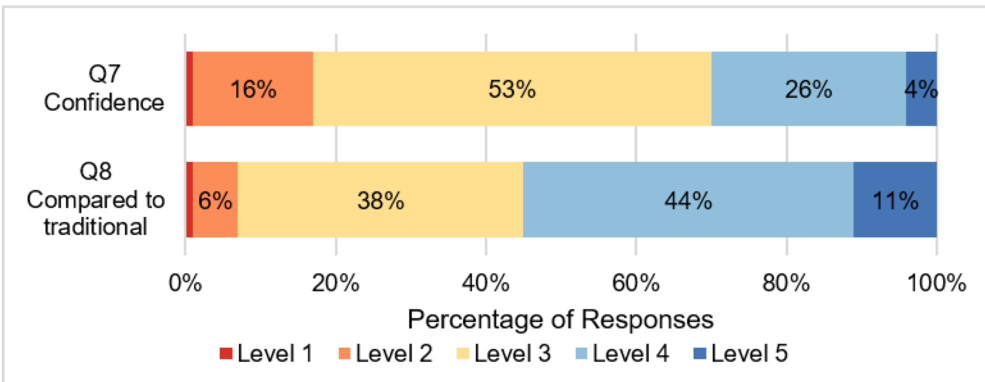

Figure 5.30. Response distribution for Q7 (Confidence) and Q8 (Compared to Traditional)

Participants were asked in Q8 to compare the chatbot's effectiveness with traditional learning methods such as lectures, written manuals, and instructional videos. Overall, students rated the chatbot as relatively effective in supporting their understanding of Autodesk Assemble, with a mean score of 3.55 (SD = 0.83) on a five-point Likert scale. The median and mode were both 4, indicating that the most common response was that the chatbot was more effective than traditional learning resources. The results suggest that more than half of the participants perceived the chatbot as highly effective for learning. Additionally, 38% of respondents selected 3, indicating that they perceived the chatbot to be comparable in effectiveness to traditional instructional approaches. Only a small proportion of participants rated the chatbot as less effective than traditional learning methods: 8% selected 2, and 1.8% selected 1.

5.6.6. Satisfaction

Students were asked in Q9 whether they would prefer to use the chatbot again in future learning activities. The results indicate a strong positive preference for continued use of the chatbot, with a mean score of 2.61 (SD = 0.55) on a three-point scale. The median and mode were both 3, indicating that the most common response was the highest level of preference. A majority of participants (65%) selected 3, indicating that they would prefer to use the chatbot again in future learning environments. Approximately 32% of respondents selected 2, suggesting a moderate willingness to reuse the chatbot, while only 4% indicated they would not use it again (Figure 5.31). These findings suggest that students generally viewed the chatbot as a valuable learning resource and expressed a strong interest in integrating similar AI-assisted tools into future educational activities.

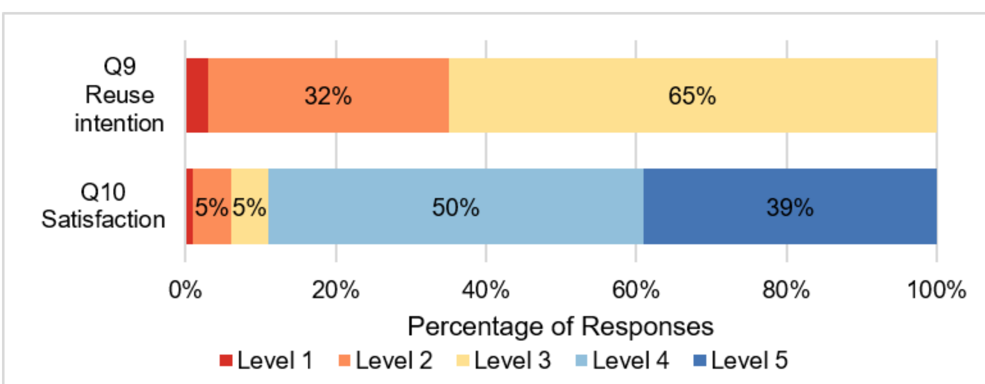

Figure 5.31. Response distribution for Q9 (Resue Intention) and Q10 (Satisfaction)

Participants were asked in Q10 to evaluate their overall satisfaction with the chatbot-supported learning experience using a five-point Likert scale. The results indicate high levels of overall satisfaction, with a mean score of 4.20 (SD = 0.83). The median and mode were both 4, suggesting that the most common response reflected a high level of satisfaction with the learning experience. More than half of the participants (50%) rated their satisfaction as 4, while 39% selected the highest rating of 5, indicating that a substantial proportion of students were very satisfied with the chatbot interaction. Only a small number of participants reported lower levels of satisfaction: 5% selected 3, 5% selected 2, and 0.9% selected 1.

5.6.7. Qualitative Results

A thematic coding approach was applied to the open-ended responses (Q11–Q13) to systematically identify recurring patterns and meanings within the data. Initial codes were generated directly from participants' statements and iteratively grouped into higher-level themes through a process of categorization and refinement. To provide a structured overview, the identified themes were further quantified by calculating their frequency within each question. The five most frequent themes for each question, along with their corresponding frequencies and representative quote excerpts, are summarized in Table 5.13.

Table 5.13. Top five themes by question with frequencies and quotes

Question	Theme	(n)	Quote examples
Q11 Improvement Suggestions	Instruction Clarity	14	"More clear with instruction of what to select…"; "It explained the steps…"
	No Issues / Positive Feedback	14	"I think its great as is…"; "It did the best it could…"
	Response Accuracy	10	"It struggled to answer my question…"; "It would be helpful if it could answer questions outside of the designated script…"
	Understanding Natural Language	7	"Clarifying the apps each step is referring to…"; "Needs to be a little more used to human speech so that it does not switch…"
	Follow-up Interaction	6	"If ask a follow up question to their explanation have a better response…"; "More prompts to further discussion after answer…"
Q12 Learning Experience	Self-paced Learning	16	"I felt like I was able to work at my own pace…"; "Didn't have to wait to ask a question…"
	Faster & Efficient	16	"Didn't have to wait to ask a question…"; "It was more efficient…"
	Step-by-Step Guidance	15	"Step by step learning is best for me…"; "It was faster and I was able to follow steps…"
	Positive General Satisfaction	13	"Very good…"; "Good, more individually paced learning…"
	Better than Traditional Methods	13	"I liked it better…"; "Chatbots are much better than traditional textbooks…"
Q13 Recommendation Intent	Positive Recommendation	69	"Yes, It helps you learn how to use it very effectively…"; "Yes!! Very helpful and could work through my own time…"
	Clear Step-by-Step	16	"Yes, It helps you learn how to use it very effectively…"; "Yes because a chatbot was very clear and concise…"
	Quick & Efficient	12	"Yes, helpful tool when looking for a quick in depth answer…"; "Yes, because it can always give you a quick answer unlike teachers or videos…"

Question	Theme	(n)	Quote examples
	Caveats or Improvements Needed	9	“Yes, helpful tool when looking for a quick in depth answer…”; “Yes, but only if the exact assignment has already been curated in the chatbot…”
	Alternative to Instructor	8	“Yes. Easy access, and it guides you through the steps…”; “Yes, it is a great tool when there is no teacher…”

Participants’ suggestions for improving the chatbot (Q11) centered on clarity and usability. The most common theme was the need to improve the agent’s instruction clarity (14 comments). Students described getting “lost on which app to click” and called for instructions that explicitly name buttons, menus, and small details. A similarly large group (14) reported no issues and provided positive feedback about the chatbot. Ten students addressed response accuracy; some users noted that the bot sometimes “struggled to answer” or simply restated their question, and they wanted it to handle troubleshooting queries outside its script.

Responses to Q12 indicate that several themes were consistently observed in students’ descriptions of their learning experience with the chatbot. Self-paced learning and perceived efficiency were among the most frequently noted aspects, with participants emphasizing the ability to proceed independently and obtain immediate responses without waiting. Closely related to this, step-by-step guidance was commonly mentioned, suggesting that structured instructions supported task completion and navigation. In addition, a number of responses reflected general satisfaction, often described in simple and concise terms, indicating an overall acceptable or favorable experience. Comparisons with traditional learning methods were also present, with some participants expressing a preference for the chatbot over conventional resources such as textbooks or instructor-led approaches. These themes collectively reflect patterns in how students described pacing, accessibility, and instructional support during the learning process.

Responses to Q13 indicate that most participants were willing to recommend the chatbot to others, with many indicating that it effectively supported learning and allowed flexible use at their own pace. In addition to general recommendations, several responses highlighted the clarity of step-by-step guidance, suggesting that structured explanations contributed to understanding the tasks. Efficiency was also noted, with participants referring to the ability to obtain quick answers when needed. At the same time, some responses included conditional statements, suggesting that the chatbot's effectiveness may depend on the scope of its content or how well it aligns with specific assignments. A smaller group of responses described the chatbot as a potential alternative source of instruction, particularly when direct instructor support is limited or unavailable. These themes reflect variations in how participants framed their willingness to recommend the tool and the conditions under which they would use it.

5.7. Discussion

5.7.1. Discussions of Quantitative Findings

The low mean scores for prior experience and familiarity (Q1 = 1.40; Q2 = 1.39) indicate that most students had little to no prior exposure to Autodesk Assemble. This is a critical point of interpretation, as it confirms that the AI agent was not evaluated with experienced users who may already possess procedural knowledge, but rather with learners encountering BIM-based QTO for the first time. Consequently, the observed learning outcomes can be attributed primarily to the AI system's instructional role rather than to prior knowledge or experience. In addition, these findings reinforce the documented gap between academic preparation and industry expectations in BIM competencies (Alathamneh et al., 2024).

The findings related to instructional quality further reinforce the effectiveness of the AI agent as a teaching mechanism. High mean scores for perceived usefulness (Q3 = 4.11) and accuracy (Q4 = 4.26) indicate that students found the system informative and reliable. Rather than simply providing generic responses, the agent appears to have delivered structured, context-relevant explanations that were aligned with learners' needs. This outcome is consistent with prior studies demonstrating that AI-powered tools enhance learning efficiency and provide responsive support in education (Camargo et al., 2025; Zhao et al., 2025). However, unlike existing implementations that position AI as a supplementary tool, these findings suggest that a structured, dialogue-driven system can function as a primary instructional mechanism, directly addressing the gap identified in the literature.

Regarding task support, the results demonstrate that the AI agent enabled students to perform technical BIM tasks with a high degree of independence. The high proportion of students reporting successful task completion (Q5 mean = 2.82 on a three-point scale) and the low reliance on instructor assistance (Q6 median = 2) suggest that the agent served as an operational guide during hands-on activities. The findings imply that the AI system was capable of scaffolding user actions, allowing students to navigate model environments, extract data, and perform QTO tasks without human intervention. This aligns with prior research highlighting the role of AI agents in supporting guided problem-solving and task execution through adaptive feedback and instructional scaffolding (Jiang et al., 2024).

The learning impact results further highlight the agent's contribution beyond immediate task execution. Students reported moderate to high levels of confidence after the activity (Q7 mean = 3.14) and perceived the chatbot as at least comparable to traditional instructional methods (Q8 mean = 3.55). These outcomes suggest that the AI agent provided not only procedural guidance but also support for the development of self-efficacy in using BIM tools. While confidence levels indicate that students were still developing skills rather than mastering them, the shift toward higher confidence reflects meaningful learning gains within a relatively short instructional period. These findings are consistent with prior studies indicating that AI-enhanced learning environments can improve student confidence, engagement, and self-regulated learning behaviors (Al Nabhani et al., 2026; Xu & Zheng, 2025).

Finally, the satisfaction and adoption-related measures indicate strong acceptance of the AI-driven learning approach. The majority of students expressed a preference for reusing the chatbot in future learning scenarios (Q9), and overall satisfaction levels were high (Q10 mean = 4.20). These findings suggest that students not only recognized the functional benefits of the system but also valued the learning experience it provided. The combination of usability, perceived effectiveness, and positive user experience positions the AI agent as a viable instructional approach within this learning topic. However, the results suggest that such benefits can be achieved even when AI is positioned as the primary instructional source, rather than as a complementary support tool.

5.7.2. Discussions on Qualitative Finding

The qualitative findings reinforce the quantitative results by highlighting how students experienced the AI agent as an instructional tool in practice. A dominant theme across responses was the value of clear, structured, and step-by-step guidance, with many students emphasizing the importance of explicitly identifying buttons, menus, and procedural details. This suggests that learners particularly benefited from the agent's ability to break down complex BIM workflows into manageable steps, reducing cognitive load and supporting task execution. This observation aligns with prior research indicating that structured and guided instructional approaches can reduce cognitive load and enhance learning effectiveness, particularly when students are introduced to complex digital workflows (Abouelkhier et al., 2024). Additionally, students appreciated the ease of interaction and the immediacy of responses, noting that the chatbot enabled self-paced learning and eliminated delays in instructor feedback.

At the same time, the feedback reveals important limitations that point to areas for improvement. Several students reported challenges with response specificity, conversational flexibility, and handling edge cases beyond the predefined instructional flow. These limitations are consistent with prior literature highlighting challenges related to AI adaptability, response accuracy, and the need for human oversight in educational applications (Hortal et al., 2025; Woźniak & Nowobilski, 2025). While the structured architecture enhances reliability, these findings suggest a trade-off between instructional control and conversational flexibility. Furthermore, requests for visual aid and enhanced troubleshooting capabilities indicate a need to extend the system beyond text-based guidance.

Overall, these findings extend existing literature by providing empirical evidence that challenges the traditional positioning of AI as merely supportive. Students were able to complete technical BIM tasks independently, demonstrated low reliance on instructor intervention, and reported high levels of perceived effectiveness, confidence, and satisfaction. These outcomes indicate that the AI agent did not function solely as a supportive tool but rather as the central source of instruction guiding the learning process. The structured dialogue-tree architecture and constrained knowledge base enabled consistent, step-by-step instructional delivery, supporting both conceptual understanding and procedural execution. Consequently, this study demonstrates that well-designed AI agents can replace portions of traditional instruction and effectively support fully asynchronous learning environments. This contribution advances the literature by moving beyond assistive applications of AI and providing evidence for its role as a primary instructional system in domain-specific, technical education contexts.

5.8. Conclusions

This chapter presented a structured framework for developing custom AI agents as primary instructional tools in construction education and examines their feasibility within an asynchronous learning environment. By leveraging a low-code platform, the proposed approach lowers technical barriers and enables educators to design domain-specific AI agents without programming expertise. The selected application, BIM-based QTO, addresses a well-documented gap between industry demands and existing educational practices, where students often lack the competencies required for effective implementation. The findings demonstrate that a custom-built AI agent, grounded in a dialogue-tree architecture and supported by a controlled knowledge base, can guide learners through complex tasks independently, enhance engagement, and support self-paced learning.

At the same time, the study also emphasizes the shadows of AI, aligning with the broader discourse that cautions against uncritical adoption. While the agent proved effective at delivering structured guidance, limitations in conversational flexibility, contextual understanding, and reliance on predefined workflows highlight the challenges of positioning AI as a standalone instructional authority. The absence of human interaction, limited adaptability to off-script scenarios, and dependence on self-reported perceptions suggest that AI should be integrated thoughtfully rather than treated as a full replacement for instructors. Ultimately, this research contributes to a more nuanced understanding of AI in construction education, advocating for responsible integration that leverages its benefits while acknowledging its limitations.

Chapter 6. Conclusions, Limitations, and Future Research

6.1. Conclusions

6.1.1. RQ1. What is the current state of BIM-based QTO, particularly in terms of its key benefits, challenges, and future opportunities in research and practice?

The first objective of this dissertation was to examine the benefits, challenges, and future opportunities associated with BIM-based QTO. Through a systematic review guided by the PRISMA method, this study screened 238 journal articles and selected 52 relevant studies from Scopus® and Web of Science® for detailed analysis. The review provided a structured understanding of how BIM-based QTO has been studied, implemented, and discussed in the literature. It also helped identify key areas where the field has advanced, as well as areas where further development is still needed.

The findings indicate that BIM-based QTO has the potential to improve the productivity, accuracy, and completeness of QTO and cost-estimating tasks. By using information-rich BIM models, estimators and quantity surveyors can extract quantities more efficiently compared to traditional manual methods. BIM databases also offer opportunities to support broader practices, such as 5D BIM, life-cycle cost analysis, life-cycle assessment, and automated workflows via APIs and other digital tools. These opportunities suggest that BIM-based QTO is not only a technical estimating method but also part of a larger digital transformation in construction management.

At the same time, the review identified several recurring challenges. The most significant challenge is the limited BIM-related skill set among construction professionals, including both experienced estimators and entry-level quantity surveyors. Software functionality, data entry procedures, model quality, standardization, and the translation of codes and measurement standards into digital environments were also identified as important barriers. These challenges suggest that BIM-based QTO implementation depends not only on software availability but also on professional training, organizational readiness, and reliable digital workflows.

A major contribution of this objective is the development of a conceptual implementation model for BIM-based QTO. This model brings together findings from the reviewed literature and organizes them into a more unified framework. The model emphasizes that sustainable implementation requires attention to technical, managerial, educational, and professional factors. Overall, Objective 1 concludes that BIM-based QTO offers meaningful benefits for construction estimating, but its success depends on addressing skill gaps and improving software and data workflows. This research also identifies the need for more focused BIM-based QTO training and education to better prepare students and professionals for digital estimating practices.

6.1.2. RQ2. How can a custom Generative AI chatbot be developed for estimating courses in construction management education, and how effective is it in supporting student learning?

The second objective of this dissertation was to examine the value of a custom-built generative AI agent, DrCGPT, designed to support undergraduate students in a construction estimating course. The agent was developed in a low-code MCS environment and supported by transcribed lecture content via RAG.

The findings suggest that a course-specific AI tutor can provide students with useful support by offering consistent, on-demand assistance. Student feedback showed that 92.08% of participants reported a neutral-to-positive experience when interacting with the chatbot. This indicates that students were generally open to using a customized AI tool connected to course content. The study also found that many students had already used general-purpose chatbots, but they had limited experience with customized agents developed for a specific course or discipline. This distinction is important because course-specific AI agents can provide responses that are more aligned with instructional materials, terminology, and course expectations.

However, the results also show that students continue to value human support. When asked about help-seeking preferences, 41% of students preferred consulting the instructor, while 34.31% preferred asking classmates. These results suggest that AI agents can support learning but do not necessarily replace the social and instructional roles of teachers and peers. Human interaction remains essential for clarification, encouragement, professional judgment, and contextual understanding. Therefore, the value of DrCGPT is best understood as a supplemental instructional tool while in some cases it may also serve as a primary instructional medium for guiding students through specific learning tasks, as reflected in Objective 3.

This objective also demonstrates the practical value of low-code platforms for construction education. By using MCS, the AI agent could be developed without requiring advanced programming expertise. This is important for educators who may have strong domain knowledge but limited technical development experience. The findings suggest that similar customized agents could be developed for other construction courses, including Structures, Construction Information Technology, Safety, Scheduling, and MEP. Overall, Objective 2 concludes that custom generative AI agents can improve access to course-specific support, but their integration should be designed to complement instructor guidance and peer learning.

6.1.3. RQ3. How can a custom AI agent with a predesigned dialogue-tree architecture serve a central instructional role in asynchronous preconstruction education?

The third objective of this dissertation examined the feasibility of using custom AI agents as primary instructional tools in an asynchronous construction education environment. This objective was built on earlier findings by moving beyond supplemental support to investigate how a structured AI agent could guide students through BIM-based QTO learning activities with limited direct instructor involvement. The study proposed a framework for developing custom AI agents using a low-code platform, a dialogue-tree architecture, and a controlled knowledge base.

The findings indicate that a custom-built AI agent can guide learners through structured and procedural tasks, especially when the learning activity follows a clear sequence of steps. In the context of BIM-based QTO, the agent supported students by providing step-by-step guidance, helping them navigate task requirements, and encouraging self-paced learning. This is particularly relevant in construction education, where students often need to learn software-based workflows that require both technical understanding and procedural accuracy. The use of a dialogue-tree architecture organized the learning process into manageable pathways, reducing uncertainty and supporting independent task completion.

At the same time, the study highlights important limitations in using AI as a primary instructional tool. While the agent was useful for structured guidance, it had limitations in conversational flexibility, contextual understanding, and adaptability to off-script questions. These limitations are important because students do not always follow a predictable path when learning complex software or technical concepts. Some students may need individualized explanations, alternative examples, or motivational support that is difficult to provide fully within a predefined AI workflow.

6.1.4. Overall Conclusion of the Study

Together, the three objectives provide a connected understanding of BIM-based QTO, construction education, and the role of customized AI tools in addressing current educational and professional challenges. The first objective established the importance of BIM-based QTO and identified major implementation barriers, especially skills-related challenges. The second objective explored how a customized AI tutor can support students in a construction estimating course. The third objective extended this work by examining how custom AI agents can function as primary instructional tools in asynchronous BIM-based QTO learning.

The overall conclusion of this dissertation is that BIM-based QTO and generative AI are closely connected, driven by the broader need for digital upskilling in construction.

BIM-based QTO offers practical benefits for estimating and cost-related workflows, but its implementation depends on professionals and students being prepared to use BIM tools effectively. Custom AI agents can help address this gap by offering guided, course-specific, and accessible learning support. However, the findings also show that technology alone is not enough. Effective implementation requires thoughtful instructional design, reliable knowledge bases, appropriate human oversight, and continued evaluation of student learning outcomes.

This dissertation contributes to construction education by demonstrating how customized AI agents can be designed and evaluated within construction management contexts. It also contributes to BIM-based QTO research by linking implementation challenges to educational strategies. Rather than viewing AI as a replacement for instructors, this study positions AI as a tool that can support learning, increase access to guidance, and help students build confidence with technical workflows. The study concludes that responsible integration of AI in construction education should focus on alignment with course objectives, transparency about limitations, and continued attention to instructors' roles in supporting student learning.

6.2. Limitations of the Study

For Objective 1, the systematic review was limited to journal articles retrieved from Scopus® and Web of Science®. Although these databases provide access to high-quality peer-reviewed literature, the exclusion of conference papers, industry reports, dissertations, and professional guidelines may have limited the range of perspectives included in the review. This is especially relevant in BIM-based QTO, where practical knowledge is often shared through industry case studies, conference proceedings, software documentation, and professional training materials. The selected 52 articles provided a focused understanding of the topic, but they may not capture all emerging practices or recent developments in the industry. In addition, the classification of benefits, challenges, and future opportunities required interpretation of qualitative findings from different studies, which may introduce some subjectivity despite the use of a structured review process.

For Objective 2, the evaluation of DrCGPT was conducted in a single construction estimating course at one university. Therefore, the findings may not fully reflect student perceptions in other institutions, at different course levels, or in other construction education contexts. Students also continued to have access to the instructor and classmates throughout the course, so the study did not isolate the chatbot as the sole source of support. As a result, student perceptions of usefulness may have been influenced by the broader instructional environment. In addition, the study relied mainly on student feedback, which provides valuable insight into user experience but does not fully measure actual learning performance, knowledge retention, or long-term skill development. The chatbot’s knowledge base was also limited to selected course materials, which may have affected the range and depth of responses available to students.

For Objective 3, the study examined the feasibility of using a custom AI agent in an asynchronous learning environment, but the findings were limited by the structured nature of the learning task and the predefined dialogue-tree design. The agent was most suitable for procedural guidance, which may not fully represent more open-ended construction education tasks that require judgment, creativity, or complex problem-solving. The reliance on a controlled knowledge base helped improve consistency, but it also limited conversational flexibility and the ability to respond to unexpected student questions. In addition, the study depended partly on self-reported student perceptions, which may not fully reflect actual learning outcomes. These limitations suggest that while the framework is promising, additional testing is needed across different courses, tasks, student populations, and instructional settings.

6.3. Recommendations for Future Research

For Objective 1, future research should expand the scope of BIM-based QTO reviews by including conference papers, professional reports, software documentation, and industry case studies. This broader approach would help capture practical implementation experiences that may not appear in journal articles. Future studies could also compare BIM-based QTO adoption across different countries, project types, and professional roles to better understand how implementation challenges vary by context. More empirical studies are also needed to evaluate how BIM-based QTO affects estimating accuracy, productivity, collaboration, and decision-making in real project environments. In addition, future research should further investigate the role of APIs, BIM databases, NLP, LCC, and LCA in advancing BIM-based QTO workflows.

For Objective 2, future research should evaluate customized AI tutors across multiple construction courses and institutions. This would help determine whether student perceptions and usage patterns remain consistent in different educational settings. Future studies should also include direct measures of learning outcomes, such as pre- and posttests, assignment performance, task completion time, and retention of knowledge over time. It would also be useful to compare different types of AI support, such as general-purpose chatbots, course-specific chatbots, and instructor-supported AI systems. Additional research should examine how students decide when to ask the instructor, classmates, or an AI agent for help. Understanding these patterns can guide more effective integration of AI tools into construction education.

For Objective 3, future research should continue testing custom AI agents as primary instructional tools in asynchronous learning environments. Studies should examine how these agents perform when students complete more complex, open-ended, or multi-step construction tasks. Future work should also improve AI agents' adaptability by combining structured dialogue-tree workflows with more flexible conversational features. Research should investigate how human oversight can be integrated into asynchronous AI-supported learning without reducing student independence. In addition, future studies should consider ethical and responsible AI issues, including transparency, student data privacy, accuracy of responses, and appropriate boundaries for AI-generated guidance. These directions would help support the responsible and practical use of AI agents in construction education.

Together, these future research directions suggest an opportunity to connect BIM-based QTO advancement with AI-supported construction education and workforce upskilling. Future studies could examine how asynchronous AI agents may support practitioners in developing BIM-based QTO skills through self-paced, interactive, and task-oriented learning environments. This direction may be especially relevant for industry professionals who need flexible training options that fit within work schedules and project demands. In addition to BIM-based QTO, similar AI-supported learning approaches could be explored for other construction management topics that require procedural knowledge, software skills, and decision-making support. By integrating structured guidance, conversational assistance, and discipline-specific knowledge, future research can further investigate how interactive AI agents can contribute to more accessible, practice-oriented professional learning in construction.

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Appendices

Appendix I: Chapter 4 Online Survey, RQ2

Information Letter

For a Research Study entitled “Effectiveness and Value of the DrCGPT Teaching Assistant ChatBot,” You are invited to participate in a research study to gain insight into the effectiveness of the DrCGPT teaching assistant chatbot. You were selected to participate in this study as you are a current student in the BSCI 3600 course where the chatbot is being utilized and you are over 19-years in age. The study is being conducted by Dr. Wesley Collins and Mr Shadi Alathamneh in the McWhorter School of Building Science at Auburn University. What will be involved if you participate? Your participation is completely voluntary. If you decide to participate, you will be asked to complete an anonymous electronic survey. Your total time commitment will be approximately 5 minutes each time you complete the survey. Are there any risks or discomforts? There are no known risks in completing this electronic survey, Are there any benefits to yourself or others? There are no known benefits for those participating in the survey, beyond the knowledge that you are contributing to a burgeoning body of research. Are there any costs? No. Participation in the survey is completely free of charge.

If you change your mind about participating, you can withdraw at any time during the study by closing your browser window. Once you’ve submitted anonymous data, it cannot be withdrawn since it will be unidentifiable. Your decision about whether or not to participate or to stop participating will not jeopardize your future relations with Auburn University, the McWhorter School of Building Science.

Any data obtained in connection with this study will remain anonymous. We will protect your privacy and the data you provide by storing it in a secured and password-protected data management system. Information collected through your participation may be used to fulfill an educational requirement, published in a professional journal or trade publication, and/or presented at a professional meeting.

If you have questions about this study, please contact Dr. Wesley Collins at wes.collins@auburn.edu If you have questions about your rights as a research participant, you may contact the Auburn University Office of Research Compliance or the Institutional Review Board by phone (334) 844-5966 or e-mail at IRBadmin@auburn.edu or IRBChair@auburn.edu.

"The auburn university institutional review board has approved this document for use from xx/xx/xxxx. Protocol# xxx xxx. Having read the information above, you must decide if you want to participate in this research project. If you decide to participate, please select "yes i consent" below.

Yes, I consent

No, I do not consent

Survey Questions:

1. Q1 Please describe your opinion regarding whether or not the DrCGPT Chatbot was a valuable resource to you for learning the quantity takeoff and estimating practices taught in this course. Open-ended

2. Q2 If you had a question about something we were working on in this specific course, would you prefer to: - Select Choice Closed-ended

    a. Ask Dr. Collins directly

    b. Ask the DrCGPT ChatBot

    c. It depends on the question

    d. I would utilize another source of data, such a a Google search

    e. Other (please describe)

3. Q3 Have you previously utilized a Chatbot, such as ChatGPT, to answer course-specific questions? Closed-ended

    a. Yes

    b. No

4. Q4 Are there any previous or current courses that you have taken where a Chatbot, such as DrCGPT, was utilized? If so, please describe. Open-ended

5. Q5 Would you like to see Chatbots similar to Dr. CGPT be developed for your other BSCI classes? If so, please list them below and describe why you feel a Chatbot would be valuable in that course. Open-ended

Appendix II: Chapter 4 Survey Results, RQ2

Responses to Questions 1 to 5

ID	Q1: Please describe your opinion regarding whether or not the DrCGPT ChatBot was a valuable resource to you for learning the quantity takeoff and estimating practices taught in this course.	Q2: If you had a question about something we were working on in this specific course, would you prefer to: - Selected Choice	Q3: Have you utilized a ChatBot such as ChatGPT previously to answer course-specific questions?	Q4: Are there any previous or current courses that you have taken where a ChatBot such as DrCGPT was utilized? If so, please describe.	Q5: Would you like to see ChatBots similar to DrCGPT be developed for your other BSCI classes? If so, please list them below and describe why you feel a ChatBot would be valuable in that course.
1	I think it is ok... When you ask a questions it just spins and then does not answer.	Ask one of my classmates	No		
2	I really did not use it at all this semester it seems that it could be a useful resource but i personally did not use it.	Ask one of my classmates	No	no	yes, i feel it could be a good resource when doing homework if the teacher isnt there
3	I never tried it.	Ask one of my classmates	No	No	I do not have an opinion on chat bots, I don't think they are the best resource at hand.
4	yes if chatbot improves	Ask the DrCGPT ChatBot	Yes	no	yes if they work better
5	I used it a few times and it was	Ask the instructor directly	Yes	In CIT we were allowed to use just	Yes

	helpful to me the times I used it.			regular ChatGPT	
6	I never used it as I see it as a knock off version of chatgpt that is much slower and not as accurate	Ask one of my classmate s	No	No	Maybe
7	IT had its ups and downs while using the survey. It allows you to ask various questions to be answered. When asking something around estimating, it would usually freeze when you use regular chatgpt they gave u a solution or a direction to go	Ask one of my classmate s	No		Understanding different answers to a question rather then one solution so I can understand better
8	Seemed to be a good resource for us to use in times where our professor was unavailable.	Ask the instructor directly	Yes		
9	I think it is helpful, but it will get better with time.	Ask one of my classmate s	Yes		As it progresses the chatbot could be a useful tool .
10	I feel like it was a valuable resource but also not used as much because of chat Gpt.	Ask one of my classmate s	Yes	Chat GPT	I feel like we could use them for other courses.
11	I think it could be useful. I did not use it, because none of my questions were really applicable for the it.	It depends on the question	Yes		I think it is easier to just use ChatGPT.

12	It was nice to have, but I much preferred referring to Dr. Collins and Shadi when I had questions	Ask the instructor directly	No	N/A	I dont think so
13	I think its a valuable resource that would be more beneficial for students taking the class in the fall or spring where its not as condensed	It depends on the question	Yes	No	Yes
14	I did not use the chatbot very much, but i believe it can be very helpful once it progresses a little more.	It depends on the question	Yes	No	Yes, I feel they will help us as students more once they progress.
15	I feel like the chatbot was helpful if you needed an answer when you were not able to directly ask Dr. Collins.	Ask the instructor directly	Yes		
16	Not really. Most times I was confused it was to the point where I didnt even know what questions to ask to solve the problem. If i had a simple question i would be willing to use the chatbot but that was very rarely the case.	It depends on the question	Yes	Yes, Infotech. Used ChatGPT for simple questions about how to do something on excel or a similar program	Yes, I feel that a chatbot with a wide knowledge of construction materials and practices as well as the business side would very helpful in the majority of future classes.

17	I used it one or twice and the questions I asked were not answered fully to the extent I was hoping for.	It depends on the question	Yes	No	Probably not
18	It was helpful when i remembered to use it	Ask the instructor directly	Yes	if needed to help me write up something i would use it	i think they could be used in all
19	I feel like I did not really use this chat bot at all.	Ask the instructor directly	Yes	I haven't used a chat bot that was specific to a course only Chat GPT.	I would like to see other Chatbots similar to the one in this class in some other courses.
20	I think it is a good intent, did I use it much though? No. With a class like this using so much new software, I don't expect the chatbot to answer question's like "How do I set up my polylength in bluebeam to get the wall area of the eifs?" The Togal was pretty cool and I could see a lot of potential in the future for AI take off.	Ask the instructor directly	Yes		
21	I never used it so I cant really say	Ask the instructor directly	Yes	No	Yes, in all courses because things like this will be more popular in the future in both school and in most industries

22	I did not utilize the DRCGPT resource. We all knew it was there but it seems like the questions we had could be more efficiently answered by asking a classmate or Professor Collins.	Ask one of my classmates	No	No	I think that other classes could use this tool to their advantage such as Structures 1 and 2.
23	I thought it was useful when I used it, I didn't find myself using it a whole lot. I normally just asked the professor or my friends whenever I needed help. Needless to say, I think it was a helpful tool to have in our back pocket.	Ask the instructor directly	Yes	Not really off the top of my memory	Yes I think they're a useful tool
24	I never thought to use it throughout this semester, so I don't think it was that valuable for me personally.	Ask the instructor directly	No	I think that a Chatbot would be more useful for a course such as Communications.	I think that it could be an interesting idea for certain aspects. However, there are some skills that I think are very important to develop without the use of a Chatbot helping you come up with answers.
25	I found Dr.CGPT to be a valuable resource for easily obtaining help in this course	It depends on the question	Yes	No	Yes, I think chat bots could be a great tool for any class that utilizes computer programs such as excel or bluebeam

26		It depends on the question	Yes	N/A	N/A
27	I think it is valuable but i find myself second guessing the answers from it most of the time	Ask one of my classmates	Yes	no	yes
28	I used it occasionally, but when I did it was helpful	Ask the instructor directly	Yes	no	yes, same way as estimating
29	I never really used it, I have used other applications like ChatGPT for it.	It depends on the question	Yes		I think if they were more integrated with the web and could still be accurate relative to the class, that would be the best scenario.
30	I did not use this source as much as I wanted too, but was useful when I used it.	Ask one of my classmates	No	No there was not.	Yes I would, it is good for "simple" questions.
31	It was valuable for some things I needed to do in class.	It depends on the question	Yes	No	They help us ask questions without the hassle and sometimes they can answer them.
32	I don't think it was very useful. Maybe it would help if we could use this on our tests to help us out? We were able to do this for Cit and everyone's grades improved.	Ask one of my classmates	Yes	Yes CIT	yes just chat gpt 4

33	I think it was valuable because if Dr. Collins wasn't imidiently reachable like after class I could ask the bot and get a somewhat simple answer	It depends on the question	Yes		Scheduling because of how intricate it is like this class
34	I only used it a couple of times. It seems like it would be useful but I usually asked the instructor or my peers if I had any questions.	Ask one of my classmate s	Yes	N/A	Yes, a chatbot would definitely be useful in almost every BSCI class, especially the vocab-heavy ones like materials and methods.
35	While I do think it has potential it should have a much larger database to choose from for asking direct questions like how to calculate something.	Ask the instructor directly	Yes	I use chatbot to help in all of my classes that need writing or small problem solving.	yes, I would love to see that for something like safety and scheduling, especially safety
36	I felt like it was slow to giving me an answer compared to other AI.	Ask the instructor directly	Yes	Almost all my courses I have used some sort of AI.	
37	yes, however it is too slow	Ask one of my classmate s	Yes		A chatbot would be valuable in structures.
38	I personally did not use it very often. mainly just looked a class recorded videos for help.	Ask the instructor directly	Yes	No	I think it would be helpful, I do not know which class though.
39	I think it has to potential to be a great tool but was	Ask one of my	Yes		

	not good enough yet for this class.	classmate s			
40	I think it was valuable. I did not use it much but I know of other students who used it.	Ask the instructor directly	Yes	No	I am not sure
41	It is easier to just use CHAT GPT, most people that use AI know how to communicate with chat GPT to get the answer(s) they are looking for. I thing Using software like togal AI is great and should be pushed, but Dr.Chat bot did not help like the regular chat gpt	Ask the instructor directly	Yes	no	If they were easier to use and communicate with, yes.
42	I think that the ChatBot is helpful for simple questions but for more complex questions the system gets a little confused.	Ask the instructor directly	Yes	no	Yes, any math related course.
43	I honestly can not say. I did not use any form of AI during estimating and I really do not use AI in general.	Ask one of my classmate s	Yes	We were allowed to use ChatGPT in CIT and it was helpful at times but just for formulas in excel.	I really do not feel like AI is necessary for our learning.
44	I think the chat bot is a great tool for students to use when it	Ask the instructor directly	Yes	Estimating	

	comes to any questions they may have about QTOs however I did not use it much.				
45	I felt that it could be useful. At this point I believe that it is not fully developed yet, but once it is, it could definitely be useful for many students to use.	Ask the instructor directly	Yes	No.	Yes, I feel like once they are developed, many questions could be answered without an instructor always being around.
46	I primarily like to use chat GPT when it comes to converting measurements and other numerical values. I did not really use DrCGPT because I already pay for an AI subscription that does not limit the answers I am looking for.	Ask the instructor directly	Yes	N/A	I would not because the information provided is very limited
47	I think the chatbot was a valuable resource to have during the semester. While i did not ask to many questions when i did it answered them very thorough and good.	Ask one of my classmate s	Yes	No	I could see chatbots being very helpful in a structures class. My first structures i did a lot of teaching myself and having a chat bot there to answer questions and help guide me along would have been very helpful.

48	I would say it is a valuable resource and does a pretty good job of answering your question. But it is very slow compared to other chat bots.	It depends on the question	Yes	Yes, they are useful in depth classes, or classes that have assignments with multiple steps.	Yes, if they can be as efficient as ChatGPT.
49	I personally did not use the ChatBot during this class, so I did not really find it helpful. If I didn't know something, I could find out how to do it either by asking my classmates or by figuring it out myself.	Ask the DrCGPT ChatBot	No	No	It might be beneficial for construction safety where there is a large amount of diverse content that can be hard to sift through.
50	If i wanted to get a broader answer or just know something concrete like the weight of a cubic foot of dirt I would ask the chat bot, but I wanted a more specific answer with an explanation I would ask Dr. Collins	Ask the instructor directly	Yes		
51	I did not personally use the chatbot much other then in class with the professor. I believe it is a useful tool but I did not need to use is	Ask one of my classmate s	Yes	no, i would use Chatgpt if I had a question or googles A.I.	yes, I believe this can be very useful to other courses

52	In all honesty, I did not use the ChatBot a whole lot. The few times I did use it, it was slow and didn't quiet give me the answer I was looking for. I do think it is a valuable resource to have, but it just needs a little more work.	Ask the instructor directly	Yes	No, this was the first class that had its own "chatbot"	Yes, like mentioned before, I think they are good but still need developing and substantial amount of work. Any help to get a different opinion is alwyas appreciated.
53	i didnt really use it but it was not as fast at GPT.	It depends on the question	Yes		i would but i think they will be very useful in the future not really my time yet
54	Yes it was	It depends on the question	Yes		Yes
55	I did not use it	Ask the instructor directly	No	Yes, I have utilized it in CIT class.	Structures
56	It was but it was a little slow	Ask the instructor directly	Yes	Yes	Yes I would, it helps expand your brainstorming
57	It is a valuable resource	Ask the instructor directly	Yes	BSCI 3600	
58	I think it valuable especially if it gets better in terms of more consistent and knowledgeable of information.	Ask one of my classmate s	Yes	No	Yes, I think chat bots for specific classes are extremely beneficial and maybe it can be turned into one big one.
59	I have not taken advantage of DrCGPT during my estimating class.	Ask one of my classmate s	No		I think a chatbot for structures (1 and / or 2) would be very beneficial for solving homeworkâ€™s when the instructor is not available.

60	Yes it has been valuable in getting further explanations	Ask one of my classmates	Yes	Yes, communications Safety CIT Estimating	Chat GBT
61	I really didnâ€™t use it that much.	Ask one of my classmates	Yes	Structures and communication	Yes. CIT, Estimating
62	Yes, in some cases it would generate a response, but not always	Ask the DrCGPT ChatBot	Yes		CIT - for specific revit and other bim specific questions
63	Yes	It depends on the question	Yes		Yes
64	I used it a few times but not very often and found the stuff I used it for could just be looked on up google.	Ask one of my classmates	Yes	No	I would be interested in a scheduling bot to help learn scheduling and give advice on it.
65	Honestly, I think that ChatGPT is more useful. I think that DrCGPT is good for some instances, but overall I think that ChatGPT provides enough relevant information to answer questions and is much faster	Ask one of my classmates	Yes	Yes. I use chatGPT in all my classes. I am first semester of the professional program	No. I think that it is largely a waste of time to develop them since ChatGPT already adequately answers the questions
66	Yes we used it several times in order to figure out typical waste factors	It depends on the question	Yes		Estimating is one I would say it is perfect for

67	I think it was helpful but sometimes frustrating because of how specific the prompts had to be	Ask one of my classmates	Yes	No	I think it would be helpful for CIT. just to help locate things in revit
68	No it wasnâ€™t. Itâ€™s just a little slow compared to other AIâ€™s, so if I use one I would use ChatGPT.	Ask one of my classmates	Yes	No, I just started using chat bots this semester	Yes if they were able to be comparable to the bigger AIâ€™s. I love the idea, but if I have a faster version of DrCGPT, why would I not use the faster version?
69	I used it occasionally. It wasn't needed as much except for when we were stuck on a lab when the professor wasn't around.	Ask the instructor directly	Yes	In CIT it is used	One for CIT and i think one for our mechanical and electrical classes would be good
70	I have not used it for any quantity takeoff except for maybe the weight for foot of rebar which was just for experimental purposes	Ask one of my classmates	Yes	Chat gpt has been used previously in prior building science courses	Yes, not sure on which classes but I feel if it is taught enough information it could become useful in the future
71	I rarely used DrCGPT only because I found that Microsoft copilot was more effective at answering my questions.	Ask one of my classmates	Yes	No	
72	Yes it has helped me. I have not used it much but	It depends on the question	Yes	I have used other chatbots but nothing that	Yes. Having chatbots that are specifically created for certain types of

	it has been useful.			is as construction specific like DrCGPT.	courses would be very helpful.
73	Yes it helped a lot when I needed information quickly.	It depends on the question	Yes	Yes in Estimating, Communications, and Safety. Very helpful for understanding material more in depth or when needing an answer.	I donâ€™t know how a different chatbot would be beneficial I think the one we are using now would do just fine moving forward.
74	Yes it was, answered most questions much faster than a normal search engine.	It depends on the question	Yes	Estimating and CIT	Structures 2, I think a chatbot could make processes like beam design way faster.
75	I feel that it is very helpful for finding general information related to construction.	It depends on the question	Yes	No	Yes, for safety. There is a lot of information that I would have to spend a significant amount time to find.
76	I know that it is a fairly accurate resource to use, unfortunately I donâ€™t use it most of the time to find answers for estimating. It is valuable but I havenâ€™t taken advantage of it yet.	Ask the instructor directly	Yes	No previous courses allowed the use of a chatbot until this semester. I use it in construction communication mostly	
77	DrCGPT was definitely a cool and unique resource; however, when I	Ask the instructor directly	Yes	N/A	Yes, courses like Construction Documents and Structures could

	tried to use it, it was often slow and sometimes would not give a relevant or right answer, making it less convenient to use.				benefit from a chat bot.
78	I think that DrCGPT in its fully realized potential would be a great resource because it would be fed information directly related to courses we are taking. Thus, able to give us better responses that are able to answer questions for assignments. I used DrCGPT a few times during estimating but I found its responses to be a bit slow and often times incorrect. In its current state it feels like its faster and more accurate for me to look online.	Ask the instructor directly	Yes	Aside from CIT, nothing like DrCGPT has been utilized.	I would like to see the possibility of DrCGPT being developed into an all around BSCI chatbot.
79	I believe it was a valuable resource.	Ask the instructor directly	Yes	Estimating	Yes
80	I did not use it that much, but it worked fine the few times I did	Ask one of my classmate s	Yes	Estimating	

81	I never really used it but do see value in it.	Ask the instructor directly	No		
82	Yes it was.	Ask the instructor directly	Yes	No	Yes
83	Did not use it much	Ask the instructor directly	No	No	Not sure
84	ChatGPT is, DrCGPT takes too long and doesn't provide accurate information in my experience.	Ask one of my classmate s	Yes	All	Yes, as long as it works
85	For an early stage BSCI AI, I think it serves it purpose well. Answers questions with relative accuracy	Ask the instructor directly	Yes	Documents and methods/mat erials	
86	I never used it.	Ask the instructor directly	No	No	No
87	Have not used it yet	Ask one of my classmate s	Yes	No	
88	I did not use either this semester	Ask the instructor directly	Yes	I havenâ€™t used DrCGPT but I have used ChatGPT	Yes any AI involvement is helpful
89	Not really	Ask one of my classmate s	Yes	Communicati ons	
90	This was helpful	Ask one of my classmate s	Yes	BSCI 3600	â€¦
91	Useful	Ask the instructor directly	Yes	Most all my classes	Always useful to have something like a chat bot to help.

					Important to use your resources
92	I did not use it in this class as much as I thought I would, but I do in all my other classes	Ask the instructor directly	Yes		
93	I have not used it much. However, when I did use it the information was great.	Ask one of my classmates	Yes	Construction communication and IT help.	Yes. It is the future.
94	Little bit slow. Chose not to use it.	Ask the instructor directly	No	Yes. Communications encourages the use of ai to develop outlines for presentations etc.	
95	It really helped when I didnâ€™t know how or where to start a takeoff at.	Ask one of my classmates	Yes	Estimating and Costing	Structures II. I feel that we could use more examples in these problems and the internet doesnâ€™t provide the best examples
96	It was somewhat valuable. Worked 50/50	Ask the instructor directly	Yes	No	Yes, I think any class would be helpful. You can use Drcpt / chat gpt in work so why not use it in classes
97	Used it rarely. Most information I used it for was things I could have googled.	Ask the instructor directly	Yes		
98	It has been a very useful resource in my estimating class. It makes	Ask one of my classmates	Yes	Estimating and finding the weight and conversions	It would be helpful in some capacity in every course.

	important information very accessible and easy to navigate.			of certain materials.	
99	Havenâ€™t used it enough	I would utilize another source of data, such a a Google search	Yes	Most of my courses I use chat gpt for ideas, information or formatting help	No I havenâ€™t
100	To be honest I have not used it so far this semester, but I do believe it could be a helpful resource.	Ask the instructor directly	Yes	Communications- for writing a case study about ethics in construction	Yes- I would like a ChatBot to be developed for structures because that is probably the most challenging class this semester.
101	When used it provided us with the information we needed so I would say it helped.	It depends on the question	Yes	Just to help me find an answer or format something I was writing.	I think any sort of chat itâ€™s are good for all classes so if possible all.
102	I didnâ€™t find myself using it very often, but I could see it being extremely useful with some refining.	It depends on the question	Yes		I think structures classes could benefit greatly from a ChatBot to answer questions. I find myself frequently rewatching lectures or asking the professor questions when doing structures homework, and a chatbot capable of answering those questions I might have would be very useful.

Appendix III: Chapter 5 Online Survey, RQ3

Information Letter

(Note: do not agree to participate unless an IRB approval stamp with current dates has been applied to this document.)

Title of research study: Enhancing BIM Education and Upskilling through a Custom Generative AI Chatbot: A Study on Teaching Effectiveness and Skill Development

Investigator: Dr. Wesley Collins

Sponsor: NA

You are invited to participate in a research study to evaluate the effectiveness of a generative AI custom chatbot in enhancing BIM education and upskilling for students and professionals in the construction industry. The study is being conducted by Shadi Alathamneh under the direction of Wesley Collins, Ph.D. in the Auburn University Department of Building Science. You were selected as a possible participant because you are an industry professional, trainee, or student in the construction management field.

What will be involved if you participate? If you decide to participate in this research study, you will be asked to complete an online survey of approximately 29 questions via Qualtrics. Your total time commitment will be approximately 15 Minutes. Participation in this survey will not affect class participation or grades.

Are there any risks or discomforts? No known risks. To minimize these risks, we will not request your name or any other personal information on the survey.

Are there any benefits to yourself or others? There are no direct benefits to participants; however, this study will help assess whether the use of a chatbot is valuable to students in Building Science courses. As novel research, it holds the potential for long-term positive impacts on construction education by enhancing learning tools and methodologies.

Will you receive compensation for participating? None.

Are there any costs? None. Auburn University has not provided for any payment if you are harmed as a result of participating in this study.

If you change your mind about participating, you can withdraw at any time during the study. Your participation is completely voluntary. If you choose to withdraw, your data can be withdrawn as long as it is identifiable. Your decision about whether or not to participate or to stop participating will not jeopardize your future relations with Auburn University, the Department of Building Science.

Any data obtained in connection with this study will remain anonymous. We will protect your privacy and the data you provide by storing them in a Box folder accessible only to Wesley Collins and Shadi Alathamneh. Copilot Studio and Qualtrics also require AU login credentials to access. Information collected through your participation may be (e.g., used to fulfill an educational requirement, published in a professional journal, and/or presented at a professional meeting, etc.).

If you have questions about this study, please ask them now or contact Dr. Wesley Collins at wac0020@auburn.edu or Shadi Alathamneh at sqa0001@auburn.edu.

If you have questions about your rights as a research participant, you may contact the Auburn University Office of Research Compliance or the Institutional Review Board by phone (334) 844-5966 or e-mail at IRBadmin@auburn.edu or IRBChair@auburn.edu.

Having read the information provided, you must decide if you want to participate in this research project. If you decide to participate, the data you provide will serve as your agreement to do so. This letter is yours to keep.

Dr. Wesley Collins

Investigator's Name

Shadi Alathamneh

Co-Investigator's Name

Survey Questions

Num.	Question	Construct	Scale	MIN	MAX
Q1	Have you used Autodesk Assemble before this course?	Prior Experience	5-point	No, this is my first time.	Yes, I have used it extensively.
Q2	Before using the chatbot, how would you rate your familiarity with Autodesk Assemble?	Prior Experience	5-point	Not familiar at all	Extremely familiar
Q3	How useful was the chatbot in explaining Autodesk Assemble concepts?	Instructional Quality	5-point	Not at all useful	Extremely useful
Q4	Did the chatbot provide accurate and relevant responses to your questions?	Instructional Quality	5-point	Never	Always
Q5	Did the chatbot help you complete tasks within Autodesk Assemble (e.g., model navigation, data extraction, quantity takeoff)?	Task Support	5-point	No, I still struggled with the tasks.	Yes, it was very helpful.
Q6	How often did you need additional help from the instructor after interacting with the chatbot?	Task Support	5-point	Never	Always
Q7	After using the chatbot, how would you rate your confidence in using Autodesk Assemble?	Learning Impact	5-point	Not confident at all	Completely confident
Q8	Compared to traditional learning (e.g., lectures, manual, YouTube), how effective was the chatbot in helping you understand Autodesk Assemble?	Learning Impact	5-point	Much less effective	Extremely effective
Q9	Would you prefer to use the chatbot again in future learning?	Satisfaction	5-point	No, I would rather use traditional methods	Yes, definitely
Q10	How satisfied are you with the chatbot experience?	Satisfaction	5-point	Extremely dissatisfied	Extremely satisfied
Q11	In what ways could the chatbot be improved to better assist learning Autodesk Assemble?	Instructional Quality	(Open-ended text response)		
Q12	How did your experience with the chatbot compare to traditional learning methods (e.g., instructor-led, textbooks, online tutorials)?	Learning Impact	(Open-ended text response)		
Q13	Would you recommend using an AI chatbot to other students learning	Satisfaction	(Open-ended text response)		

	Autodesk Assemble? Why or why not?		

Appendix IV: Chapter 5 Survey Results, RQ3

Responses to Questions 1 to 10

ID	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10
1	1	1	5	4	3	2	5	4	3	5
2	1	2	4	4	3	3	2	4	3	4
3	3	1	4	3	3	2	4	4	3	4
4	1	3	4	5	3	2	3	4	2	4
5	1	1	4	4	3	2	4	4	3	5
6	1	1	4	4	3	2	4	4	3	2
7	1	1	5	5	3	3	4	4	3	5
8	1	1	5	5	3	2	4	4	2	5
9	1	1	4	5	3	2	3	4	3	4
10	3	3	5	5	3	2	3	5	3	5
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22	1	4	5	5	3	2	5	5	3	5
23	3	3	4	5	3	2	4	3	3	1
24	1	1	3	5	3	1	2	3	2	4
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39	1	1	5	4	3	2	3	3	3	4
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41	1	1	5	4	2	2	4	3	2	5
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66	1	1	5	5	3	2	4	5	3	5
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69	1	1	4	5	3	2	3	4	3	5
70	1	1	4	4	3	1	4	3	2	4
71	1	1	4	4	3	2	3	4	3	5
72	1	1	3	5	3	3	4	3	3	4
73	1	3	3	4	2	2	3	4	3	4
74	2	1	4	4	3	2	2	4	3	5
75	3	3	3	4	2	3	2	3	2	4
76	2	1	4	5	3	2	3	4	3	4

77	2	2	3	4	3	1	3	3	2	4
78	1	1	5	4	3	2	4	5	3	5
79	1	1	4	5	3	2	3	4	3	4
80	1	1	4	4	3	1	1	2	2	3
81	2	2	5	5	3	1	4	5	3	5
82	1	1	5	5	3	3	3	4	3	5
83	2	2	5	5	3	2	3	4	3	5
84	1	1	5	5	3	5	3	4	3	5
85	2	1	4	4	2	2	3	3	2	4
86	2	1	4	4	3	2	3	2	1	3
87	2	1	4	5	3	2	3	3	3	4
88	2	2	4	4	3	2	4	4	3	5
89	1	1	5	5	3	2	3	5	3	5
90	1	1	5	4	3	2	3	4	2	4
91	1	1	4	4	3	2	2	3	3	4
92	1	1	4	4	3	2	3	3	3	2
93	1	1	3	4	2	3	2	3	2	2
94	1	1	5	5	3	2	3	4	3	5
95	1	1	5	5	3	2	4	4	3	5
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106	1	1	5	5	3	2	4	5	3	5
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108	1	1	3	4	2	2	2	2	2	4
109	3	4	4	4	3	2	4	4	3	4
110	1	1	5	5	3	2	3	4	3	5
111	1	1	4	5	3	2	3	3	3	5
112	1	1	4	4	3	1	3	3	2	4
113	1	1	5	4	3	1	5	5	3	5
114	1	1	4	4	3	2	3	4	3	4

Responses to Question 11

Q11. In what ways could the chatbot be improved to better assist learning Autodesk Assemble? Instructional Quality (Open-ended text response)

- It struggled to answer my question
- More clear with instruction of what to select
- Adding more functions on how to merge sheets on excel
- I think its great as is
- Needed too many inputs, could've answered more concisely.
- It explained the steps
- Clarifying the apps each step is referring to, even if it seems repetitive. It did not clarify sometimes and I got lost on which app to click what button in.
- More technical help or including images to help with navigation
- Pictures
- It did the best it could
- If ask a follow up question to their explanation have a better response
- It would be helpful if it could answer questions outside of the designated script.
- If i was shown how to use it and how it could be used in as many ways i would love it

- It seems like it goes off of set questions. like if u ask it exactly this then it give you the answers. i would call it more of a step by step with set answers and questions you can ask it, not necessarily a teacher where it really understands and can give you the feedback you want. still useful though
- N/A
- I think the chatbot was very useful but i got stuck on one part early in the set-up that was a little confusing.
- Needs to be a little more used to human speech so that it does not switch to live agent.
- It provided the answers I needed
- Dont see any needed improvements
- AI in general does not always give the most direct responses which can cause confusion.
- "if it could understand questions and what you are asking if you get stuck."
- Better at answering questions that I ask it.
- I can't think of any.
- More prompts to further discussion after answer
- It broke and I had to reload it. Kept giving me "upload and export" and wouldnt say anything else

- Updated terminology.
- I thought it was great.
- It worked great
- N/A
- it didn't always understand what I was asking. Some responses seemed scripted
- it was very helpful. maybe a website link
- none
- maybe make the steps it gives a little more defined
- I think it needs to hear more conversation
- N/A
- more training
- 2 I had to tell it what I needed again
- Go more in depth with step by step instructions
- More accurate responses, sometimes I was trying to problem solve with it and the responses were not accurate
- Responding to question that you ask freely. It was good at giving step but if you tried to go off course and type something else, it didn't understand

- None.
- I think Assemble was a great assist.
- Understand more tasks.
- visual aid
- Some explanations lacked detailed steps and some new users may find themselves stuck without help.
- For the first round make it simpler and require the user to click next multiple times instead of throwing 10 steps at once.
- I thought it was great the way it was.
- 2 it lost its "train of thought" and I had to start the prompts over.
- instructions are kind of hard to follow. very wordy
- n/a
- I think it explained everything well, but maybe some prompted pictures would be helpful
- None
- It was good.
- As far as how we used it I feel like the chatbot is pretty well developed

- I did not have any problems on my project, but I can see how troubleshooting some specific problems may be an issue.
- Maybe add even the very small details for buttons to press when saving the screenshots.
- I had issues & would ask a question but would just restate the prompt. So, I would have to ask others for help.
- No idea
- It seemed very useful in the introduction type things, we did not use it extensively, so my experience was great.
- Maybe a more detailed explanation of how to get places on Assemble
- Answer a broader range of questions.
- Making it quicker when answering questions that are not a part of its prompt.

Responses to Question 12

Q12. How did your experience with the chatbot compare to traditional learning methods (e.g., instructor-led, textbooks, online tutorials)? (Open-ended text response)

- Step-by-step learning is best for me
- Very good
- I felt like I was able to work at my own pace while getting effective responses that helped me understand
- Didn't have to wait to ask a question.
- I liked it better
- Chatbots are much better than traditional textbooks
- Good, more individually paced learning
- It was more efficient.
- Less but sufficient
- It was faster and I was able to follow steps
- This step-by-step method is easier than it often is following along with an instructor in CIT 2.
- it was nice when it broke everything down for me

- faster and at my pace.
- N/A
- I think it was more in depth and didn't leave anything to question.
- Incredibly more in-depth and useful.
- It was good
- Very detailed responses with no uncertainty
- It was nice, because it gave a quick response and knew what it was talking about.
- good step by step guidance
- It was good. it was basically like an instruction guide
- It was very helpful and got to the point.
- It was a great experience and very easy to follow along.
- Quicker response
- It was quick, easy, and simple
- I liked it because I could work at my own pace.
- The chatbot made getting a step by step explanation very fast which is much nicer than having to search for an accurate tutorial or review an old lecture. I can see this being very helpful for thesis.

- Very interactive
- I liked the step by step guide it gave
- it was more just answering questions then learning understanding
- it was comparable to chatgpt
- I like the step by step process
- great
- it was better than youtube but personally i prefer in person lectures
- It is faster and relevant
- N/A
- "abt the same"
- I could go at my own pace
- It was more self-paced and easy to ask the chatbot to clarify if something was confusing and if i had a problem i could tell it exactly what was wrong and it would give me an answer to fix it
- New ways of learning when things can be done many different ways for the same end goal
- good to use alone, but would love additional guidance

- It had good steps, but it was hard to interact
- It was good i like the trouble shooting aspect because in online learning and textbooks not all the answers to small issues are available
- It was different and took getting used to
- Much faster and effective.
- Easier to follow.
- good
- I liked the way you can ask personalized questions and get an answer right away
- It allowed me to go at my own pace.
- Quick and easy and able to learn at own pace.
- Easy to follow along at my own pace
- I liked that it went at our own pace, but you couldn't quite ask it anything because it can't "see" ur screen.
- Lacks personal connection. and is frustrating when it cant explain something to you in a more simple/straightforward way.
- Much better than a textbook, and more student pace led than an instructor.
- way better

- I liked how quick and easy it was compared to regular teaching methods
- Better than most instructors
- It has a quicker response and more detailed explanation
- I liked it, but i also do like having human interaction. It i nice we can go back and use it again and again whenever we ma need help with assemble.
- It allowed students to go at there own pace due to the fact you do not have to wait for the teacher for questions the chatbot can help with wasted time
- It was easy to use and showed me step by step instructions
- It was exceptional compared to traditional teaching methods. This is due to the fact that there is only one professor per class, and attention is divided among students.
- The chatbot is very good for a CIT class because it allows students to work at their own pace.
- I would prefer an online video.
- Way better
- It was nice to have a step-by-step guide that I could follow along at my own pace.
- Better, made it easier to catch on to things faster
- Not quite as effective as instructor-led or a video tutorial, but certainly more effective than a textbook.

- Whereas I usually have to wait for the instructor to be able to help me, the chatbot is always available, which was very helpful.

Responses to Question 13

Q13. Would you recommend using an AI chatbot to other students learning Autodesk Assemble? Why or why not? (Open-ended text response)

- Yes, It helps you learn how to use it very effectively
- yes!! Very helpful and could work through my own time
- yes because a chatbot was very clear and concise whereas a person can make explanations confusing
- Yes
- yes
- Yes. Easy access, and it guides you through the steps
- Yes, helpful tool when looking for a quick in depth answer, maybe not as good for technical questions
- yes, it was very useful
- Yes, it is a great tool when there is no teacher
- Yes, it was easy and useful
- Yes, but only if the exact assignment has already been curated in the chatbot.
- 1000% just show them step by step what todo and it would be very useful

- yes because everyone works at different speeds but i feel like it needs to get a better understanding at different questions and problems.
- N/A
- Yes, it is very useful especially if you've never used Autodesk assemble before, it is very detailed and easy to understand.
- Yes, this is the future.
- Yes-it was useful
- yes, detailed responses with written step by step instructions
- Yes, because it can always give you a quick answer unlike teachers or videos.
- yes. it will help you get familiar with the program
- Yes for this assignment
- I would because it because it teaches very well.
- Yes, it was very helpful to get me familiar with autodesk assemble.
- Yes, very focused on what you are doing
- Yes, assemble is a very easy program to learn to use. the chatbot didnt over complicate it
- Yes, it is able to give you quick and straight forward answers if someone is not around to help.

- Yes.
- Yes, quick responses and mostly accurate and in-depth explanation made it fairly easy and quick to pick up on.
- Yes. It was very useful and very easy to understand
- Yes, it was helpful. I just learn better through person to person
- yes, it helps you orient yourself pretty well
- yes
- yes, easy way to get instructions without having to get in touch with professor
- yes it gives step by step
- "yes, it helps strongly with basic stuff new students are learning"
- Yes because it usually gives a quick answer
- Yes
- Yes, any resource can be useful
- I think so because it was helpful just being able to go at my own pace and ask questions and not just have my hand raised
- yes for the above reason
- Yes, It is much more time efficent

- yes, gives great step by step and you don't have to watch a video.
- Yes for an assignment but it needs improvements interacting
- Yes, very simple
- Yes
- Yes, very easy to understand and learn.
- Yes.
- Yes
- yes it is easy to use
- yes
- Yes, I think it is a helpful tool that can help new users slowly work into the program.
- Yes, I would because it allows for trial and error.
- Yes I thought it worked well.
- yes because it is an easy to way to get quick help
- Yes
- yeah, but they still need someone familiar with the software there to help them
- "Yes, because it saved me a lot of time and allowed me to work at my own pace."
- more data and more in depth in where things are in assemble

- Yes, itâ€™s very quick and effective
- Yes
- Yes for sure. It is easier to you and very helpful
- Yes, but still need professors to help with specific questions. The chatbot only knows as much as it has been taught.
- Yes it is a great way to get step by step instruction for something you are not familiar with
- Yes, because it gives you a better understanding of what is going on and is helpful
- Yes, it makes learning efficient and effective.
- Yes, because it can answer questions without a teacher and you can work at your own pace.
- No, it is good for step-by-step instructions but if anything, different happened it was not useful. I would also prefer images.
- Yes, it has quick response time and will help with thesis
- Yes, it was super easy to use and allows you to read the steps over and over so that if you miss one thing during a lecture you don't fall behind.
- Yes, so they can also use it to their advantage for help
- Sure, it was pretty straightforward.

- Yes. It was very easy to follow.