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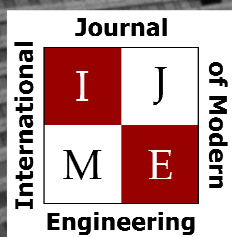
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AI MEETS MANUFACTURING



Philip Weinsier, TIIJ Editor-in-Chief

AI in manufacturing refers to the application of artificial intelligence technologies to optimize and automate various manufacturing processes. These technologies enable machines to perform the tasks that traditionally require human intelligence, such as problem solving, decision making, and learning from experience. AI helps manufacturers achieve higher efficiency, precision, and flexibility, making it a key driver of Industry 4.0.

Process Optimization

Siemens uses IoT sensors and AI-powered predictive maintenance in its Amberg plant in Germany to identify early warning signs of potential failures. AI is also integrated into their supply chain operations. BMW employs AI in its quality control processes along with an image recognition system for inspecting vehicles for defects. Data from their high-resolution cameras, so precise that they can even detect paint inconsistencies or surface scratches, are fed into AI algorithms to look for even the smallest of defects in vehicle components.

Supply Chain Optimization

DHL, the world leader in the logistics industry, uses AI and advanced analytics to enhance its global supply chain resilience. The company also uses algorithms to effectively predict delivery delays, optimize routes, and manage warehouse workloads.

Demand Forecasting and Inventory Optimization

Unilever uses forecasting models and machine learning algorithms to analyze historical sales data, seasonal patterns, weather, and market shifts to anticipate demand to fine-tune inventory, cut carrying costs, synchronize production schedules, reduce stockouts, boost cash flow, and thereby increase customer satisfaction.

Robotics and Automation

To automate quality control, Audi makes use of AI-powered robots with computer vision systems. AI-driven robotic arms scan car bodies for paint defects. Their automated systems are so precise that they, as with BMW, are capable of spotting minuscule scratches, bubbles, or dust particles on the car bodies that are not visible to the human eye. This ensures flawless finishes and cuts down inspection time from minutes to seconds.



Product Design and Innovation

With AI, designers are able to rapidly test prototypes, which results in quicker time-to-market cycles. GM employs AI-driven generative design to fast-track product development. The company feeds its design requirements into AI software to generate various innovative part designs, which leads to the creation of lighter and stronger components.

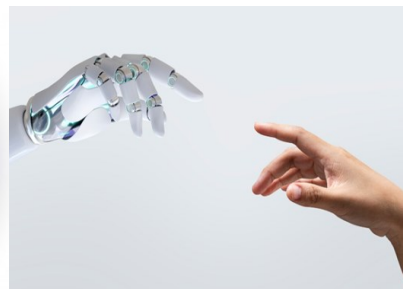
Natural Language Processing (NLP)

NLP enables machines to understand and interact with humans through voice or text inputs. As NLP allows programs to read, write, and communicate in human languages, its use in manufacturing affords less-experienced workers the ability to quickly analyze maintenance logs, customer support, and human-robot interaction. The multinational conglomerate General Electric leverages AI-driven NLP in its Predix platform.

And while these cases show us the power and potential of AI, the industrial world is not there yet. AI relies on high-quality, structured, and application-specific data that many manufacturers simply are not yet reliably able to provide.

- This is especially true in areas such as quality control, where incomplete defect data can impact model accuracy.
- Professionals with AI expertise in data science and machine learning are scarce. This shortage makes it challenging for companies to fully use AI without investing in workforce development.
- To make full use of AI integration, manufacturers need to increase their digital connectivity, which opens them up to more potential points for cyberattacks.
- AI adoption requires a large upfront investment in technology and infrastructure, which can be a barrier for smaller companies.

In our featured article (p.12), the authors present a structured framework to demonstrate AI as a viable solution for improving efficiency in estimating automation projects and illustrating how efficiency improvements correlate with increased value. The results indicated that AI was able to achieve a high level of performance while surpassing human efficiency. The results of this study confirmed that AI can accelerate the review of industry-specific technical specifications, thus showing significant efficiency improvements.



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COMPARATIVE STUDY OF SIMULATION AND EXPERIENTIAL LEARNING IN ENGINEERING TECHNOLOGY EDUCATION

Narendra Datta, The University of West Alabama; Syed Raza, Delta State University

Abstract

In the current technologically evolving world, utilization of the latest tools and techniques in imparting education has become vital. In the context of engineering technology, several experiential methods, simulation methods, tools, websites, and software have been developed of late to disseminate concepts to students in creative, interesting, and captivating ways. Electrical and mechanical concepts are often difficult for students to ascertain the science behind what is being taught in a tangible manner. Typically, learning theory has been the concentration of universities, while the implementation of theory has been relegated to students after graduating and receiving a job, where they have on-site training with equipment.

The reason for this is the cost-prohibitive nature of equipment. Simulation software has allowed students to access and apply the materials in a digital world but, by definition, it lack hands-on learning. Affordable training modules are now offered by companies that provide electrical and mechanical modules, each equipped with all the necessary components to function as complete teaching aids. In this current study, conducted at the University of West Alabama, the authors undertook a comparative analysis to assess student learning outcomes across courses within the scope of engineering technology. While the results indicated that experiential learning yielded higher student performance compared to simulation-based learning, the findings were context-specific and should be interpreted as evidence of improved outcomes within the scope of this study rather than a definitive conclusion about the superiority of one method over the other.

Introduction

Modern classroom instruction employs a variety of methods for effective knowledge dissemination, with simulation and experiential learning playing particularly significant roles. Simulation provides students with a dynamic means of engaging with real-world scenarios in a controlled environment. Experiential learning, on the other hand, offers students hands-on experience that equips them with practical skills and real-world understanding. This approach not only enhances student interest and engagement in the courses but also fosters the development of critical problem-solving abilities. Moreover, experiential learning has been shown to foster collaboration, teamwork, and communication among students, thereby better equipping them to meet

the demands of professional environments (Lestari, 2021). The goal of these methods is to engage and inspire students to actively participate and learn the concepts (Huang & Soman, 2013).

Experiential Learning

Experiential learning provides practical skills and real-world understanding as well as enhances student engagement, motivation, and problem-solving abilities, making it a valuable approach in modern education. The various stages of experiential learning are well illustrated by Kolb's Experiential Learning Theory (ELT), which includes: a) concrete experience, b) reflective observation, c) abstract conceptualization, and d) active experimentation (Kolb, 1984). These interconnected stages collectively provide students with a comprehensive, hands-on learning experience. In this framework, concrete experience involves students actively engaging in an experiment or activity to gain initial understanding. This is followed by reflective observation, where students thoughtfully review and analyze their experiences to deepen their comprehension of the concepts explored.

Critical thinking becomes essential in the subsequent stage of the process, which is abstract conceptualization, where the student tries to understand and interpret the knowledge and how the process has taken place in the experiment. The student begins to think of different circumstances and scenarios under change of problem conditions. Using all the accumulated information and theories/scenarios, the student then tries to put them to the test in the active experimentation stage. Analysis, predictions, and results would be obtained, and the cycle of learning continue. All these activities give student a remarkable understanding of how the process works in a real-time environment. In this current project, the authors utilized this concept as well where students went through four stages of experiential learning.

Research supports these benefits and studies have demonstrated that implementing experiential learning using a STEM approach significantly improved student problem-solving abilities. In a study by Lestari (2021), the author found that students showed high levels of improvement, particularly in describing problems and planning solutions. Furthermore, experiential learning has been shown to enhance student motivation and classroom engagement. According to a review, experiential learning facilitates

active learning through real-world experiences, allowing learners to interact with and critically evaluate course material (Kong, 2021). This engagement leads to improved motivation and the development of problem-solving skills. In a similar fashion, the goal of Bloom's Taxonomy is to promote thinking, analyzing, and evaluating the processes used in the experiments (Bloom, 1956). Anderson and Krathwohl (2001) further identified that, in the process of experiential learning, recalling, explaining, analyzing, evaluating, and producing results are key integral parts.

Practical assignments by Vallim, Farines, and Cury (2006) were identified that could boost motivation and create a sense of professional belonging. The course incorporated the idea that new knowledge builds from prior learning, and students facilitate each other's learning. This collaborative approach enabled students to tackle problems in groups that they might not solve individually (Vallim et al., 2006; Soares, 2011). Framing problems in a competitive context was identified to enhance motivation. Reflection was also identified as a key factor for a profound learning experience. This helps to internalize student experiences, thereby leading to deeper learning (Boud, Keogh & Walker, 2013). Reflection is deemed to be vital in developing expertise in complex fields.

This type of learning has been widely adopted in various educational settings such as engineering, healthcare, and business. Utilization of experiential learning helps bridge gaps between theory and practice, thereby enhancing technical skills as well as decision-making skills (Lasater, 2007). In a similar study, Prince and Felder (2006) observed that project-based learning fosters innovation and collaboration and prepares students for real-world challenges. This approach engages students in a practice that mimics real-life complex problems in a professional environment. It also helps students to apply themselves creatively and work efficiently in teams.

Perrenet (2000), through various examples, demonstrated that active learning could be successful if implemented in a domain that reflects the reality of the profession. Consequently, in the engineering domain, it is more suitable to use project-based learning. In research conducted by Mills and Treagust (2003), the authors observed that experiential learning enhanced students' problem-solving skills to adapt to new situations and promoted them to self-directed learning. In real-life practice, it is crucial for students to utilize the available resources and strategize a solution to get the optimized outcome in a given project (Tynjälä, Slotte, Nieminen, Lonka & Olkinuora, 2006). This type of learning provides students with holistic understanding of concepts and, by working on projects, students develop essential professional skills in the form of communication, teamwork, and time management to name a few that are necessary for future careers. (Kolmos, 2009; Thomas, 2000).

Simulation

Simulation involves the use of computer-aided or software-based environments that can simulate real-world problems or mechanisms in a virtual space (Lin, Wang & Lu, 2012). Simulation is often utilized in scenarios where the actual real-time equipment or prototypes are deemed to be expensive or dangerous to operate. Lin et al. (2012) observed that computer-aided teaching methods were flexible and effective. They stated that very few studies focused on the aspect of user experience. Their findings indicate that the learner's perception of instruction tools may influence learning outcomes. Results indicated that student-learning outcomes were highly affected by the simulation-based learning. Simulation-based learning seems to be very advantageous in the scenarios where the environment is prone to be unsafe or impractical in real time.

Utilization of 3D simulation seemed to be beneficial in these circumstances (Koh et al., 2010; Di Blas, Bucciero, Mainetti & Paolini, 2012). In yet other studies, it was observed that the ability of simulation and educational games could create virtual learning environments where students utilized integrated tools and resources to address complex problems. This helped students in enhancing their conceptual understanding, deductive reasoning and critical thinking, reflective thinking, and advanced problem-solving skills. (Ainsworth, 2006; Gros, 2007; Squire, 2005; Schon, 1983). In this current study, the authors used both aspects of learning (i.e., experiential- and simulation-based learning) and compared the outcomes in four engineering technology courses.

The inclusion of simulation-based learning in education has shown tremendous positive outcomes (Faria & Wellington, 2004). Simulation games in courses improved students' strategic thinking and decision-making abilities. In addition, the games offered an interactive environment where students could develop their skill sets while being monitored by instructors in order to provide direct feedback. This practice also showed student progress and could be used to effectively update the courseware and, based on feedback, lead to continuous improvement. A study conducted by Zacharia and Olympiou (2011) identified that, in environments where it can be challenging to create an experimental setup, utilizing simulation was an excellent way to provide a safe and interactive learning experience for students to foster confidence and a deep understanding of complex concepts.

In this current study, the authors compared both experiential- and simulation-based learning in four engineering technology courses. The results demonstrated the efficacy of combining these methodologies to enhance student learning and engagement. By blending these approaches, the authors observed improvements in the students' ability to apply theoretical knowledge to practical problems, collaborate

effectively, and develop innovative solutions. Furthermore, freshman-, sophomore-, and junior-level courses were identified for analyzing the modalities. Data were gathered from each course in the form of assignments, laboratory experimental reports, and quizzes. The same assessments, instructional hours, and grading rubrics were consistently applied across all groups to ensure comparability. The assignments and quizzes had an intermediate level of difficulty and were comprised of moderately complex problems for which students were required to make detailed analyses and applications of multiple concepts for each topic.

Conversely, experimental reports had an advanced level of difficulty. These reports required the students' in-depth understanding of topics, critical thinking, problem-solving, and integration of ideas to formulate a solution. These elements were chosen so that the students had initial experience at a basic level and were aware of questions they were expected to attempt in the future. The initial instruction in the classroom focused on problem identification, breaking the problem into simpler elements, and utilizing available resources to tackle problems in a systematic way to efficiently get the desired output. Several practice assignments and experiments were conducted in a classroom environment before the test data were collected.

Data Analysis Methods

Statistical analyses of data were performed using the following methods and the arithmetic mean was calculated using Equation 1:

- arithmetic mean
- median
- standard deviation
- analysis of variance (ANOVA)

$$A = \frac{1}{n} \sum_{i=1}^n x_i \quad (1)$$

where,

A = arithmetic mean

n = number of samples used

x_i = the set of values used in the data

Median was identified as the middle most value from the given dataset when the data had been arranged in an ascending order. Standard deviation was calculated using Equation 2:

$$\sigma = \sqrt{\frac{\sum (x_i - A)^2}{N}} \quad (2)$$

where,

σ = standard deviation

N = total number of samples taken

A = mean

x_i = the set of values used in the data

Analysis of variance (ANOVA) was used to compare the data for inter-correlations and statistical significance. It compares the amount of variation present between two groups of data to the amount of variation present within each group of data. The resulting F was compared to the $F_{critical}$ to determine if the two sets of data had statistical significance. Here, the probability that a given result happened due to an actual observed phenomenon and not by random chance was checked using the calculated F and critical F . In the process of calculation, an alpha value of 0.05 was used. The importance of alpha is that the data can be considered non-random if the same results would be obtained 95 times out of 100. Similarly, probability constants can be computed for each analysis, which can be compared to alpha. Computed probability constants less than alpha indicate statistical significance in the results, meaning that the results are not likely to have occurred by random chance (Littell, Stroup & Freund, 2002). For this current study, an alpha of 0.05 was used for identifying significance; and, for each course, two sample data sets were used—one that represented simulation-based learning and the other data set that represented experiential-based learning.

Results and Discussion

The focus of the current study was on the implementation and analysis of how different modes of instruction impacted student performance. As such, students engaged in both simulation- and lab-based experiential exercises across four engineering technology courses: AC-DC (Freshman level, Year 1, Fall/Spring), solid state electronics (SSE, Sophomore level, Year 2), and programmable logic controllers (PLC) and electrical motor controls (EMC) (Junior level, Year 3). These courses were selected as they represented both foundational and upper-level instruction within the engineering technology curriculum. The simulation component utilized Intelitek's platform, enabling students to practice troubleshooting and analysis in AC-DC circuits, PLC programming, SSE, and EMC within a virtual environment without the need for physical hardware.

Complementing this, experiential exercises involved hands-on training with lab benches and equipment, including breadboard wiring of resistive, inductive, and capacitive circuits in AC-DC, programming Allen-Bradley PLCs to operate solenoids and motors, constructing and testing transistor amplifier circuits in SSE, and wiring starter circuits with overload protection in EMC. While simulation assignments were completed entirely using software, experiential assignments required direct interaction with hardware; however, both modalities were assessed using the same rubrics for assignments, reports, and quizzes to ensure consistency in evaluation. A total of 113 student sample data points were used in this study. Table 1 shows the data obtained for both simulation- as well as experiential-based learning methods in each of the aforementioned courses.

Table 1. Details about each course, modality, and number of students.

Course	Modality	Number of students	Total number of students
AC -DC	Simulation	24	113
	Experiential	24	
SSE	Simulation	13	
	Experiential	13	
PLC	Simulation	12	
	Experiential	12	
EMC	Simulation	6	
	Experiential	9	

Figure 1 shows box plots for mean, minimum, and maximum scores for the AC-DC course. The authors observed that the mean score for simulation-based learning was 65.89 and 76.6 for experiential-based learning, which shows a considerable difference between modes. Table 2 gives the details about mean, median, and standard deviation (Std. Dev.). An ANOVA on the data set was calculated, indicating that the statistical F was greater than the critical F , which means that the observed differences between each mode of instruction were statistically significant at the chosen significance value; that is, the sample averages could not be due to random chance alone. The results shown in Table 3 suggest that, within the scope of this study, students demonstrated improved performance and engagement in the experiential-learning environment compared to the simulation-based setting.

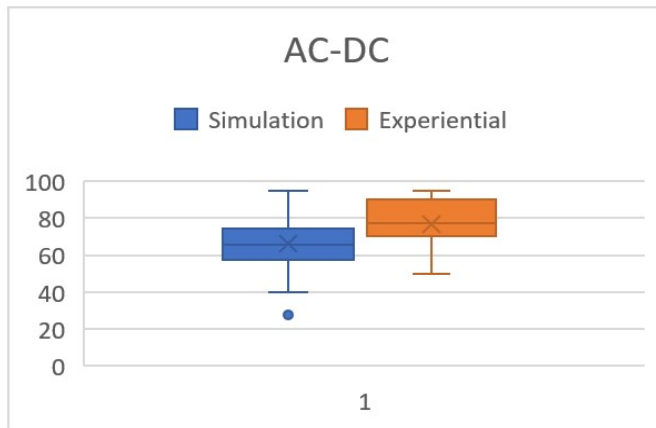


Figure 1. AC-DC.

In a similar fashion, the mean, median, and standard deviation values were calculated for student scores in the solid state electronics (SSE) course; Figure 2 shows a box plot of the data while Table 4 provides the tabulated results. The key difference observed here was that the mean and median values were considerably higher. The standard

deviation in the simulation mode showcased the level of scatter from the mean value, but the experiential mode results showed that each score was not far off from the mean value obtained in this particular course. Table 5 shows the ANOVA-SSE calculation for this course, which complements these findings as the F value turned out to be greater than the critical F .

Table 2. AC-DC. Mean, median, and Std. Dev.

	Simulation	Experiential
Mean	65.89	76.6
Median	65.83	77.5
Std. Dev.	15.42	13.16

Table 3. ANOVA AC-DC.

Source of variation	SS	df	MS	F	P-value	F crit
Between groups	1393.208	1	1393.208	6.7765	0.0124	4.0517
Within groups	9457.333	46	205.5942			
Total	10850.54	47				

where,

SS = sum of squares

df = degrees of freedom

MS = mean square

p-value = probability

F crit = F -critical value

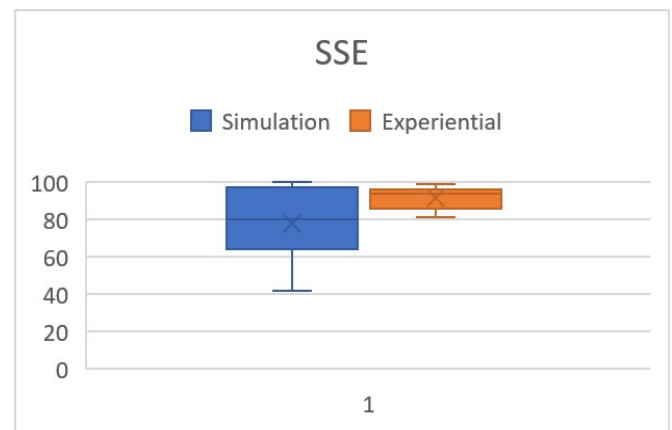


Figure 2. SSE.

Using Table 5 it can be inferred from the data that the experiential-learning mode had a significant effect on the learning outcomes in comparison with the simulation-based learning outcomes. Similarly, the mean, median, and standard deviation values for student scores in the programmable logic controllers (PLC) course were calculated. Figure 3 and

Tables 6-7 show the box plot and tabulated results, respectively. The primary distinction observed here was a notably higher mean value along with an increased median value. The results from the standard deviation values indicated that the results closely clustered around the mean value. Additionally, the ANOVA results also supported these findings and suggested a similar pattern for the previous courses in which there was considerable interest and motivation in the students towards experiential learning.

Table 4. SSE. Mean, median, and Std. Dev.

	Simulation	Experiential
Mean	77.53	91.58
Median	80	93.825
Std. Dev.	19.0465	6.0557082

Table 5. ANOVA-SSE.

Source of variation	SS	df	MS	F	P-value	F crit
Between groups	1282.648	1	1282.648	6.422218	0.018209	4.259677
Within groups	4793.29	24	199.720			
Total	6075.938	25				

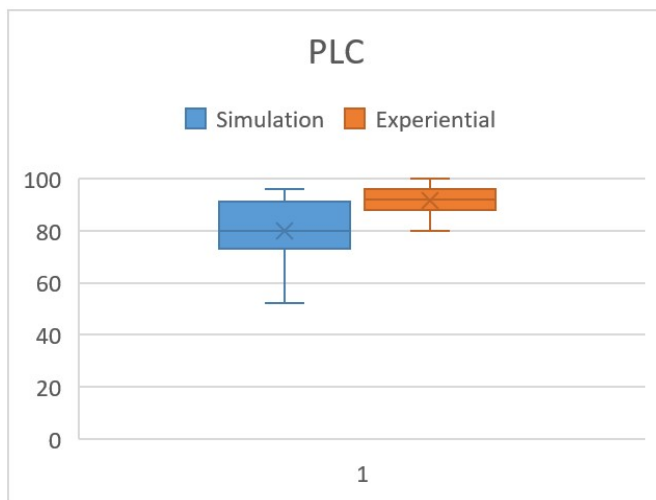


Figure 3. PLC.

Figure 4 along with Tables 8-9 seem to be in-line with observations made in the other courses. The pattern in Table 8 of higher mean and median scores was also noticed in this course, and a similarly low standard deviation suggested that the scores were close to the mean value. The ANOVA-

EMC results shown in Table 9 suggested a similar outcome to previous courses as well. However, here the calculated F value was even higher in comparison to the other courses. Though the sample size was reduced considerably in comparison with the AC-DC course, the outcome of the study suggested similar results.

Table 6. PLC. Mean, median, and Std. Dev.

	Simulation	Experiential
Mean	79.8	91.6
Median	80	92
Std. Dev.	12.31	5.25

Table 7. ANOVA-PLC.

ANOVA						
Source of variation	SS	df	MS	F	P-value	F crit
Between groups	840.1667	1	840.16	9.39	0.0056	4.3009
Within groups	1968.3	22	89.469			
Total	2808.5	23				

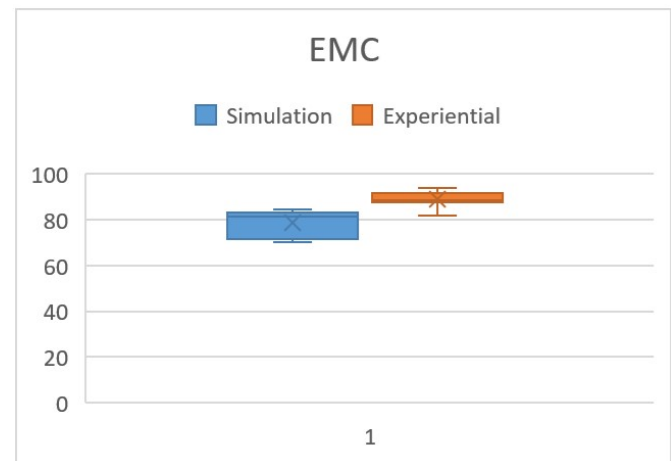


Figure 4. EMC.

Table 8. EMC. Mean, median, and Std. Dev.

	Simulation	Experiential
Mean	78.52	89.03
Median	81.10	88.5
Std. Dev.	5.91	3.54

Table 9. ANOVA-EMC.

ANOVA						
Source of variation	SS	df	MS	F	P-value	F crit
Between groups	397.67	1	397.670	18.795	0.00080	4.6671
Within groups	275.05	13	21.1577			
Total	672.7	14				

Limitations

Some of the limitations of this current study include the fact that it was conducted on a data set comprised of two iterations. Recreating the study for a longer duration in a cycle of four years could provide an elaborate picture of potential benefits of both styles of learning. Additionally, the authors feel that extending the scope of the study to different courses could provide valuable insights into for observing the pattern. Another area where the authors identified required future work was with data collection for senior-year coursework.

Conclusions

This study, conducted on four courses in the engineering technology discipline, provided excellent statistical information.

- The study conducted across four courses within the engineering technology discipline provided valuable statistical insights and offered a detailed comparison between different learning modes.
- The findings clearly underscored the distinction between simulation-based learning and experiential learning, emphasizing their respective impacts on student performance and outcomes.
- The statistical analysis of student performance indicated that experiential learning was associated with improved learning outcomes compared to simulation-based approaches.
- The tendency of scores to remain close to the mean suggested that the mode of learning played a significant role in stabilizing and influencing student outcomes.
- Analysis of variance (ANOVA) performed on each course complemented the findings and confirmed the statistical significance of the observed differences between the two learning modes.

The overall conclusion of this study suggests that, within the specific context and scope of the courses examined, experiential learning was associated with higher levels of

student engagement and improved academic performance when compared to simulation-based methods. These findings highlight the potential value of incorporating more hands-on, practice-oriented instructional strategies in engineering technology education. However, given the limited sample size and course selection, caution should be exercised in generalizing these results. For future research, it would be beneficial to conduct a longitudinal study involving a larger and more diverse student population, covering multiple academic years and a broader range of courses. Such an approach would provide a more comprehensive and reliable dataset for analysis. Additionally, further investigation into how different combinations of experiential- and simulation-based methods can be optimized, based on subject matter, resource availability, and learning objectives, could offer valuable insights for the development of more effective and inclusive teaching practices.

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UTILIZING AI TO IMPROVE EFFICIENCY IN ESTIMATING AUTOMATION PROJECTS: SPECIFICATION REVIEW 2024

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Abstract

Automation organizations are facing significant profit declines due to various operational inefficiencies. In this paper, the authors focus on the review of documents in the estimation phase of a project as one of these inefficiencies. Using a structured framework, the aim is to demonstrate AI as a viable solution and illustrate how efficiency improvements correlate with increased value. A survey involving 27 subject matter experts (SMEs) was used to establish the minimum set of features necessary to create value and determine risks, referred to as the minimum viable product (MVP). The MVP survey revealed that the most important feature was a high-level list of deliverables, followed by a document summary. The survey identified missing information as the biggest concern, necessitating a performance evaluation.

Three specification documents were used in the study as the dataset to establish performance. A 34-prompt questionnaire was developed and responses were evaluated using Precision, Recall, and F1 scores: standard metrics where Precision measures the relevancy of responses, Recall measures the ability to find necessary information, and F1 reflects the ratio between the two. The chatbot scored the three at 86%, 92%, and 89%, respectively. Following the performance study, five specification documents were used to evaluate time savings. Loading the questionnaire and obtaining responses from the chatbot took 30 minutes, on average. Historical data from five specifications on annotation time was extracted, revealing that the chatbot could achieve desirable results in 25% of the time compared to human annotators. This efficiency translated into a 50% cost reduction. The results indicate that AI can achieve a high level of performance while surpassing human efficiency. The high Recall score demonstrated that the chatbot had a low tendency to miss information.

Index Terms—Artificial intelligence, Chatbot, Contracts, Factory automation, Formal specifications, Industrial controls, Large Language Model (LLM), Natural language processing (NLP), Prompt engineering, Proposals, Question answering (information retrieval), Question generation.

Introduction

In recent years, control automation organizations have been faced with shrinking profits, largely due to competitive bidding and rising salaries (Meisels, Nikulin, Hardin, Sloane & Dwivedi, 2023; Coykendall, Hardin & Morehouse, 2023). Consequently, executives and managers have been challenged to improve their companies' profitability.

Negotiating higher sale prices is not a sustainable long-term solution, as the market and competitors dictate the value of such services. Therefore, innovative ways must be found to lower costs while increasing the value of offerings. Artificial intelligence (AI) presents such an opportunity for reducing operational costs. In this paper, the authors propose using AI to alleviate one or more of these inefficiencies, aiming to lower the cost of operational processes and, ultimately, increase profitability.

AI has significant potential for alleviating efficiency problems in job-related activities. The technology can be used to target and automate specific functions in an organization by making corporate data easily accessible. In 2017, McKinsey & Company reported that 50% of the hours spent on job activities could be automated using AI, but advancements in generative AI in 2022 adjusted this figure to 60–70%. Given these figures, the adoption of AI creates more value, particularly in higher-wage jobs. The most impact would be seen in the fields of education and technology, particularly in automating tasks performed by highly educated individuals, a technical change referred to as skill bias (Chui et al., 2023). As a result, many companies are currently utilizing AI. The advancements and accessibility to content-generating AI in 2022 have spurred a surge in the adoption of this technology in the workplace. Since 2017, about 50% of organizations have integrated AI in at least one essential task, with adoption rates rising from 55% to 72% in 2023. Companies are focusing on using AI where it provides the most value, with the consensus across industry being that organizations will allocate over 5% of their digital budgets to AI (Singla, Sukharevsky, Yee & Chui, 2024).

To drive successful AI initiatives, organizations need a clearly formulated business strategy with specific goals that outline the business value. The business value must be directly linked to measurable metrics that quantify the goals. These metrics are essential for reporting value creation and performance to stakeholders and helping to determine if the initiative is successful (Gudigantala, Madhavaram & Bicen, 2023). Instead of relying on existing demand, companies can adopt a “technology push” approach. This strategy allows them to identify and prioritize opportunities that help automate one or multiple phases of an automation project (Brem, Giones & Werle, 2021). However, implementing AI comes with inherent risks. One major challenge are the ethical implications of AI, which can hinder initiatives. A study showed that, to remove these difficulties, the AI needs to be unbiased, fair to all, and have a level of explainability for its predictions. To achieve these goals, the involvement of stakeholders is required, along with guidance and training for responsible AI (Crockett, Colyer, Gerber & Latham,

2021). Privacy concerns also arise, especially when sharing data. Low-level privacy risks can be addressed through notices and consents. Higher risks call for techniques such as cryptography, which alters or codes original data to prevent unauthorized access and perturbation, which modifies data to hide sensitive information while maintaining relevance to authorized users (Curzon, Kosa, Akalu & El-Khatib, 2021).

AI in the Estimation Phase of a Project

The estimation of an engineering project starts with a request for proposal (RFP) from the end user, which may include scope of work, equipment sections, and engineering artifacts such as drawings. AI can add value by substituting time-consuming tasks critical to project estimation. This aligns with the fuzzy front end of the innovation process in which exploring and selecting problems comes before exploring and selecting solutions. This process is best accomplished with the involvement of SMEs to select tasks suitable for AI solutions (Kakatkar, Bilgram & Füller, 2018; Bouschery, Blazevic & Piller, 2023). Reading large amounts of text in RFPs is cumbersome and requires SMEs due to subject-specific content. However, natural language processing (NLP), a branch of AI dedicated to giving machines the ability to understand context and generate text, has significantly evolved. Traditionally, SMEs were needed to review technical documents, but generative pretrained transformer-based (GPT) models such as GPT-3 can now summarize and extract the most meaningful information from a body of text (Bouschery et al., 2023). In this context, AI has the potential to enhance the work of executives, managers, and SMEs. In the case of RFPs, extracting insight from the documentation using AI and complementing it with human insight can produce value and efficiency gains.

Despite advancements in AI applications, few studies have specifically addressed its use in automating the review of complex technical specifications, particularly to improve profitability through increased efficiency. In this study, the authors aimed to fill this gap by providing a practical solution for AI-enhanced project documentation review in the automation industry. The contributions include

- Providing a framework to specifically focus on the value creation of AI.
- Demonstrating AI's ability to understand specific technical automation terminology and context through measurable performance metrics.
- Quantifying efficiency gains and dollar savings achieved by implementing an AI solution.

Literature Review

In this study, the authors explored current applications and work that could enhance the review processes for automation project documentation. The authors examined practices employed in the methodologies and whether the applications were mature and viable solutions in the

industry. The contract phase of the project included several steps, starting with distributing documentation, including specifications, master service agreements, and terms and conditions. Careful review of document language must be done prior to budget development. Extensive work was found in this area (Shaghaghian, Feng, Jafarpour & Pogrebnyakov, 2020; Candaş & Tokdemir, 2022). Popular NLP models, such as ALBERT on the Keras website (Keras, n.d.), are trained on libraries found on global searches. ALBERT, specifically, is trained on English Wikipedia and BooksCorpus. This model can summarize articles but still struggles to understand nuanced legal context. When using these models, there is the need to input label data using supervised learning to produce the desired outcome (Shaghaghian et al., 2020). One question emerged during this study: what type of language is being sought for extraction from contracts? This is highly applicable in the automation industry, as different disciplines have distinct interests in extracting specific language content. For example, is the intent being extracted risky language from the contract or is the intent to extract deliverables?

Earlier research was conducted to automate language classification in contracts by discipline (Candaş & Tokdemir, 2022). In that study, the authors highlighted how SMEs can improperly classify clauses in a draft contract. The methodology employed supervised machine learning using multilabel datasets to teach the NLP model. This means that clauses extracted are assigned a category for each discipline. That study used the FIDIC Silver Book, which guides engineering procurement and construction contractors in reviewing and preparing contract conditions. The experiment tested six different models using labeled data from the Silver Book, revealing one model that tested the best by multiple accuracy metrics. The authors of that study presented a successful case in which multidisciplinary text could be extracted from documents. They also highlighted the scalability of the NLP model by using classification methods with multiple classes instead of binary classification (Candaş & Tokdemir, 2022).

Named entity recognition (NER) is a machine learning technique that identifies, extracts, and classifies text into predetermined categories such as organization or person. The NER application starts by annotating the data set, where selected relevant documents are manually labeled. An experiment using open-source software, called Label Studio, annotated 30 documents, averaging 173 sentences each. The labeled text was classified into seven entities: PERSON, LOC, DATE, etc. The annotated data then fine-tuned two popular NER transformer-based pipelines from spaCy, enhancing their accuracy with legal language. Favorable results were obtained with the `en_core_web_trf` pipeline, a language model optimized for language extraction and syntax parsing, having F1, Precision, and Recall scores of 0.60, 0.41, and 0.48, respectively. These scores indicate a potential for legal applications with further development (Naik, Patel & Kannan, 2023).

Construction projects are similar to automation projects; some need a review of RFP to extract pertinent material related to automation. SMEs believe the process can only be done manually due to the nature of the meaning behind the words, a topic addressed in a survey in a subsequent section. RFPs define project scope and deliverables, but different RFPs with similar provisions might be worded differently. To address these semantic conflicts, an experiment was conducted that involved creating a semantic thesaurus, using a NER model to categorize the extracted text and creating a provision-pairing model to compare provisions across different documents. A survey was conducted using SMEs to select entity names. The performance evaluation revealed that, by identifying the most relevant provisions, the specification's review was improved. Similarly, a case study showed a 24% increase in the F1 score and a 22% reduction in review time, indicating that the tool could aid, but not replace, the review process or the SME. Additionally, the experiment group using the automated review process showed more consistent results than the control group reviewing manually (Moon, Lee & Chi, 2022).

Successful language extraction from contracts requires careful framing of the business case and the desired goal, as well as an expert for labeling datasets, supervised training, and validation. Both cases used similar technologies for different purposes (Shaghaghian et al., 2020; Candaş & Tokdemir, 2022). The complexity of legal language can be challenging, as understanding the nuanced meanings can be difficult even for trained professionals. One term can have many synonyms or abbreviations. The same can be said for specification documents. To overcome these challenges, traditional NER models must be fine-tuned with vast amounts of labeled data to improve performance (Candaş & Tokdemir, 2022). Large language models (LLMs) such as GPT are transformer-based models pre-trained with vast amounts of general data. These models can generate ideas, perform analysis, or even generate code, aiding prototype development. Creating early prototypes enables individuals to test which features produce value and application acceptance.

For example, an automotive application prototype was built (Bilgram & Laarmann, 2023) using ChatGPT and features were added through iterations of prompts. Teams interacted with the LLMs to stimulate the development process, and managers observed that the output was similar to drafts from proficient assistants. Studies have shown that factors that positively influence adoption include effort expectancy, or ease of use; performance expectations, which is the perceived helpfulness of the chatbot; and, habit, or continuous behavior. In contrast, perceived threats can negatively affect adoption. The findings demonstrated that, when evaluating an application, enhanced features and performance directly correlated with high use (Al-Emran, AlQudah, Abbasi, Al-Sharafi & Iranmanesh, 2023).

Methodology

Many AI opportunities appear promising in the early stages but fail to come to fruition because they fail to align with business objectives. In this current study, the authors used a three-part methodology to address this issue. First, a survey was used as a qualitative exploratory methodology to deliver a solution with a high likelihood of success. Second, a quantitative exploratory methodology was used to measure performance—a test that compared actual predictions versus known outcomes was designed. Third, a quantitative confirmatory methodology was used to validate the solution's value creation, demonstrating how AI could enhance the documentation review processes to achieve greater efficiency.

1. Executed Process for MVP Survey

The MVP (Tripathi, Oivo, Liukkunen & Markkula, 2019) is the initial version of the solution with the minimum set of features that address the problem and produce value. A survey (Tripathi et al., 2019) was distributed to determine the minimum features needed to develop a solution. Additionally, the purpose was to gain insight into people's acceptance and potential risks. The data were collected from 28 participants, including engineering group managers, project managers, account managers, estimators, and business development managers. The participants were SMEs, who had been employed in their positions for at least one year and reviewed specifications at least once a week as part of their responsibilities. The participants selected features based on survey questions regarding the idea of creating a tool leveraging AI chatbots designed for estimators and account managers. This tool not only generated responses tailored from customer specifications but also efficiently summarized and extracted key information from these specifications. By accelerating the spec review process through intelligent summarization, it provided an overview of project deliverables at a high level, thereby enhancing productivity and precision in the estimation process of an opportunity.

- How much do you like or dislike the idea of a tool or chatbot to review specification documents?
- What do you like most about this idea for a tool?
- What do you like least about this idea for a tool?
- How important is each product feature (Table 1) to you?

2. Executed Process to Measure Performance

To determine the chatbot application's ability to replace a task that a human does, it must have comparable results. First, three specification documents were collected. The specifications had been previously annotated by SMEs, who provided background about the quality of human annotations. Second, a 34-prompt questionnaire was developed as a baseline on which specific questions were asked with the purpose of generating a high-level list of deliverables that one might get from human annotations. In a study by Bsharat, Myrzakhan, and Shen (2023), the authors

Table 1. Feature selection example.

	Extremely important	Somewhat important	Slightly important	Not very important	Not at all important
Summarize	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
List Deliverable	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Text Extraction (i.e. Material)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Retain section numbering	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

introduced principles for prompting various chatbots. The approach to the questions was to use these prompt engineering techniques to improve the responses. For example, Figure 1 shows how the question is enhanced by providing instructions. The phrase, “List who is responsible for each” specifies that the response must be in the form of a list. Third, the previously collected specification documents were uploaded to the AI chatbot without annotations. The responses were evaluated manually by comparing the predictions to the expected outputs. The prompts and responses of the experiment are provided in the Appendices.

AI Response to Prompt

7. Are any of the following mentioned? DCS cabinet, PLC cabinet, Switchgear, panel board, MCC, Communication racks, junction marshaling boxes, RIO.
List who is responsible for each

Based on the provided context, the following are mentioned:

- PLC Cabinet** (page 38, item 15): The PLC (Programmable Logic Controller) is housed inside the main control panel. The responsibility for the PLC cabinet, including its installation and wiring, falls to the electrical Contractor in Contract #1.
- Communication Racks** (page 43, item b): While not explicitly called “communication racks,” the document refers to Ethernet and SCADA connectivity, which implies the use of communication racks or similar structures. The installation Contractor in Contract #1 would be responsible for providing conduit and routings for communication cables.
- Junction Marshaling Boxes** (page 27, item 2.12; page 30, item 2.21; page 33, item A): Referred to as “junction boxes,” these are mentioned several times with different functions (SBR Junction Box, POST-EQ Junction Box). The electrical Contractor in Contract #1 is responsible for the field wiring and installation of these junction boxes.

The document does not explicitly mention “DCS cabinet,” “Switchgear,” “Panel board,” “MCC (Motor Control Center),” or “RIO (Remote I/O).” However, it does detail various control enclosures and panels that would typically be part of a larger control system, which may include some of these components. The responsibility for these would likely also fall to the electrical Contractor in Contract #1, as they are responsible for the

Annotated Text from Estimator

- Adhesive anchors of 304 stainless steel shall be provided for anchoring the level sensor mounting bracket.
- 2.20 POST-EQ JUNCTION BOX** Junction box
A. Description: NEMA 4X 304 stainless steel junction box shall be provided. The junction box shall contain intrinsically safe relays and terminal blocks for terminating electrical controls and components. Field wiring and installation of the junction box shall be the responsibility of the electrical Contractor in Contract #1.
- 2.21 POST-EQ CONTROLLER**
A. Description: Furnish one (1) Multi Parameter Probe Module(s) per basin. The module shall

Figure 1. Example prompt from questionnaire.

If the application performed as well as or better than a human, then it could replace the task that the human was performing. The goal of the experiment was to deduce whether or not higher efficiency could be achieved by either eliminating or speeding up the task, thus validating the hypothesis.

3. Executed Process Performance vs Financial Metrics

In the previous step of establishing performance, specification documents were selected to conduct the experiment. The specifications selected had time and cost recorded when they were annotated by humans, which were then compared to the time and cost of using an AI chatbot to generate questionnaire responses. The data gathered during the study when the human produced the output was used as the baseline. Having the true cost of the human annotations was essential for comparing the cost of annotations to the cost of the chatbot. Because the same dataset was used to obtain the quality and duration of the output, the model versus human was the only variable in the experiment. By conducting this study, further validation of the previously stated efficiency hypothesis was sought.

Results

This section summarizes the data collected from all the experiments and provides a comprehensive analysis of the results. The objective is to draw meaningful insight from the qualitative data from the survey and validate the previously made hypothesis using the quantitative data during the performance evaluation. In the MVP survey, the following question was asked: “How much do you like or dislike the idea of a tool or chatbot to review specification documents?” Seventy-seven percent of the participants responded positively, which included: (1) like a great deal; (2) like a moderate amount; and, (3) like a little. Fifteen percent of the participants’ answers were neutral and neither liked nor disliked the idea. Eight percent of the participants answered negatively, which included: (1) dislike a little; (2) dislike a moderate amount; and, (3) dislike a great deal. Figure 2 illustrates the results of the survey question. Additionally, the question “What do you like most about this idea for a tool?” revealed that the predominant theme in the answers were the possible gains in efficiency and quality.

Two examples from the raw data include

- I believe tools can increase productivity and efficiency.
- I think that it will help us get through the more mundane tasks and focus on critical details.

Q3 - How much do you like or dislike the idea for a tool, Chatbot, to review specification documents?

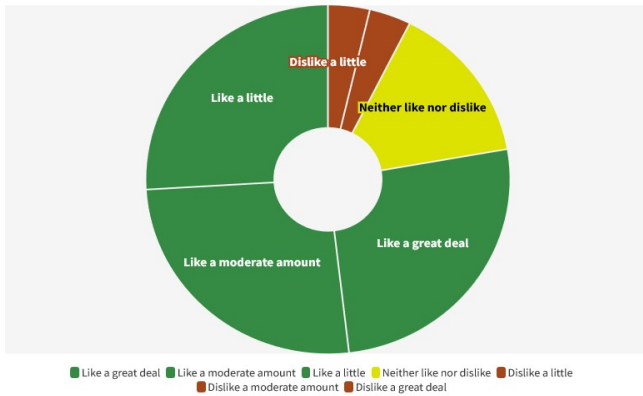


Figure 2. How much do you like or dislike the idea of a tool?

Another question given to participants was “What do you like least about this idea for a tool?” The predominant theme in the answers was apprehension about missing information and the evaluation process.

- Concern that it will miss some parameters due to non-standard language or special non-standard instructions.
- How will we know if it doesn’t work?

The final question of the survey was “How important is each product feature to you?” Evaluating the list of features, the List of Deliverables ranked first among the features desired by the end users. The second most desired feature was Summarize the Spec. The remaining ranked items (3-10) were Text Extraction, Retain Section Numbering, Retaining Section Callouts, Mobile Application, Chat with Document in Detail, Extracting Information from Plans, Page Numbering, and Being Able to Preload Multiple Questions at a Time. Figure 3 further illustrates the results of the survey. The raw data for all the questions are given in the Appendices.

In the MVP survey, 77% of the participants responded positively to receiving an AI tool that would aid with the manual tasks of reviewing specifications. Figure 3 shows how the positive results indicate that the AI Adoption risk is low. The responses to the question “What do you like the most about this idea for a tool?” indicated that efficiency and possible quality improvements would be positively received. These benefits aligned directly with the project’s objective, which was to increase the efficiency of the organization. The responses to the question “What do you like least about this idea for a tool?” indicated that missing relevant information was the predominant apprehension

about the potential of using an AI tool to review specifications. Another common dislike was not knowing how it would be evaluated. It can be inferred that the two responses were related, as the evaluation procedure determined the baseline for missing information.

Q6 - How important is each product feature to you?

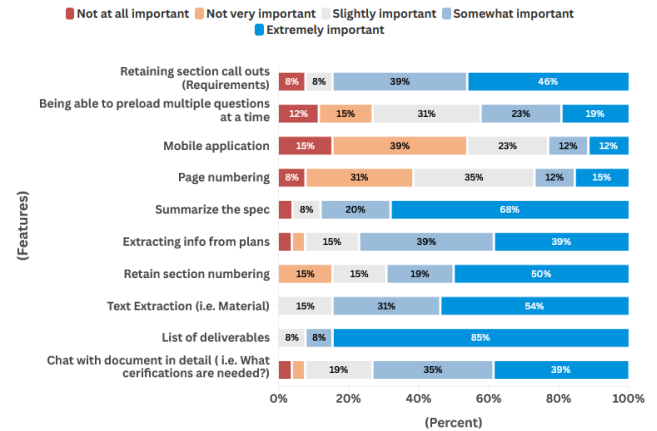


Figure 3. How important is each product feature to you?

The MVP survey aimed to determine the essential features necessary to develop a successful application for solving a business problem. A list of deliverables and summary ranking the highest indicators that the end users desired to get a high-level overview of the project. It was inferred that a high-level overview of the project could increase efficiency when creating an estimating strategy. Although there were mostly positive responses to the idea of having an AI specification review tool, the risk of adoption was not entirely removed. Ensuring buy-in by the end users to participate in the process was necessary to mitigate risk. By comparing the predictions made by the application versus the known outputs, one can record the number of predictions made as a true positive, false negative, false positive, or true negative. The F1, Precision, and Recall scores (Bhate, Mittal, He & Luo, 2023) could be the primary metrics used to evaluate the application. The authors recommend that the Recall metric be emphasized during the performance evaluations. Recall is a metric that can assess the model’s ability to retrieve correct answers without missing important information.

The following question was asked in the survey: “How important is each product feature to you?” A Likert matrix question was used to select the level of importance of each feature. The Likert scale used consisted of the following five descriptors: extremely important (5), somewhat important (4), slightly important (3), not very important (2), and not at all important (1). The responses were analyzed by the frequency of each category. The question could also be modified to a ranking order. Changing the style of the question could facilitate the evaluation process, when compared to other questions, and still achieve the primary purpose of the question.

The dataset of approximately 6400 sentences contained in specifications ranging from equipment to responsibilities was analyzed to determine the correct responses for comparison with predictions. The dataset included three documents, approximately 6480 sentences (with the average number of sentences per document being 2160), and 82,325 tokens without stop words. Table 2 shows that, by comparing the predictions made by the application to the known outputs, one can record the number of predictions made as a true positive, false negative, false positive, or true negative in a confusion matrix. The classes recorded were defined as follows.

- True Positive = The number of positive cases correctly predicted.
- False Negative = The number of negative cases incorrectly predicted to be positive.
- False Positive = The number of positive cases incorrectly predicted to be negative.
- True Negative = The number of negative cases correctly predicted

Table 2. Confusion matrix.

		True Class	
		Positive	Negative
Predicted	Positive	163 True Positives (TP)	15 False Positives (FP)
	Negative	27 False Negatives (FN)	170 True Negatives (TN)

Using the mathematical relationships of Equations 1-5, the outcomes of metrics for Accuracy, Precision, Recall, Specificity, and F1 can be calculated.

- Precision = $(TP+TN)/(TP+TN+FP+FN)$ (1)
- F1 Score = $(2*TP)/(2*TP+FP+FN)$ (2)
- Precision = $TP/(TP+FP)$ (3)
- Recall Sensitivity = $TP/(TP+FN)$ (4)
- Specificity = $TN/(TN+FP)$ (5)

Table 3 shows the results obtained from the different calculations. Due to the unbalanced nature of the samples, the F1 score was used to evaluate the overall performance of the application. The F1 score was defined as the harmonic mean of Precision and Recall for the positive class. An F1 score of 89% was considered a good result. Precision resulted in 92%, a high score indicating how well the chatbot made positive predictions. Recall, which was the fraction of positives correctly predicted, scored 86%. Given that one of the risks identified in the MVP survey was Missing Important Information, the Recall metric was of particular interest. The chatbot achieved good results for F1, Precision, and Recall.

Table 3. Results from evaluation of the confusion matrix.

Accuracy	88.80%
F1	88.59%
Precision	91.57%
Recall Sensitivity	85.79%
Specificity	91.89%

Few-shot prompting was used in Question 1. Examples of entities were provided within the prompt, but the chatbot responded incorrectly in some cases. Modifying the questions slightly, for example, entities to organizations, worked in those cases. The authors recommend, then, to prompt two versions for the questions that tend to provide incomplete responses. Two words in the questions, “report” and “instrument,” seemed generic enough to cause the AI to have trouble producing the correct response. The word report in Question 18, “Is there mention of reports relative to the HMI or SCADA or DCS?” Although words like HMI were included to give it context, the chatbot still responded incorrectly, providing responses such as “Yes, project status reports are mentioned.”

In the case of the word “instrument,” the chatbot produced partially correct responses. It identified level and pressure sensors correctly, but in three out of nine cases, it misidentified PLCs and PCs as instruments. These instances were recorded as false positives. In the cases where no instrumentation was specified, it correctly responded “The document does not explicitly list instrumentation”; however, it often appended general statements suggesting that such requirements might include PLCs. For future iterations, the authors recommend including explicit entity definitions, such as flow transmitters, level switches, and pH analyzers, as examples of instruments in the prompt. Providing specific examples may improve accuracy by restricting general interpretations.

When loading the question, “Does the document mention DCS?” the response was “No.” The chatbot provided additional context in the response by adding, “It primarily discusses the upgrade of PLC.” Remarkably, the chatbot understood the context of the question and associated DCS with a programmable logic controller (PLC), which performs similar functions. The annotated specification documents included mostly highlights of text. Establishing human performance from the data was not possible, due to the lack of context behind the markings. The study could be expanded by using SMEs to annotate the content related to the questionnaire and provide additional notes for context. Another recommendation would be to increase the number of specifications in the study to include more variation in the dataset. It would be desirable to do the same study with different chatbots to compare the performance of different applications under the same conditions.

The specification documents collected varied in size; therefore, the number of hours it took to annotate varied. In contrast, the time it took to load the 34 questions into the chatbot and obtain responses took 30 minutes in all five evaluations. The total number of hours spent on human annotation was 10 hours at a cost of \$250. The same specifications loaded into the chatbot totaled two and a half hours at a cost of \$25 each, totaling \$125 in the experiment. Using a chatbot with a predesigned questionnaire took 75% less time than using human annotations. Figure 4 illustrates the time and money difference between annotators and a chatbot for the same dataset.

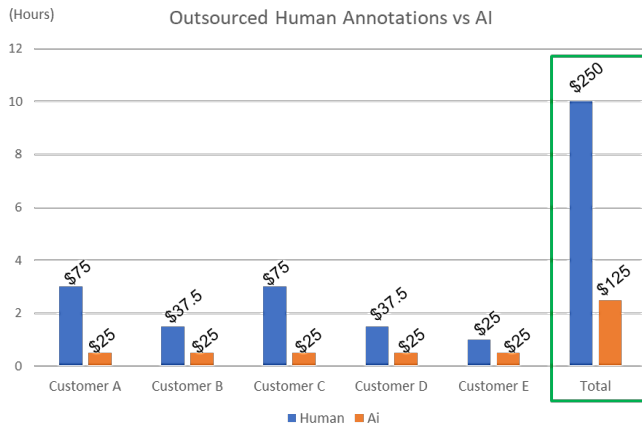


Figure 4. Value of outsourcing human annotations versus AI.

The authors found that using a chatbot with the predetermined questionnaire took 75% less time than an outsourced annotator; as a result, using a chatbot cost 50% less than using outsourced human annotations. When the specification review was performed by other SMEs, the cost was more impactful. It can be inferred that at the higher cost of \$100/hr for an account manager, the difference was \$250 to review specifications aided with AI as opposed to \$1000 without the use of AI. The dollar amounts in the experiment initially appeared insignificant. However, the estimated bill for outsourcing specification annotations for the years 2022 and 2023 was \$120,000. Internal to the organization, the yearly cost for the estimating phase was \$522,000, and the percentage of that cost from specification review was estimated to be anywhere from 40% to 60%. The increases in efficiency can have a significant impact on the yearly costs for this task.

Conclusions

The results of this study confirmed that AI can accelerate the review of control industry-specific technical specifications, thus showing significant efficiency improvements. The methodology presented accomplished two objectives. First, it identified how to enhance the work of SMEs. Second, it validated the model's predictions against actual outputs, which was further developed by directly correlating financial metrics. It was clear from the MVP survey that the

most desired features were a high-level list of deliverables and a summary. The MVP allowed for rapid experimentation, considering that time was criticality important. The survey results identified that missing information when using a chatbot was a risk that could derail the tool's adoption. Initially, methods such as BLEU (bilingual evaluation understudy) would be used to evaluate the outputs. These methods did not produce the results needed, as their score was based on matches of predicted words with exact expected words. A gap was identified during the performance metrics research. Most of the literature on testing chatbots was about usage and adoption. This gap was closed by using the testing methodology traditionally used for classifiers. F1, Precision, and Recall proved to be the best for the evaluations, because the words used in the responses were not as important as whether the response was right or wrong. The chatbot scored an F1 of 89%, a Precision of 92%, and a Recall of 86%, indicating that the application produced correct responses and a low percentage of missing information.

One aspect that could be further explored would be the use of semi-structured interviews to identify the MVP features. Another area that could be explored in future research is to conduct a comparative study of various chatbots and LLMs. Such a study would provide insight into the strengths and weaknesses of each model's performance for specification review. The ultimate measure of success was to compare what the application could do in comparison to a human. The questionnaire, created to identify the deliverables in the specification relevant to the control system, was essential. The authors concluded that loading the questions into the chatbot took 30 minutes. The dataset of specification documents was selected because it included historical data on the duration of the review at the time of production. It was shown that a 50% decrease in cost was possible, demonstrating remarkable potential. While traditional methods for cost control can be effective techniques, it's important to recognize that AI presents a unique alternative to cost reduction. The current approach does not require reducing overhead expenses or negotiating better supplier pricing agreements. Instead, it proposes AI as a novel approach to improving profitability in an organization, facilitating the specification review task.

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Appendix A

Chat With Specifications: Customer B

The document pertains to Contract #6 for the Wastewater Treatment Plant SBR Equipment, as part of the County Public Service District in West Virginia. The addendum issued on June 20, 2023, by a Civil Engineering Group., includes clarifications and responses to vendor queries about the project, with the bid submission deadline set for July 11, 2023. The addendum updates various specifications, including timelines for substantial completion and final payment, removal of manufacturer-specific language, material changes for certain components, revised lists of acceptable manufacturers, and adjustments to spare parts quantities. The agreement between a County Public Service District (the Buyer) and the vendor (the Seller) outlines the procurement of goods and services, project details, duties of the engineering firm, and contractual obligations such as delivery times, liquidated damages, payment procedures, and the right to assign the contract.

The SBR equipment specifications cover the design and functionality requirements, quality assurance, performance guarantees, and submission and handling protocols. The SBR system must operate effectively under specified conditions and meet effluent standards. Key components include influent plug valves, mechanical mixers, pivotal mooring systems, decanter assemblies, and related accessories. The addendum includes detailed technical specifications for these items, emphasizing the importance of compliance with the outlined standards and coordination with the project's Contractor in Contract #1.

Q1) Exxon Inc., PepsiCo, and Phillips 66 are examples of entities. List the entities mentioned in the document, separating them based on their role.

Based on the provided context, the entities mentioned in the document can be categorized as follows:

- Buyer: County Public Service District. 1-True Positive.
- Seller: Not explicitly named in the provided excerpts. 1-True Positive.
- Engineering Firm/Engineer: Civil Engineering Group, Inc. 1-True Positive.
- Manufacturers: Customer B.; Equipment Manufacturer; Or Engineer's approved equal, which suggests that other manufacturers could be considered if they meet the project specifications. No Score.
- Surety: Not explicitly named, but references are made to a "Surety's Consent to Assignment," indicating the involvement of a surety entity. 1-True Positive
- Contractor/Assignee: The entity or entities that would be involved in Contract #1 for the installation of the equipment are not named in the excerpts provided. 1-True Positive.

Please note that while the document references various roles and responsibilities, specific names for the Seller, Surety, and Contractor/Assignee are not provided in the excerpts. The document does mention the need for evidence of authority to sign for corporations and public bodies, which would typically involve named individuals from those entities, but such names are not included in the provided text.

Q4) Are any of the following mentioned in the document relative to drawings? Plot Plans, One-line Diagrams, MCC Elevation, Motor elementary or loop, Panel Layout, Schematics, or Instrument Loop or Loop sheets.

The document does not explicitly mention "Plot Plans," "One-line Diagrams," "MCC Elevation," "Motor elementary or loop," "Panel Layout," "Schematics," or "Instrument Loop or Loop sheets." However, it does refer to "Procurement Drawings" and "contract drawings," which could potentially include some of these types of drawings within their scope. The document also mentions "wiring schematic drawing" in the context of control panel wiring, which suggests that schematics are indeed part of the documentation. Additionally, the document refers to "finalized drawing set" in relation to the control testing of the enclosure assembly, which may encompass various types of detailed drawings relevant to the project. 1-True Positive, 6-True Negatives.

Q11) List the PLC requirements.

The PLC (Programmable Logic Controller) requirements as per the document provided are as follows:

- Automatic Control: The PLC is responsible for the automatic operation of the Sequencing Batch Reactor (SBR) system. 1-True Positive.
- Mounting: The PLC is to be mounted inside the main control panel. 1-True Positive.
- Components: The PLC system shall consist of a power supply, CPU, discrete input and output modules, and analog input and output modules. 1-True Positive.
- Processor Unit: The processor must include built-in USB and two Ethernet IP communication ports. All input and output points, including unused ones, must be wired to terminal blocks. 1-True Positive.
- Processor Design Characteristics: The processor should have 1.0MB user memory size, a real-time clock and calendar, battery-backed RAM, and an operating temperature range between 32°F and 140°F. No Score – Combined with 4.
- Acceptable Manufacturers: The PLC processor shall be from Allen Bradley, ABB, or an Engineer's approved equal.
- Modular Equipment: Specific Allen-Bradley components are listed to complete the PLC system, including power supply (1769-PA4), discrete input

modules (1769-IA16), discrete output modules (1769-OW16), analog input modules (1769-IF8), and analog output modules (1769-OF4). 1-True Positive.

- PLC Power Supply: The power supply should have an input voltage range of 85-265 / 170-265 VAC, 47-63 Hz, a maximum inrush current of 30 amps, backplane output current of 4 amps at 5V or 2 amps at 24V, internal fuse protection, and an ambient operating temperature of 32°F to 140°F. It must be UL Listed. 1-True Positive.
- Programming Software: The PLC should be programmable with Rockwell Software RSLogix 5000, which is IEC-61131-3 compliant. 1-True Positive.
- Testing and Quality Assurance: The PLC and operator interface program must be loaded and functionally checked, with point-to-point testing of all wiring prior to the application of power. The intended supply voltage should be applied to the enclosure, and all components should be tested for proper operation and calibration. 1-True Positive.
- Factory Checkout: A control panel checklist must document all testing completed, and upon successful completion of control testing of the enclosure assembly, all applicable documentation should be placed in the drawing pocket of the enclosure. 1-True Positive.

These requirements ensure that the PLC is suitable for controlling the SBR system at a Wastewater Treatment Plant and is capable of interfacing with other components of the control system, such as the HMI and SCADA system. Two missing answers: 1) HF Noise Protection and 2) Ethernet connectivity. 2-False Negative.

Q17) Is there mention of a historian relative to the HMI or SCADA or DCS or PLC?

Yes, there is mention of a historian in relation to the SCADA system. Specifically, the document on page 39 under section B, item 7, states that the SCADA system includes historical data logging, which provides long-term storage of data to assist with plant optimization. This historical data logging is a key function of a historian, which is a software application that records and retrieves production and process data by time; it then stores this data in a database for future analysis. Historians are commonly used in conjunction with SCADA systems to capture the high-volume data generated by industrial processes. 1-True Positive.

Q18) Is there mention of reports relative to the HMI or SCADA or DCS?

Yes, the document does mention reports in relation to the SCADA system. Specifically, on page 39, it outlines that the SCADA system will have a consolidated alarm summary for all monitored areas, plus an alarm log. Additionally, it will have an event log that may capture operator commands as well as process/equipment functions. These logs and summaries can be considered as reports that

provide insights into the system's performance and events. There is no direct mention of reports specifically for the HMI (Human Machine Interface) or DCS (Distributed Control System), but since the HMI is a component of the overall SCADA system, any reporting functionality described for the SCADA system would implicitly include the HMI. 1-False Positive.

Q33) Does the document mention heat trace?

No, the document does not mention "heat trace" in the provided excerpts. Heat trace, or heat tracing, refers to a process of maintaining or raising the temperature of pipes and vessels using heat tracing cables or tubing, which is often used to prevent freezing or to maintain process temperatures. This specific term does not appear in the context information you have provided. 1-True Negative.

Appendix B

MVP Survey

What do you like most about this idea for a tool?

- If it works, that would be great.
- That it should quickly and efficiently summarize the customer requirements and provide a complete overview.
- If it works, it will help streamline that process.
- Quicker searches for relevant information and keywords
- Quicken the evaluation (or 'go/no-go') process to enable us to better focus on valid projects only.
- I think that it will help us get through the more mundane tasks and focus on critical details.
- Opportunity to create efficiencies in estimating.
- To possibly find hidden details like project schedule or to skip past a bunch of boilerplates and see if anything may be important in the boilerplate.
- Assistance in identifying specifications that can affect job cost and effort.
- I believe tools can increase productivity and efficiency.
- Maybe that it could provide a few project aspects that could help in deciding if the project is worth pursuing a finer filter process.
- It can provide a quick reference for design requirements. i.e., wire color, relay contact rating, listing of acceptable manufacturers for components pull out the highlights of a complex spec.
- In my mind, I'm thinking that programmed keywords would return a summary of findings, which would ultimately reduce time spent reviewing specifications.
- May streamline the review.
- It will allow us to share our knowledge and experience by listing critical questions that may have gone overlooked without such a tool.
- This tool is a good idea if used to weed out projects that are not a good fit.
- Searching for keywords in specifications.

- It likely does not remove the need to review specifications, but a quick summary could be helpful as a broad-scope overview.
- It will help eliminate errors in the sales cycle and will help summarize the key points that can be easily reviewed at all stages of the process: sales, design, programming, etc.
- Consolidating all necessary information and parsing out unnecessary information is the most intriguing aspect; limiting how much time I have to spend determining what is important and what is not would be great!
- Ease the review and bidding process.
- Reading specifications.
- Gets all parties on the same page.
- It could possibly be useful for Standard Terms and Conditions and Special Terms and Conditions.

What do you like least about this idea for a tool?

- Don't believe it can pick up and understand all the slang and abbreviations people throw out there .
- Concern that it will miss some parameters due to non-standard language or special non-standard instructions.
- How will we know if it doesn't work?
- Who is going to implement and test this system?
- AI evaluations may be potentially unreliable; it will take significant time to evaluate how effective AI may be.
- There is some value in the discipline of reviewing all details.
- Don't depend on AI completely.
- We get such lacking information in from clients that have concern about a tools ability to determine the intent or what needs done.
- That it will miss important details that may make us look unfavorable to competition. My personal experience with new tools are always bugs. But, I think if you know what it's weaknesses are going forward, it will help mitigate those errors.
- Becoming too reliant on a tool that may not always be correct and losing internal knowledge.
- Data collection and security risk. There are capabilities and limitations of most AI chatbots.
- You won't know the AI is correct until you put in the time to follow up manually. It will still require a manual review. The manual review is not overly time-consuming, particularly when compared to how much time it will take to develop the program.
- It's insufficiently granular or so much detail that the data is meaningless
- Engineers may use this in lieu of reviewing the specifications.
- The tool could miss information that falls outside the format of a typical written spec.
- Can miss things
- The fear of the unknown - meaning, what if we miss something because the tool doesn't phrase something correctly, then one is on the hook for something we should have caught during the spec/plan review process.

- Nothing really comes to mind.
- It will add time to the review process.
- Removing human review can cause missed context and details.
- Errors in the data being reviewed can cause issues in the output.
- replacing human intuition about the scope for differing equipment designs.
- My experience with AI is practically none, so I'm unsure how reliable it would be in deciphering important information as it relates to applicable sections or parts of a whole as it pertains to scope for a given project/customer. On some projects, deciphering this without AI tools can be challenging on its own and will come down to what was sold by the customer (separate documentation) rather than specification-driven.
- As with any new technology, there is the question of accuracy. I am a little concerned about how long we will need to double-check the things this tool sees. Secondly, will it be able to look through plans/P&IDs to determine at least which pages are relevant, or determine where our panels will be installed?"
- Potentially missing things, such as an item we do not specialize in or external factors like relationships and scope limitations. This also could be the "human" element of a review and bid process, such as our ability to add value during the bid process and clarify obvious gaps.
- Not reading and interpreting the information from the specs that require human evaluation.
- May have redundant problems.

Large Project Specifications come in so many forms and formats that it would be extremely difficult to develop the appropriate queries to get any type of useful output based on the product features listed on the following page of this survey. Many of the (10) features listed on the following page appear to be quite random and do not address any specific task. Project Estimates are developed based on, an overall understanding and, an accurate interpretation of the Scope of Work which requires a blend of matching the Specifications and Drawings. Most projects require extensive previous experience and judgement to sort through "the copied and pasted boiler plate BS, the repetition, and the errors, that are all too common in most of the specifications we review. Until I can see an example from the developer, of how this would provide any benefit at all, I would have to Vote NO to putting any additional efforts or funds into developing this idea.

EFFECTIVENESS OF 3D MODELS FOR VISUALIZATION

Euysup Shim, California Baptist University; Seongchan Kim, Western Illinois University

Abstract

Most of the design information for construction projects is depicted on two-dimensional (2D) planes for preparation of construction plans and management of construction processes; however, 3D visualization is one of the key skills required for construction management (CM) students or construction practitioners. Existing studies show benefits of using 3D models in construction classes, but effectiveness is measured either by student questionnaires or by student performance in class assignments. In this paper, the authors report the results of a pilot study on the effectiveness of 3D BIM models in the development of 3D visualization skills in a CM course. Specifically, effectiveness was measured by a spatial skill test (the Revised PSVT-R test) as well as student questionnaires with mixed conclusions from the two measurements. While students perceived that the 3D models were helpful and effective in understanding 2D drawings, there was no significant difference in PSVT-R test results.

Introduction

Construction documents, such as drawings, plans, and technical specifications, are fundamental in construction projects. The scope of the work required for a construction project is typically depicted or specified in the construction documents along with quantity takeoff and estimating. Thus, one of the student learning outcomes required by the American Council for Construction Education (2014) is to “analyze construction documents for planning and management of construction processes.” 2D drawings are design documents that depict the spatial relationships, dimensions, details, and components of a building. However, due to limited space and representation of information in the 2D format in physical paper drawings, reading and understanding 2D drawings are not always straightforward and easy in the visualization of building components. As such, it is not uncommon for CM majors or young construction professionals to fall behind in reading and interpreting drawings (Ghanem, 2022).

One of the skills required for understanding 2D drawings is to be able to visualize information from 2D planes in 3D shapes. This visualization, or spatial skill, is the ability to recognize, perceive, and visualize objects in both two and three dimensions, and involves understanding cut-away, isometric views, and object rotation (Bairaktarova, Reyes, Nassr & Carlton, 2015). Having a good visualization ability is critical for CM students to develop, plan, and manage construction processes (Glick, Porter & Smith, 2012). Thus, visualization training has been of interest to many educators and trainers in the architectural, construction, and engineering industries. The authors of this current paper developed

3D building information models (BIM) for class activities and assignments in an entry-level cost-estimating course in a CM program at a four-year college. The key learning objectives in the course were to be able to interpret (or understand) construction documents and perform quantity takeoffs. The authors investigated the effectiveness of using 3D BIM models on student learning as well as development of 3D visualization skills.

Literature Review

The size and spatial arrangement of components for buildings or facilities within a construction project have been traditionally conveyed on 2D planes in either digital or paper forms. Thus, the ability to transform the information in 2D planes to 3D shapes and install building components in correct sizes and locations, 3D visualization skills are essential for CM majors and construction professionals. 3D visualization skills are used daily by construction practitioners in decision-making on transformation of abstract images to real-world finished products (Williamson & Andrew, 2018). The importance of 3D visualization skills in architecture, engineering, and construction (AEC) fields has been recognized and/or suggested by many educators (Fogarty, McCormic, & El-Tawil, 2018; Metz, Sorby & Jarosewich, 2016), who recognized that the ability to visualize and manipulate objects in one’s mind is a vital skill. Several researchers (Han, Hasan, Bouferguène, Al-Hussein & Kosa, 2014; Kamat & Martinez, 2000) and educators have emphasized the importance of 3D visualization skills in construction education and have implemented 3D visualization training in their construction courses. For example, Glick et al. (2012) noted that 3D visualization skills could help CM students grasp newly introduced construction concepts, if the skills are properly acquired. They also pointed out that an insufficient 3D visualization skill could make CM student learning difficult and frustrating.

Teaching CM students to visualize objects depicted two-dimensionally as 3D objects may be challenging, because the development of the 3D visualization ability is affected by individual capability (Batra, Richardson & Webb, 2020). As Bairaktarova et al. (2015) mentioned, 3D visualization skills or abilities vary depending on different environmental factors for everyone, such as ethnicity and sex. Visualization skills play an important role in STEM education and have been studied by many researchers (Tartre, 1990). Several visualization (or spatial) training tools have been developed and used by many researchers and educators in the STEM area: for example, tornado-drawing activities (Sorby, Casey, Veurink & Dulaney, 2013) and orthographic projection by manual sketching (Kelly, Branoff & Clark 2014). Visualization training in those studies included multiple training activities, such as: 1) sketching, selecting,

and matching 2D images from 3D images or 3D images from 2D images; 2) sketching, selecting, and matching images after rotating an object; and, 3) sketching, selecting, and matching images after cutting an object vertically or horizontally. Visualization training in STEM has been proven to be effective in student learning. For example, free-hand sketching increased GPA and graduation rates (Mohler & Miller, 2008) and drawing was the most common training method for the development of higher spatial skills (Porter & Glick, 2022). A study by Ha and Fang (2016) revealed that visualization training could lead to increased performance in spatial skills tests.

In the field of construction education, specifically, 3D BIM models have been used to help CM students develop visualization skills in diverse CM courses, as compared to visualization training activities in STEM areas, as mentioned above. Several studies on the impact or effective use of 3D BIM models in student learning have been performed. Ghanem (2021) found a positive impact of 3D modeling in a CM materials and methods course, and Lucas and Thabet (2008) concluded that using 3D models increased student cognitive learning. In the study by Glick et al. (2012), the authors showed that 3D models helped students better understand new and complex course materials. Additional studies found positive or beneficial impacts of 3D models in student learning: materials and methods course (Ghanem, 2021; Glick et al., 2012; Schreyer, 2014), mechanics of materials course (Hain & Motaref, 2020), concrete design course (Irizarry, Meadati, Barham & Akhnoukh, 2012), safety course (Burgett, 2016), plan reading course (Ryoo & An, 2021), structure course (Fogarty et al., 2018), and mechanical and electrical courses (Na, Aljagoub & Webber, 2022).

In two studies that utilized 3D models for estimating courses, the results were not quite positive. Ghanem (2021) found that usage of 3D models in an estimating course was less effective than in a means and materials course. Gier (2008) reported that 3D models could reduce time for estimating but did not improve accuracy in estimating cost. Multiple types of tests have been developed to measure 3D spatial skills in STEM education. They include mental rotations test (MRT), mental cutting test (MCT), differential aptitude test: space relation (DAT:SR), Lappan test, revised Minnesota paper form board test (RMPFBT), Purdue spatial visualization tests: visualization of rotation (PSVT: R) (Gorska & Sorby, 2008). Out of these spatial skill tests, the PSVT: R test was developed by Guay (1976) for measurement of 3D spatial visualization abilities in 3D mental rotation. Uttal, Meadow, Tipton, Hand, Alden, Warren, and Newcombe (2013) argued that the PSVT: R test is effective in measuring both intrinsic and static spatial skills (such as mental visualization and transformation).

The PSVT: R test method is the most commonly used spatial ability test in engineering education (Ernst, Williams, Kelly & Clark, 2017). However, the PSVT: R test

includes figural errors of the instrument. Thus, Yoon (2011) developed a revised PSVT: R by correcting the errors. The Revised PSVT: R test is argued by Yoon (2011) to measure unidimensional subcomponents of spatial ability.

While the standard spatial skill tests have been typically used in STEM education, the tests have not commonly been used to measure CM student visualization skills. Most of the existing studies on the impact of 3D BIM models on student learning in construction education are based on one or both of the following methods: 1) evaluation of student performance in class assignments and 2) questionnaire to evaluate student perceptions on the effectiveness of the model. Kim and Irizarry (2017) measured the effectiveness of using the 3D BIM model along with augmented reality (AR) to determine changes in student spatial skills using contents from the PSVT: R, the DAT:SR, and the MRT. Their study concluded that student spatial skills were improved by using the 3D BIM model. However, the authors did not mention the CM course in which the 3D BIM model was used.

In the study by Kelly et al. (2014), the authors found that experienced learners have better 3D spatial skills than less-experienced or novice learners. 3D BIM models as a kind of training tool can help CM students, who have difficulty in 3D visualization. For this reason, 3D BIM models have been used by many CM educators in diverse CM courses. Usage of 3D BIM models has been found to be effective or helpful in student learning. However, measurement of the effectiveness was based mostly on either student performance on class assignments or student perception. Therefore, the authors of this current paper explored the effectiveness of using 3D BIM models in CM courses to help students develop or improve 3D visualization skills. Specifically, the Revised PSVT: R test was used to measure the effectiveness.

Research Objective and Questions

The aim of this current study was to examine the effectiveness of using 3D BIM models as a training tool for the development of 3D visualization skills in a CM course. The effectiveness of the 3D BIM models was measured by answering the following questions.

- Can the use of 3D BIM models as a tool in 3D visualization training help students improve their Revised PSVT: R test scores?
- How do students perceive the effectiveness of 3D models in their learning? This question was sub-divided into the following questions:
 - How effective/helpful were the 3D models in understanding building shapes/structure from 2D plans?
 - How effective/helpful were the 3D models performing quantity takeoff assignments?
 - How effective/helpful were the 3D models in improving overall 3D visualization skills?

Methodology

The first tool used for 3D visualization training in this study was basic 3D training through a lecture and an online quiz. The lecture explained different views in construction documents: floor plan, (exterior) elevation, cross section, and 2D isometric projections. Students were then required to take an online quiz consisting of 30 questions. Figure 1 shows a sample quiz question. This basic 3D visualization training was performed at the beginning of the semester for this study.

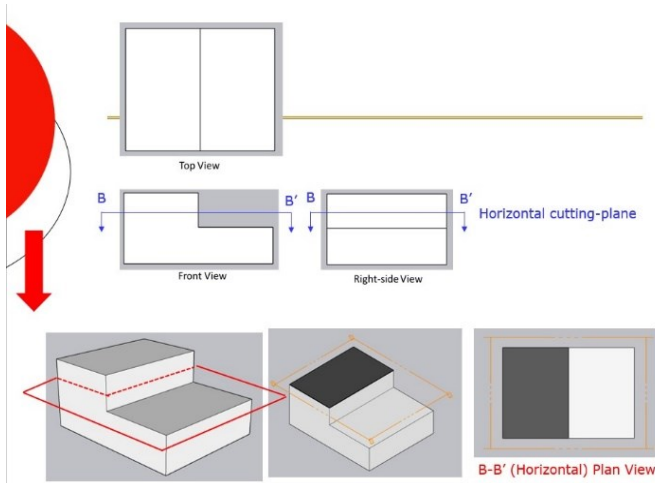
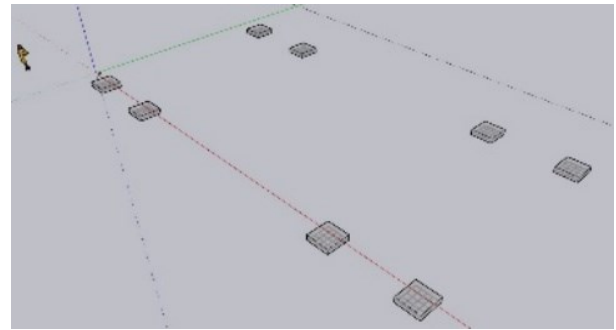


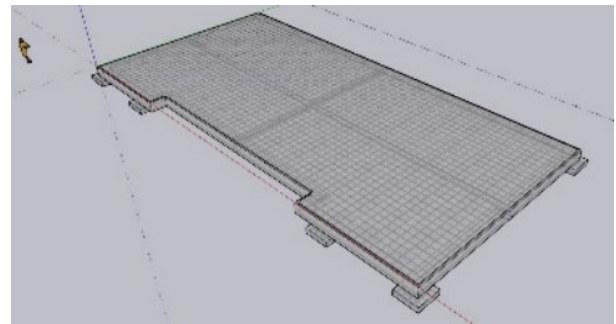
Figure 1. Example of basic 3D visualization training.

The second tool for 3D visualization training used for this study was the creation of 3D BIM models for class assignments and sharing the models with students. A total of 14 sets of 3D BIM models were developed for the class assignments. Figure 2 shows some of the 3D BIM models used for building components and/or the construction sequence, each of which contained sub-models. These BIM models focused on the structural components of buildings. These 3D BIM models were developed using SketchUp, and sub-models for each set model were developed by controlling “tag” in SketchUp. Next, all models were stored in the Sketchup 3D Warehouse, an open library for 3D models, and were embedded in the learning management system (LSM) for the course. The embedded models allowed students to interactively review the models, as recommended by Sampaio, Ferreira, Rosário, and Martins (2010): animation from the scenes, rotating, panning, and zooming. No installation of or license for the software (SketchUp) was required.

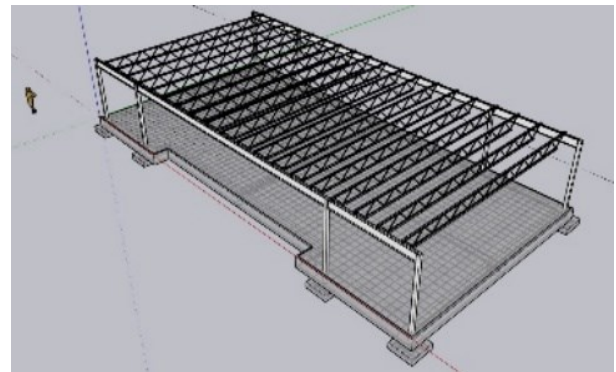
Two measures were used to evaluate the effectiveness of the 3D BIM models for 3D visualization skills in this study. The first measure was the Revised PSVT-R test. Students had to take the test two times: as a pre-test on the first day of the class and as a post-test on the last day of the class. The Revised PSVT-R test included a total of 30 questions. The change between the two test scores was used to measure improvement in the students’ 3D visualization skills.



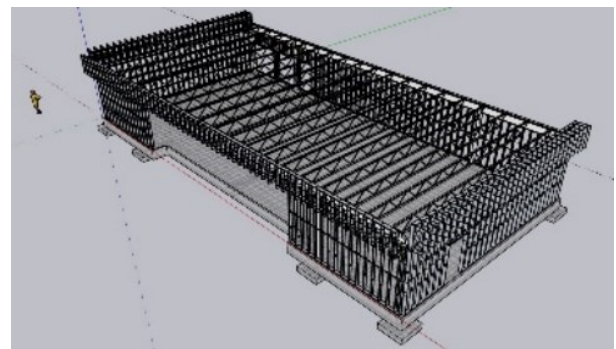
(a) Footing.



(b) Grade beam and slab on grade.



(c) Roof frame.



(d) Wall frame.

Figure 2. Sample 3D BIM models for class assignments.

The second measure for the effectiveness of the 3D BIM models was to ask for the students' opinions on how helpful or effective the 3D models were via a questionnaire on the last day of the class. The questionnaire considered three different benefits of the 3D models: 1) understanding 2D drawings, 2) performing quantity takeoff, and 3) overall 3D visualization skill, as described in the Research Objective and Questions section on the previous page. This study was administered in an entry-level estimating course in the spring 2023 semester as a pilot study. The main learning objectives for the course were to understand and interpret construction documents and to perform quantity takeoffs manually. A total of 24 CM students were enrolled in the course: eight sophomores, 15 juniors, and one senior. The ages of the students ranged from 19 to 22. Twenty-three students out of 24 participated in this study: that is, taking the pre- and post- Revised PSVT-R tests and the questionnaire.

Results

Table 1 shows the statistics for the two Revised PSVT-R test scores. While the average score slightly improved for the post-test, the difference (1.17 points) was not statistically significant at the 95% confidence level. Thus, it was concluded that the use of 3D BIM models was not effective for development of 3D visualization skills. Figure 3 shows the students' responses to the first question on the questionnaire. As for the effectiveness of understanding and interpreting 2D construction drawings (the first question), 18 students out of 23 (78.26%) said that the 3D models were effective in helping them understand and interpret the 2D drawings for the class assignments.

Table 1. Comparison of the revised PSVT-R test scores.

Test	No. of students	Average score (maximum of 30)	Standard deviation
Pre-test	23	16.17	4.59
Post-test	23	17.35	5.01

Figure 4 shows that, for the effectiveness of the 3D models in performing quantity takeoffs (the second question), eight (60.9%) of the students responded with "strongly agree" and six responded with "somewhat agree" that the 3D models were helpful for their quantity takeoffs. Figure 5 shows the response to the third question regarding the effectiveness of 3D models on 3D visualization skills: 17 students (73.91%, where 11 responded with "strongly agree" and six responded with "somewhat agree") felt that the 3D models were effective in the development of 3D visualization skills. Figure 6 shows the mean values of the students' responses to the three questions on the questionnaire based on a five-point Likert scale.

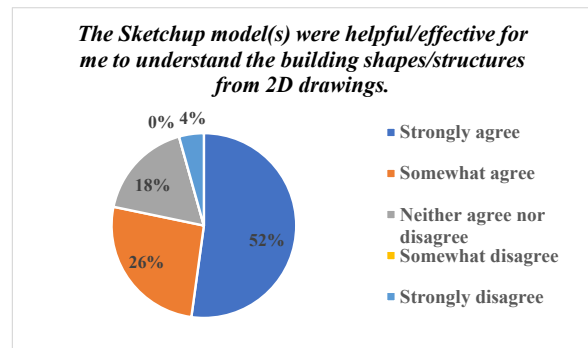


Figure 3. Responses to question 1.

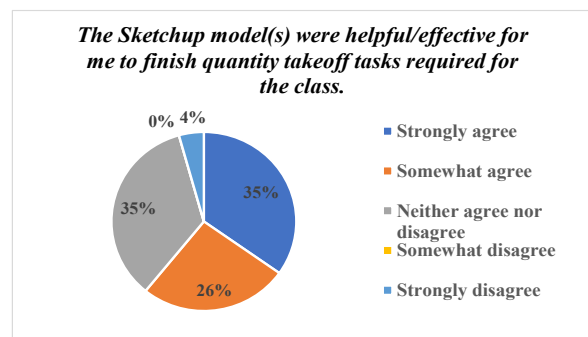


Figure 4. Responses to question 2.

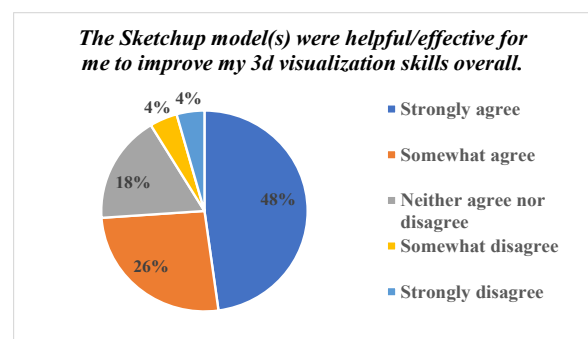


Figure 5. Responses to question 3.

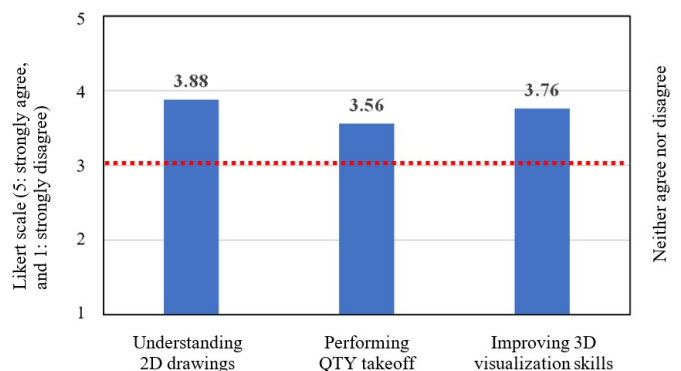


Figure 6. Mean values of the responses to the questions.

Discussion

The results from the two measures (Revised PSVT-R tests and student questionnaire) provided mixed conclusions about the effectiveness of 3D models on 3D visualization skills. The authors acknowledge that the sample size of 23 students could have been one of the factors leading to this issue. This study was administered as a pilot study but the authors plan to continue the work through future semesters. Another point that the authors were interested in was the effectiveness of 3D BIM models on different skill sets or knowledge in CM education. Existing literature shows that the use of 3D BIM models is effective in print-reading courses. However, as two of the existing studies concluded, using 3D BIM may not be very effective or helpful for actual estimating (Gier, 2008) or may not be as effective for materials and means course (Ghanem, 2021).

The CM course for this study included print-reading contents and quantity takeoffs (a part of estimating). Thus, the authors plan to keep track of the effectiveness of 3D BIM models in estimating (or quantity takeoff tasks) in future research. It should be noted that the 3D BIM models were used as a tool for 3D visualization training rather than a tool for actual tasks, such as performing quantity takeoffs. Also, it should be noted that the results of this study could have been affected by the limited amount of 3D representation in the training and by the time spent on the training.

Conclusions

3D visualization skill is one of the most essential skills needed for CM students and for construction practitioners. However, the 3D visualization ability for each person varies depending on diverse factors. The purpose of this study was to explore the effectiveness of 3D BIM models in the development of 3D visualization skills. Specifically, the effectiveness was measured by using, 1) the Revised PSVT-R test and 2) a student questionnaire. The Revised PSVT-R test was taken twice (pre-test and post-test) by students in an entry-level estimating course, and students were asked three questions on the questionnaire. The results of the two measures indicated mixed conclusions. Changes in the test scores indicated that the 3D BIM models were not effective in the development of 3D visualization skills. However, students perceived that the 3D models were helpful in developing their 3D visualization skills. Since this study was a pilot study, the sample size for this study was only 23. Thus, the authors plan to continue to collect more data from future semesters.

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THE MANUFACTURING TECHNOLOGY REVOLUTION: MIGRATION OF IIoT TO AIIoT TECHNOLOGIES IN INDUSTRY

Steven K. Wright, Indiana State University; Ayman Abuhamdieh, Indiana State University

Abstract

Over the years, as computers have evolved on a consumer platform, the ability to network electronic devices together has been a relatively common practice of having a client and a host PC. Development of independent devices that connect to a host as sensory monitors has transformed the computer industry, enabling watches to track biometric data and household devices to monitor and control other systems. These devices, collectively known as the Internet of Things (IoT), have made wearable technology an integral part of everyday life. The growing need for IoT in industrial settings, referred to as the Industrial Internet of Things (IIoT), has enabled remote sensing and control of manufacturing equipment.

As advances in artificial intelligence (AI) continue to emerge, integration into traditional IoT technology becomes increasingly important. IIoT technology introduces challenges that AI seeks to address. In this study, the authors explored the coupling of AI with IIoT to advance industrial predictive maintenance, while reducing human involvement in what is called Artificial Intelligence of Things (AIIoT). Manufacturing equipment utilizing extensive AIIoT technology could monitor production and report to SCADA (Supervisory Control and Data Acquisition), while identifying product quality (real production counts) and all aspects of the machine with a pre-production health check. In this paper, the authors first discuss aspects pertaining to IoT and then AI exploration to better understand its significance in AIIoT. Next, the authors provide the reader with a better understanding of what the future holds for manufacturing technology as it incorporates AI. Finally, the authors present their findings of the examination and evaluation of data models to better decide how AI could play a significant role in the next manufacturing revolution.

Introduction

Manufacturing processes that deliver goods and services to customers face numerous challenges that can hinder production. In today's rapidly evolving technological landscape, manufacturers are under increasing pressure to produce high-quality products at scale and deliver them promptly. To meet these demands, the adoption of advanced computing technologies is essential. IIoT plays a critical role in enabling fast, efficient, and intelligent production workflows, helping manufacturers maintain competitiveness and operational excellence. IIoT is capable of detecting

possible malfunctions in machinery by utilizing a simple sensory network to deliver the status of the production machine through a PC that collects and computes the data; however, traditional IIoT technology has many advantages and several disadvantages, such as security issues and deep learning-driven data. The utilization of technology such as this leverages smart manufacturing abilities. It becomes necessary to find resolutions to modern problems with the previous technology of IIoT. An introduction to IIoT and its similarities and differences to IoT technology follows. The main contributions of this paper focus on the following key issues.

- IIoT provides data and controls by utilizing basic sensory networks. Although this is effective, utilizing and advancing a deep learning model could provide more accurate measures and enable the management of a machine's ability to not only produce a quality product but provide a predictive approach for meeting the production goals in manufacturing.
- Collect data through machine learning (ML) and big data analytics (BDA) by utilizing methods of delivering refined data through the use of smart devices. The authors examined smart manufacturing architecture and the role of intelligent devices in enhancing efficiency, improving reliability, and fostering a safer work environment for manufacturing employees.
- Machine material maintenance requires human intervention to clear material jams during operation. The utilization of modern robotics and AI neural networks (ANN) in this area may give industry the ability to produce efficiently and promote safety.

Although the internet facilitates quick communication and, therefore, a quick marketing process, it introduces a new problem of being able to effectively and efficiently produce a product to keep up with demand. The need to monitor and maintain production flow is a challenge in and of itself, and to meet these high demands requires the digital connectivity of IIoT technology that is made up of different types of industrial connected devices over a variety of network media types. Recent advances in manufacturing employing IIoT technology and other comparable technologies are known as Industry 4.0. This revolution refers to the interconnection of digital technology to connect sensors and data driven devices to drive these big-data types of analytics (Shang & You, 2019). In the scope of Industry 4.0, the utilization of big data driving analytics to monitor production performance efficiencies and track orders using multiple database platforms and IIoT device sensory networks are

often referred to as machine-type devices (MTD) with integrated ML capabilities. ML capabilities in an IIoT framework foster a deep learning application that is further explained in regard to its functionality in a manufacturing environment in the following section (Qvist-Sørensen, 2020).

Machine Learning

By optimizing ML techniques to collect raw data and process it into high-quality data is a hurdle that may need human intervention to find anomalies in the data (Shang & You, 2019). Previously, the process of analyzing collected data was rather challenging. Therefore, leveraging these ML capabilities into the IIoT framework employed a greater depth of data capturing and monitoring by employing algorithms for detection of anomalies using the K-nearest neighbor (KNN) method (Rakholia, Suárez-Cetrulo, Singh & Carbajo, 2025). The use of ML in IIoT networks gives the production process intelligent data information to define the production process strengths and weaknesses to make an informed decision about the next resolution steps (Zhang, Zhao, Jia & Chen, 2021). A significant amount of attention has been brought to the advancement of making predictive decisions using ML, which effectively bridges the data gap between the physical machinery and its monitoring and data-collection capabilities, particularly through SCADA systems (Rakholia et al., 2025).

Most modern manufacturing systems involve a SCADA system to collect raw data through intelligent sensory networks to drive BDA processes. This gives supervisory teams information about captured data utilizing ML techniques over host and client computer networks. However, leveraging BDA coupled with ML brings about the concept of smart manufacturing techniques with data refinement. Smart manufacturing uses extreme data analytics to provide the machine with the ability to prevent people from taking on physical labor tasks that were once deemed necessary (Lampropoulos, 2023).

To better understand how the manufacturing architecture with SCADA is involved with utilizing big data, Figure 1 demonstrates the data transition process and how it begins by coordinating the planning and logistics of a customer job. The model of Figure 1 further illustrates how the system enables comprehensive data collection across corporate-, plant-, and machine-level processes. By leveraging a smart manufacturing database management system (DBMS), it employs structured data-collection and migration methods to support a closed-loop framework between operational systems and decision-making groups. The corporate level entails a communication link to the grouping of Machine Learning & Decision Making that encompasses the Logistics & Planning and Scheduling of Production subsets. Using this method of data collection and migration leverages the next cell in the diagram called Monitoring & Sensing of Operations, which brings the SCADA Controls

& Monitoring and Manufacturing Environment subsets together. The technology of a data-intensive environment of data collection, using an automated method of real-time events regarding input versus output, provides a leap forward in leveraging the Smart Components cell in the diagram. The Smart Components cell consists of devices that are generally capable of gathering data of various types, as noted previously. The diagram of Figure 1 shows how incorporating the use of smart components significantly broadens the ability to gather data at a more sophisticated level while increasing the closed-loop data feedback, thus providing a larger overall dataset.

Through previous scheduling and planning efforts, ML develops the understanding of these patterns and how the data are appropriately analyzed and stored. The ML process builds a database history to continually monitor and adjust the process. This involves the utilization of the ML algorithm to understand the duration, priority, and schedule opening retrieved from the plant database; derived from SCADA monitoring, it efficiently schedules and coordinates the correct job type with accurate machine specifications that are needed. As the data for the scheduled job are coordinated and transferred to the smart manufacturing database, SCADA monitoring logs the job and loads it into the machine's programmable logic controller (PLC). During the machine's runtime, the machine's sensory controls collect data pertaining to performance and efficiency. These data are then used to adjust the scheduling and planning of the next production job in the queue within the Enterprise Resource Planning (ERP) system (Shang & You, 2019).

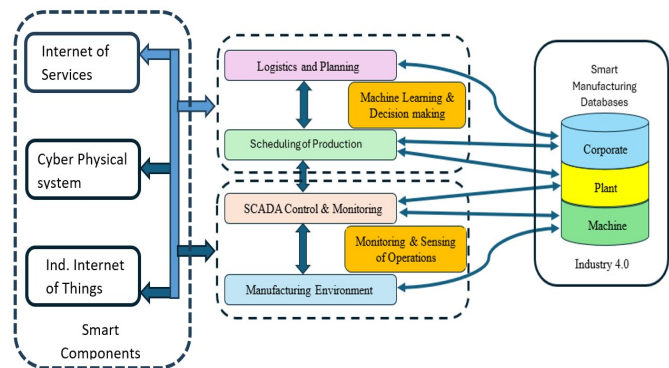


Figure 1. Plant ML and control structure utilizing SCADA and smart manufacturing controls.

SCADA Machine Learning Model

The model in Figure 1 also incorporates several smart components. These include IIoT technologies formed as artificial neural networks (ANN), cyber physical systems (CPS), and the Internet of Services (IoS) (Venegas, Ivorra, Ortega & Sáez de Ocáriz, 2022). These smart components interface with the two component processing structures of ML and decision making and monitoring and sensing of operations. CPS is a complex system of architecture that

leverages network capabilities of the internet, nodes, and IIoT devices to gather and co-process data before becoming processed within the next processing plane, where the data become big data comprising other variables of the system (Yao et al., 2019). Many researchers use IIoT and CPS terms interchangeably, due to the reasoning that both terms use a vast network of physical and virtual devices. However, CPS is often a physical system with communication and computational cores, whereas IIoT presents connected sensory components with specific sets of capabilities (Lesch, Züfle, Bauer, Iffländer, Krupitzer & Kounev, 2023).

Artificial Intelligence in Smart Manufacturing

To be able to meet the stringent competitive needs of the complex smart manufacturing environment of industry, many items need to be addressed. These items include safety, sustainability, security, and efficiency to attain the proper amount of automation with safety and yet be able to meet the needs of the customers (Shang & You, 2019). The need for artificial intelligence in smart manufacturing is to provide an array of ML techniques used in industry driven to make critical thinking decisions as a human would (Kim, Kong, Lee & Lee, 2022). Deep-learning data analysis techniques such as AI are beginning to replace traditional manufacturing techniques with its human-like performance (Radanliev, De Roure, Van Kleek, Santos & Ani, 2021).

Complex components along with CPS have been coupled with AI to improve AI's resiliency in the processing hierarchy of services. This form of AI in industrial manufacturing processes has further developed into the term, AIIoT. Technology such as AIIoT may be comprised of many types of sensory devices or intelligent devices, while utilizing complex systems and definitions of CPS (Lesch et al., 2023). Intelligent sensory devices, including LiDAR (Light Detection and Ranging) systems, collect and transmit high-resolution data for advanced processing. This advanced technology enables more precise and comprehensive detection of machine environments compared to earlier-generation IIoT devices.

Manufacturing Area and Machine Area Mapping

AIIoT in a smart manufacturing environment needs to provide complex definitions of the surrounding areas and be capable of processing data at a decision-making level of a human being. One of these intelligent sensor devices is LiDAR. This technology has been implemented in visual technology for remote sensing and robotics; it also has the ability to detect obstacles and has been utilized for self-driving cars. LiDAR could be used as an AIIoT sensory device for the application of robotic motion area mapping of the surroundings that was previously considered challeng-

ing. An intelligent sensory device such as LiDAR can promote safety by supporting a map or overview of the placement of materials, humans, and the placement and positions of other automation devices for extensive efforts of coordination (Raj, Hashim, Huddin, Ibrahim & Hussain, 2020). The integration of technologies such as LiDAR for spatial data processing enhances robotic safety by preventing collisions and reducing the risk of human presence within guarded machine zones—whether due to oversight or intentional bypassing of safety mechanisms. While LiDAR provides in-depth sensory data of one-dimensional, two-dimensional, and three-dimensional spatial data, to complete an overall three-dimensional map, it does not deliver a complete scope of the surroundings as well as human beings.

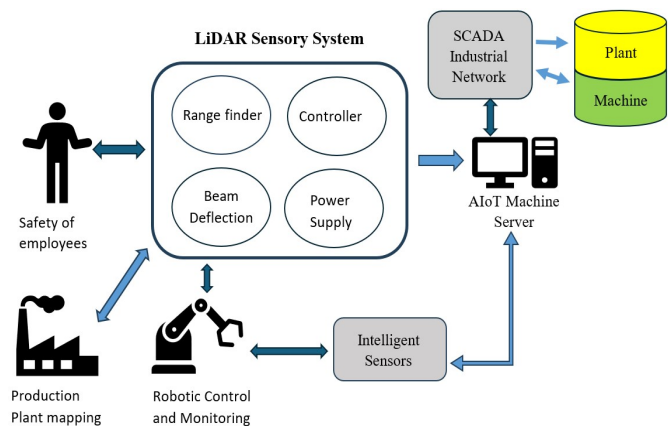


Figure 2. LiDAR manufacturing implementation within an AIIoT environment.

Figure 2 shows that if this technology is integrated with other intelligent sensory devices, it could demonstrate cross-functionality. This model demonstrates a further breakdown of smart componentry that was demonstrated in Figure 1. A smart component leveraging LiDAR technology within an AIIoT ecosystem enhances an industrial robot's situational awareness by providing comprehensive, high-resolution perception of its surrounding environment. Data captured by the LiDAR system and other intelligent sensors translates critical insights not only into production performance but also into employee safety. This information is transmitted to the AIIoT server enabling detailed documentation of human-robot interactions and supporting more-accurate object-recognition and obstacle-avoidance capabilities. Figure 2 further illustrates how the system executes SCADA-level controls, facilitating remote monitoring and computed process data delivery to both machine-level and plant-wide databases. This advanced technology could allow for a full range of motion detection for manufacturing robots to prevent human intervention with a machine, while at the same time reducing costs. This combination of advanced technologies allows a machine to intelligently coordinate its movements with the action of people and other objects that may typically be obstacles (Rakholia et al., 2025).

Not only would this be an efficient method of operation, but it could allow AIoT to monitor a group of machines' operational movements and provide adequate responses to a human approaching any given machine during a specific operation, as safety in an industrial environment should be of the highest priority. Figure 2 shows that LiDAR is made up of four main components: range finder, beam deflection, controller, and power supply. Of the four main components, its laser capabilities (for beam deflection) and its range finder are used to generate, receive, and transmit brief laser pulses (You, Oh, Park, Song & Kim, 2021). LiDAR's capability of mapping two-dimensional and three-dimensional spatial data delivers capabilities of full depth and distance of an object. This type of data could be invaluable for a robot to determine not only the best method for picking up a component but also to have the ability to quickly observe, measure, and identify specific material properties and possibly correct the flawed component using artificial critical thinking, though without human interaction, at a remarkably high rate of speed (Raj et al., 2020).

Limitations with LiDAR Mapping

In previous sections, it was noted that LiDAR technology significantly enhances machine safety, reliability, and rapid object identification; however, it also presents certain limitations. These key drawbacks include limited laser precision and a restricted field of view (FOV), which can impact the overall effectiveness of LiDAR systems in certain industrial applications. The accuracy of LiDAR sensors can be significantly affected by factors such as laser power, wavelength, and the classification of the laser integrated within the AIoT device. While testing over a duration of time within a manufacturing setting, the authors discovered that the environment in which the LiDAR was used played a role in its accuracy (Raj et al., 2020). It was further observed that a single strand of a spider web would activate a false detection. Additionally, the LiDAR lenses needed daily cleaning, sometimes even twice a day in extremely dirty environments.

The FOV with LiDAR may have limitations in its ability to achieve a view angle. What this means is that for LiDAR to achieve a larger field of view, it relies on a motorized mirror for optical detection. The limitation of the FOV and the speed of detection are usually tailored for the specific purpose of the FOV; therefore, the motor and the motor feedback encoder are a limiting variable of its FOV (You et al., 2021). An AIoT device integrates multiple sensory models to simulate a more human-like understanding of a machine's environment. This intelligent perception supports proactive maintenance and safety strategies by enabling early issue detection and preventing potentially catastrophic failures. When thermal imaging technology is incorporated into an AIoT device, the AIoT system gains a powerful capability to monitor environmental conditions and spatial dynamics, offering a highly effective means of preventing operational disruptions. In subsequent sections, thermal

imaging technology is examined in depth, highlighting its contributions to AIoT systems and its role in enhancing environmental awareness, predictive maintenance, and operational safety.

Thermal Imaging in Predictive Maintenance

Industrial maintenance of manufacturing equipment falls into several categories of machine maintenance, building maintenance, utility maintenance, and many more. Although the term maintenance can encompass various responsibilities, the authors focus specifically on industrial machine maintenance. Leveraging ML (a subcategory of artificial intelligence) for predictive maintenance represents a steadily advancing approach aimed at preventing catastrophic machine failures and ensuring a long, productive operational life for manufacturing equipment (Venegas et al., 2022). Traditionally, machine maintenance has been mostly a reactive measure to repair a machine, which typically occurs during the process of a production job. This can often be rather costly to the manufacturer with respect to rush shipment of parts, downtime, delays in shipment of products, associated outside assistance, and employee overtime salaries to counter machine downtime delays. In the past, temperature could only be monitored through the use of a thermocouple or a resistive temperature detector to detect change; but what if temperature data could be consistently captured, recorded, and monitored for an entire machine (Wang, Zhan, Bai, Dong, Cheng & Jia, 2022)? In this section, achieving a measured and monitored form of preventive maintenance and how the systems coherently work together with little to almost no human intervention is explored.

The ML approach for preventive maintenance contributes to the larger scope of the ANN, otherwise known as AI technology using IoT. Using an AIoT deep learning type of thermal imaging device to offer the ability to sense mechanical failures or possibly electrical failures from a distance could give maintenance professionals the insight needed to prevent large costly repairs (Nazmul Huda & Taib, 2013). If a thermal imaging AIoT device consistently monitors a machine's mechanical components heat signature, it should develop a baseline window for a normal running condition in the AIoT devices' onboard database also containing the thermographic history for reference. This type of detection is called infrared thermography (IRT), which captures infrared electromagnetic radiation through a non-contact means of gathering temperature data from both mechanical and electrical components to provide a predictive means of preventing machine failures that could potentially cause catastrophic failures to other components. Infrared light is an invisible light with a wavelength of 760 nm to 1mm that can detect temperatures higher than 0°K allowing it to produce electromagnetic radiation that can be captured.

Capturing data from an IRT device by building a secure database within each AIoT device allows it to build through the machine learning of a baseline that it has developed through normal production (Nazmul Huda & Taib, 2013). AIoT devices should utilize ML capabilities through an intelligent database interface (IDI) building technique. IDI is a portable means of efficiently providing expert means of logging data in a remote database that accesses the smart manufacturing database management system (DBMS). Although the AIoT device using IDI is an independent database, it is dependent on the smart manufacturing DBMS in some ways (McKay, Finn & O'Hare, 1990). The AIoT primary DBMS only registers and reports data from actual alarm events that are sent from the vast amount of logged data from the AIoT device ML database.

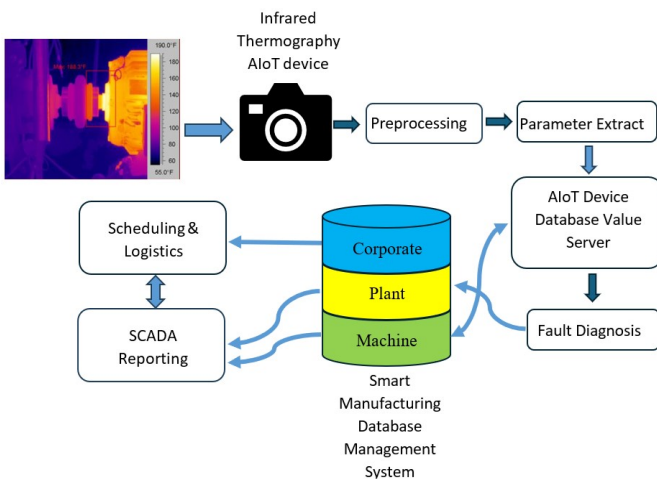


Figure 3. AIoT infrared thermography diagnosis and reporting.

While infrared technology has long been used in manufacturing to identify and regulate thermal changes, its integration with AI marks a significant advancement in thermal imaging capabilities. By combining the reliability of established infrared systems with intelligent data processing, AIoT devices offer a new level of precision in detecting mechanical issues such as bearing wear that often go unnoticed by the human eye. Early identification of such problems helps prevent escalation into catastrophic failures, enhancing both operational safety and equipment longevity. Figure 3 shows that when infrared thermography is used in conjunction with AI within an AIoT device, the system can autonomously identify mechanical issues. Once a potential problem such as bearing wear is recognized, based on its internal database, the device applies its algorithm to assess the severity and determine appropriate next steps to maintain uninterrupted production.

Based on its predictive algorithm and the rate of temperature increase, it may deliver more grease through means of an automatic greaser to the specific bearing and determine if the temperature decreases and, if so, its rate of decrease (Venegas et al., 2022). Figure 3 further shows how the AIoT

system can then perform a fault diagnosis and transmit the results to the smart management DBMS at which point the fault is logged within the database to support reporting, scheduling, and subsequent maintenance actions. By leveraging smart manufacturing database cross-platforms spanning the corporate, plant, and machine domains, the AIoT architecture provides enhanced operational visibility for management personnel and enables real-time, automated tracking of customer-service activities. At this stage, the smart manufacturing database draws on historical machine-issue data to estimate the expected repair duration, applying ML algorithms to refine its predictions. These ML-driven insights enable the system to determine whether the existing production schedule contains an appropriate gap for maintenance or whether workloads should be dynamically redistributed across other manufacturing equipment to accommodate a timely, planned repair (Shang & You, 2019).

The SCADA system as a maintenance scenario provides a visual supervisory interface to the production reports and efficiencies, where supervision could understand what needs to be corrected and issue a maintenance request for the change of the bearing on a scheduled date. If AIoT technology were used with IRT, this problem would typically be caught in the early stages before catastrophic failure. It would be quite possible that the machine could continue its production run and the machine could service itself without human interaction, which would only be possible if the machine were constantly monitoring and recording temperature changes of the bearing.

Technologies such as AIoT incorporating an older technology could be distributed around production equipment to provide a larger scope of potential problems that may occur. Similar to mechanical issues, IRT can also be utilized to monitor and report electrical issues. If production electronics are monitored through an AIoT device incorporating IRT technology, it may detect electrical contact wear, transformer issues, loose connections, overloading of equipment, and other electrical problems. IRT technology provides a robust and valuable dataset within AIoT systems. However, as discussed in the following section, certain limitations highlight the need for a multi-sensor approach combining complementary technologies within an AIoT network to achieve more comprehensive environmental awareness and decision-making capabilities.

Limitations of Thermal Imaging for Preventive Maintenance

Preventive maintenance using thermal imagery is a remarkable method for detecting mechanical issues that would otherwise have gone undetected and instead target faulty electrical relay contacts. However, there are limitations with thermal imagery such that, when it is incorporated into an AIoT network with developed baselines, many

of these limitations can be significantly reduced. These limitations can be reduced by utilizing the onboard database and algorithms that determine the discrepancies that are presented by discovering new occurrences. Within electrical components, not all failures produce a heat signature that an IRT scanner could discover, nor would it be able to detect and warn a smart manufacturing network with advanced notice (Venegas et al., 2022). Even with this limitation, IRT coupled with AIoT technology can revolutionize the preventive and predictive maintenance that allows for efficient machine productivity.

For mechanical applications, IRT technology usually works with a specific region in which it may not give a complete FOV with all mechanical components to identify all mechanical failures. The FOV is a limiting component for preventing some catastrophic occurrences (Nunes, Santos & Rocha, 2023). For instance, a small brass gear in a gearbox may not create a significant heat signature, due to it being exposed to an oil bath and because of the size of the gear, and thus may fail without notice. In AIoT technology, which is a form of ML, some of the issues are learned issues that may not be detected as failures until they have already occurred. But, as AIoT's algorithms develop, once the issue occurs more than once, it should be detected in the future. With this being said, IRT technology may provide some inaccuracies with false positives (FP), false negatives (FN), true negatives (TN), and true positive (TP) cases. The accuracy of the technology can be derived using Equation 1 (Venegas et al., 2022).:

$$accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

Conclusions

While further testing and evaluation are needed, AIoT technology is in its infancy and should prove to be very beneficial for a more productive and safer manufacturing environment. In this paper, the authors explored the influence of AI integrated with ML, CPS, and BDA technology, highlighting their significant impact on manufacturing. The co-existence of these items within the architecture of a smart manufacturing database would produce efficient scheduling, logging, reporting, and logistics planning. Also discussed was LiDAR as an AIoT device equipped with an onboard database and algorithms, enabling a more precise approach to data analysis, identification of robotic issues, and enhancement of machine safety. The future of this could be to monitor robotic work to mitigate human intervention, prevent injuries, and reduce safety malfunctions during routine maintenance. At the time of this writing, LiDAR demonstrates limitations in FOV. Ongoing testing and evaluation of LiDAR as an AIoT device are intended to overcome these limitations and enhance overall performance. The utilization of IRT technology as an AIoT device was discussed as a method for detecting and determining mechanical and electrical maintenance issues.

The authors presented information on the importance of leveraging this technology and key components that would drive this technology further to produce a more efficient and productive manufacturing environment in the future. Although this method captures thermal data without physical contact, certain threats to validity remain and will be addressed through future testing and development. The main issues that still need to be resolved include true positives, true negatives, false positives, and false negatives, and the concept of leveraging AI and ML to build a comprehensive solution for mitigating these issues and increasing the accuracy of the data of the thermal data collected. The information presented here should assist in the delivery of information regarding the development of ML technology and AI in the industrial manufacturing environment. While AI is a growing and controversial technology, with the understanding that it could reduce employment, the authors hope to deliver a better understanding of the usefulness that it could bring to industry. Further testing and development should provide greater understanding in the use of smart databases, smart devices, and smart controls to create a safe, productive, competitive, and efficient workplace.

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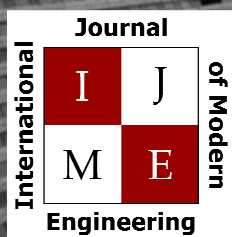
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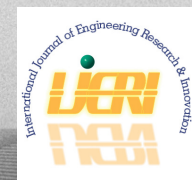
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