DISSERTATION

EXPLORING THE ROLE OF HUMAN CENTERED AUGMENTED REALITY IN CONSTRUCTION: CHANGE DETECTION, WORK EFFICIENCY, AND HUMAN-AI COLLABORATION

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ABSTRACT

EXPLORING THE ROLE OF HUMAN CENTERED AUGMENTED REALITY IN CONSTRUCTION: CHANGE DETECTION, WORK EFFICIENCY, AND HUMAN-AI COLLABORATION

The architectural engineering and construction (AEC) sector is characterized by its intricate project workflows and the constant exchange of extensive, detailed information among multiple stakeholders. This complexity necessitates the adoption of cutting-edge digital solutions that can handle vast data streams while improving communication, collaboration, and operational efficiency. This dissertation examined the Augmented Reality (AR) and Artificial Intelligence (AI) technologies in the construction industry, with a focus on their interaction with key human factors, including safety hazard detection, trust in technology, spatial cognitive skills, and workforce demographics. It responded to the challenges posed by increasingly complex construction projects and the need for enhanced efficiency, safety, and sustainability by emphasizing the importance of evaluating technological solutions not only for their technical merits but also for their effects on human performance and cognition.

To achieve the research objective, 100 industry craft workers and 219 students participated in an assembly task on a full-scale Mechanical, Electrical, and Plumbing (MEP) model. First, the research investigated how AR head-mounted displays (HMDs) affect workers' ability to detect changes and safety hazards compared to traditional information formats in dynamic construction environments. Findings showed that AR HMD usage impaired hazard detection, especially as the density of information presented on the display increased. This impairment was notably greater

among older workers, while spatial cognitive ability did not significantly moderate this effect. These results demonstrated the potential for immersive AR interfaces to distract users from critical environmental awareness, thereby raising essential safety concerns about their implementation.

Furthermore, the research investigated how varying levels of detail (LOD) in AR models, compared to traditional paper-based instructions, affect work performance during assembly processes. The study demonstrated that higher-detail AR models significantly improved outcomes by speeding up task completion, reducing errors, and minimizing the need for rework. These performance gains were most pronounced among novice workers, indicating that AR has strong potential to bridge skill gaps and enhance inclusivity within the workforce. The research also explored the relationship between spatial cognitive ability and task performance, identifying that cognitive skills contributed positively to novices' success, while experienced workers compensated through expertise, resulting in a neutralizing effect on age- and cognition-related performance differences.

Lastly, the study investigated trust in AI versus human-generated design information and its relationship to AR visualization. The findings revealed no significant overall difference in trust between AI and human sources; however, trust in AI declined significantly when errors involved safety-critical information, showing that participants' trust in the origin of design information was proportional to their perceived level of risk associated with that information. Importantly, AR visualization was found to reduce skepticism toward AI origin by enhancing understanding and confidence in the conveyed information. Work efficiency benefited from AR use regardless of the design source, though individual cognitive ability remained the primary predictor of task speed.

Overall, this work highlights the crucial role of human factors in effectively integrating AR and AI technologies into construction workflows. It demonstrated AR can help a diverse workforce

engage more effectively with complex project information, improve work performance, but at the same time, may compromise the user's ability to detect changes in a dynamic construction environment. Additionally, the findings provide practical guidance for developing transparent, reliable, and explainable AI systems, supported by intuitive AR interfaces, to foster trust and ensure human oversight for safe and widespread adoption of technology.

By employing ecologically valid experimental methods that involved realistic assembly tasks and diverse user populations, this research advances knowledge about real-world human-technology interactions in the construction industry. It laid the groundwork for future construction ecosystems where digital innovations harmoniously support human cognitive diversity, enhancing safety, productivity, and worker experience. The proposed framework prioritizes cognitive factors, risk awareness, trust, and inclusivity as pillars for successful AR and AI integration, paving the way for a technologically advanced yet human-centered construction industry.

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DEDICATION

I dedicate this dissertation to the cherished memory of my grandparents, whose tireless hard work, resilience, and unwavering love laid the foundation for all that I have achieved. Though they are no longer with us, their spirit and dedication continue to inspire and guide me every day.

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CHAPTER 1 – INTRODUCTION

1.1 Research Background and Motivation

The construction industry is experiencing rapid global growth, with projections indicating that investments will reach approximately $15.5 trillion by 2030 (Nassereddine et al., 2022). As the industry expands, the complexity and dynamism of projects are also increasing, necessitating more sophisticated processes to handle a high density of information, extensive communication, and information exchange among various stakeholders throughout the project lifecycle (Machado and Vilela, 2020). In the era of Industry 4.0, where manufacturing, production, and related industries are going through digital transformation, the construction sector is adopting these techniques relatively slowly (Seyman Guray and Kismet, 2023).

Modern construction projects have evolved into highly complex, information-intensive endeavors requiring unprecedented levels of coordination, communication, and precision. The density of information required for successful project execution has increased exponentially, encompassing detailed architectural specifications, intricate MEP systems, safety protocols, quality standards, and real-time project updates. This information complexity creates significant cognitive demands on field personnel, who must accurately interpret, process, and execute tasks based on vast amounts of technical data (Lee et al., 2020). Consequently, it demands systems that can be customized to deliver varied densities of information tailored to individual requirements.

Despite the digital revolution in design processes, particularly the widespread adoption of Building Information Modeling (BIM), a critical disconnect persists between digital design capabilities and field information delivery. While architects, engineers, and project managers work

with sophisticated 3D models containing rich geometric and semantic information, craft workers continue to rely predominantly on traditional paper drawings and written specifications (Chalhoub and Ayer, 2018). This disconnect represents a fundamental bottleneck in the construction value chain, where the most advanced design information fails to reach those responsible for the physical execution of work.

The consequences of this information density and delivery gap go beyond efficiency issues to include safety, quality, and economic impacts. When field personnel cannot easily access or understand design information, the resulting mistakes, rework, and safety incidents lead to significant costs for projects and organizations (Alkan and Basaga, 2023). Industry research consistently identifies a lack of necessary information and communication failures as major obstacles to construction productivity, emphasizing the urgent need for better information delivery systems (Pekuri et al., 2011). In this context, Augmented Reality (AR) is emerging as a tool that can improve the visualization of design data, helping workers process information more easily and boosting overall performance and productivity.

Productivity is a crucial issue, as it directly impacts the revenues and profitability of the sector. According to Barbosa et al. (2017), a strong correlation exists between labor productivity and the digitalization index across various industries. This is supported by Alkan and Basaga (2023), who stated that the construction sector's lag in adopting digital technologies is a primary reason for its stagnant productivity over the past two decades. This digitalization gap has prevented the sector from achieving the efficiency gains seen in other industries, which is further compounded by pressing demographic challenges. The sector faces persistent labor shortages and a crisis of an aging workforce. Workers over fifty-five years of age now constitute a growing share of skilled craftspeople, carrying critical institutional knowledge but often less comfortable adapting to new

tools (Albattah et al., 2015). On the contrary, the industry struggles to attract younger talent who expect modern, technology-enhanced work environments (Buckner and Bender, 2020).

This suggests that as the construction industry turns to emerging technologies, like AR, as potential solutions to productivity and workforce challenges, a critical gap has emerged in how these technologies are designed, implemented, and evaluated. The prevailing focus on technical capabilities and quantitative performance metrics has overshadowed fundamental human factors considerations that ultimately determine the success or failure of technology adoption (Alkan and Basaga, 2023). The technology-first approach overlooks the reality that construction work is fundamentally human-centered, requiring complex cognitive processes, spatial reasoning, hazard recognition, and collaborative decision-making. Technologies that enhance measurable outputs while compromising worker safety, situational awareness, or decision-making confidence may create net adverse outcomes despite apparent performance improvements (Baumeister et al., 2017). The construction industry's unique operational environment, characterized by dynamic conditions, safety-critical tasks, and diverse skill levels, needs technologies designed with explicit consideration of human factors from the outset.

Furthermore, the emergence of Artificial Intelligence (AI) in construction design generation processes introduces entirely new dimensions of human-technology interaction that remain largely unexplored. As AI systems increasingly generate design solutions and recommendations, fundamental questions arise about trust, acceptance, and collaborative decision-making between human workers and intelligent systems (Klein et al., 2024). The industry lacks a comprehensive understanding of how these human-AI dynamics influence performance, safety, and worker satisfaction in practical construction contexts.

This work stemmed from the recognition that the construction industry's challenges cannot be resolved solely through the implementation of technology but instead require a fundamental understanding of how human factors influence the effectiveness of technology in real-world construction environments. The prevailing paradigm of evaluating technologies primarily through efficiency metrics overlooks the full spectrum of factors that determine successful technology adoption and sustainable improvements in performance and productivity.

This research specifically focused on AR and AI technologies, adopting a human-centered perspective that prioritizes understanding how these emerging technologies influence not only task performance but also safety awareness, spatial cognitive abilities, trust dynamics, and overall worker experience in a construction assembly task. By focusing on these human factors alongside traditional performance metrics, this work aimed to generate insights that support technology implementations that genuinely enhance both productivity and worker well-being.

The ultimate vision driving this research was a construction industry where technology genuinely empowers workers rather than simply replacing or constraining them. By establishing a foundation of human-centered technology research, this work contributes to a future where the construction industry successfully navigates its digital transformation while maintaining its fundamental character as a human-driven enterprise that creates the built environment through skilled craft and collaborative problem-solving.

1.2 Previous Work and Need for Additional Research

1.2.1 AR Technology in Construction Assembly

Augmented Reality (AR) technology has emerged as a transformative tool in construction, fundamentally changing how design information is visualized and interpreted on-site. AR is defined as a technology that superimposes computer-generated graphical information onto the

user's view of the real world, enhancing the real environment with virtual information that makes the interpretation of design information more intuitive and potentially reduces cognitive load (Tan et al., 2022). Over the past decade, research on AR Head-Mounted Displays (HMDs) has gained significant popularity in construction assembly for accelerating digitalization and enhancing labor task performance.

Research evidence demonstrates both promising outcomes and concerning limitations in the implementation of AR. Performance enhancement studies have consistently shown positive results. For example, Chalhoub and Ayer (2018) conducted comprehensive studies on electrical conduit assembly with industry craftworkers and university students, revealing that AR significantly reduced design comprehension time, improved productivity, and led to fewer errors compared to traditional paper plans. Similarly, Kwiatek et al. (2019) found that pipe assembly tasks were completed faster with improved spatial cognition when information was delivered through AR devices. These findings are supported by numerous studies, including those on wood frame wall assemblies (Qin et al., 2021), piping assemblies (Hou et al., 2015), and prefabricated timber elements (Bartuska et al., 2023), all of which demonstrate improved efficiency and accuracy. However, most of these studies have significant limitations, which are further discussed in section 1.3.

Additionally, very few studies in the construction domain have examined the impact of AR HMDs on individual situational awareness, and almost none have explored it on users' ability to detect safety hazards. For example, studies by Qin et al. (2023) and Abbas et al. (2020) confirmed that while performance may improve, the cognitive load of AR users increased significantly during complex assembly and rebar inspection tasks. However, their work primarily examined self-reported scores on situational awareness without an actual scenario to conclude the effects on

awareness. With this limited safety-focused research on AR in construction, a critical gap exists in understanding the safety implications of this technology, including deterioration of change awareness and compromised change detection abilities. The construction industry's dynamic nature, where multiple trades and equipment operate simultaneously, creates hazardous and rapidly changing conditions and thus requires a more in-depth and comprehensive examination.

1.2.2 Emerging Human-AI Collaboration Challenges

The integration of AI in construction design processes introduces an entirely new dimension of human factors research that remains largely unexplored in construction contexts. AI is increasingly being used to create architectural solutions and create building design data, with expectations that it will eventually encompass entire design processes (Nauata et al., 2020). However, this technological capability intersects with complex trust dynamics that fundamentally impact user acceptance and performance (Metzger and Flanagin, 2013).

Trust is a fundamental factor that critically influences whether new technologies are accepted or rejected by users. In construction, where safety, precision, and collaboration are paramount, workers' confidence in a technology's reliability directly affects their willingness to rely on it. It ultimately determines the technology's effectiveness in practice (Bach et al., 2024). Even when advanced technologies possess strong technical capabilities, reduced user trust can significantly undermine performance outcomes by causing hesitation, misuse, or outright rejection (Bach et al., 2024).

The influence of the perceived origin of design information, whether it is generated by human experts or produced by artificial intelligence systems, on users' trust and confidence is a crucial but underexplored aspect in construction assembly. This distinction is significant because it influences workers' acceptance and interpretation of the information, ultimately affecting their

decision-making and task execution. Despite the growing presence of AI-driven design tools and the transformative potential of integrating AR and AI in construction workflows, the complex dynamics of how trust evolves based on design origin and how AR environments may mediate trust issues have not been systematically investigated in real-world, hands-on construction settings.

Understanding these dynamics is essential because AR and AI technologies are poised to play increasingly collaborative roles in the future (Sahu et al., 2021). Hence, this research aimed to elucidate the complex dynamics between AR technology and users' trust in the origin of information, i.e., Human vs. AI, which will provide critical insights into fostering effective human-AI partnerships on job sites.

1.2.3 Construction Workforce and Technology Interaction

The construction workforce comprises multiple generations, each characterized by distinct cognitive capacities, learning preferences, and varying levels of familiarity with technology (Albattah et al., 2015). This multigenerational composition introduces substantial variation in how workers engage with and benefit from emerging technologies, specifically AR and AI. Age-related cognitive factors, such as declines in attention, working memory, and information-processing speed, significantly influence workers' ability to interpret digital information, respond to hazards, and perform complex tasks in AR-assisted environments (Hashiguchi et al., 2020). Simultaneously, spatial cognitive ability plays a crucial role in construction activities by enabling individuals to mentally manipulate complex information and effectively translate designs into physical assemblies.

Examining the impact of technologies on user performance, safety, and productivity represents an important dimension of research. However, it is equally vital to explore how these technologies interact with individual differences, particularly age and spatial ability. These factors moderate the

effectiveness of AR and AI systems, influencing outcomes such as safety awareness, task accuracy, and trust in digital content. Incorporating user characteristics into research enables a comprehensive understanding of technology adoption and usability across a diverse construction workforce. Moreover, acknowledging differences in age and cognition informs the design of adaptive interfaces, targeted training, and inclusive implementation strategies that maximize benefits for all workers regardless of cognitive profiles or generational cohorts.

Existing studies have insufficiently addressed how these individual characteristics moderate the effectiveness of AR technology and trust in AI within construction contexts. This thesis work aimed to fill this gap by examining the nuanced interplay between age and spatial cognition in the context of AR and AI interventions.

1.3 Gaps in Literature and Research Objective

The comprehensive literature review discussed in each chapter (2, 3, and 4) identified several key limitations and gaps related to the topics discussed above, as outlined below.

- Scale and Ecological Validity: Most existing studies on the use of AR in construction assembly have used scaled-down models and performed experiments in laboratory settings, failing to capture the real-world complexity and spatial demands of construction.
- Participants and Sample Sizes: Most studies recruited student participants to perform the experiments, and the sample size was not sufficient to generalize the results.
- Safety and Hazard Awareness: Very few studies have considered the safety implications of AR HMDs in dynamic construction environments, and almost none have examined their impact on hazard detection abilities.
- Information Density Effects: No research has examined how different LODs in AR models impact performance and safety.

- Human vs AI: No construction-specific research has examined the trust dynamics and performance impacts of workers using AR systems to interact with AI-generated versus human-generated design information.
- Individual Differences Integration: Limited understanding of how age and spatial cognitive ability moderate the effectiveness of AR across diverse construction populations.

This research aimed to close critical knowledge gaps by systematically examining how traditional information formats and AR models impact the work performance, hazard recognition, and error detection abilities of construction craft workers. It also explored how the perceived source of design information, whether human-generated or AI-generated, affects workers' trust, confidence, and decision-making during construction tasks in an AR-assisted environment.

The key limitations identified were addressed through a comprehensive experimental approach that included: (1) full-scale experimental model, with nearly 70% of experiments, conducted in real industrial settings; (2) significant samples of the participants that included not just the students but also the experienced industry crafts (100 craft workers and 219 students); (3) systematic safety assessments via change detection scenarios; (4) a comparative analysis of traditional paper plans with AR models with different LODs; (5) a novel investigation into how human versus AI design origins impact trust and performance; and (6) a thorough examination of individual differences, such as age and spatial cognitive ability.

This methodologically rigorous approach provided the ecological validity, sample representativeness, and comprehensive scope necessary to generate actionable insights for the technology adoption decisions of the construction industry, while contributing fundamental knowledge about human-centered factors in AR and AI implementation.

1.4 Experimental Framework and Methodology

To achieve the research goal and improve the ecological validity of our procedures, we recruited twenty subject matter experts (SMEs) in structured brainstorming sessions. The aim was to identify the main types of engineering deliverable displays currently used by SMEs, along with their associated issues and benefits, and to determine which construction tasks require better display support. The SMEs were from structural, mechanical, and electrical trades, each with a minimum of five years of industry experience. Based on the discussions, a full-scale replica of a typical MEP system—common on many industrial construction sites—was built, featuring mechanical pipes and electrical conduits mounted on panels. The model consisted of two metal peg boards, each measuring 3 feet by 5 feet, which formed three experimental sides and were referred to as panels 1, 2, and 3 for the assembly task, as shown in Figure 1.1. Figure 1.2 presents a 3D view of the experimental model, providing a clearer understanding of how all three panels were connected. Before recruiting participants, pilot tests were conducted with 40 undergraduate students to ensure the clarity and completeness of the experimental setup. A comprehensive experiment was conducted in which participants were tasked with installing missing mechanical pipe pieces and electrical conduits to complete the unfinished MEP assembly. Three different information formats were provided to facilitate the assembly task: traditional paper drawings and two 3D AR models with LOD 300 and 400. The AR models were projected in the environment using the Microsoft HoloLens 2 HMD.

For the broader generalizability of the results, 100 industry craft workers and 219 undergraduate students were recruited to participate in the experiments. The experiments with students were conducted in a controlled lab environment, while seventy percent of the experiments with industry craft workers were conducted in an actual industrial environment. This diverse

participant pool aimed to capture a range of skills and experiences to better understand the impact of different information formats on the assembly task. Figure 1.3 illustrates the experimental overview, including the primary factors and studies conducted as part of this comprehensive experiment.

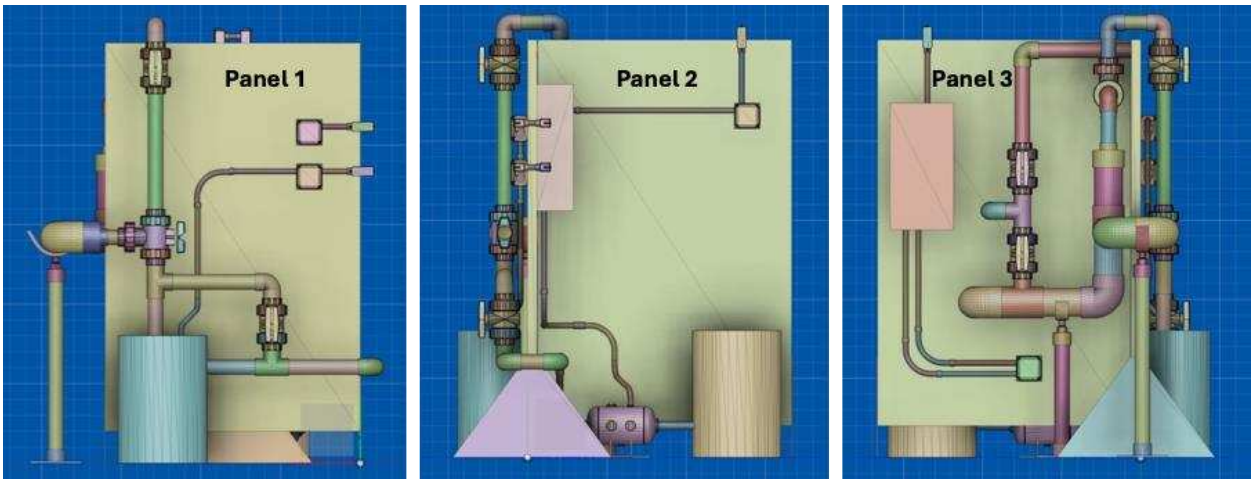


Figure 1.1 Three Panels of the Experimental Setup

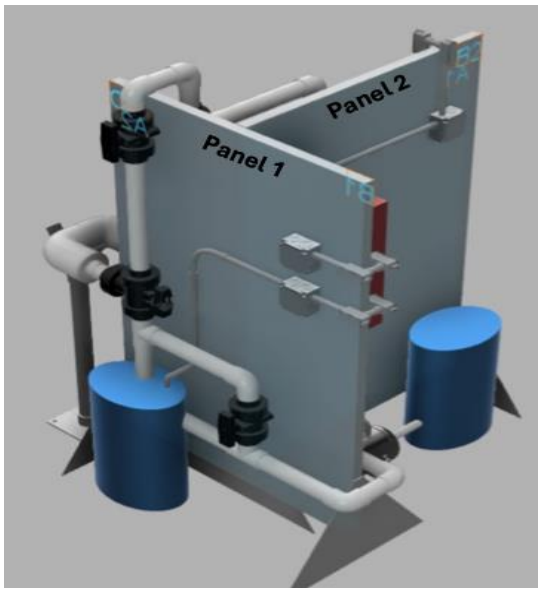


Figure 1.2 3D Model of the Experimental Setup

Participants were randomly assigned to control groups based on the origin (human or AI) and format (traditional drawings or augmented reality models) of the design information they received

to complete the task on each panel, as shown in Tables 1 and 2. Due to time constraints, each industry participant completed the assembly task on a two-panel setup, whereas student participants completed it across all three panels. The experimental setup incorporated hazard and intentional error scenarios to emulate real-world construction challenges and safety concerns.

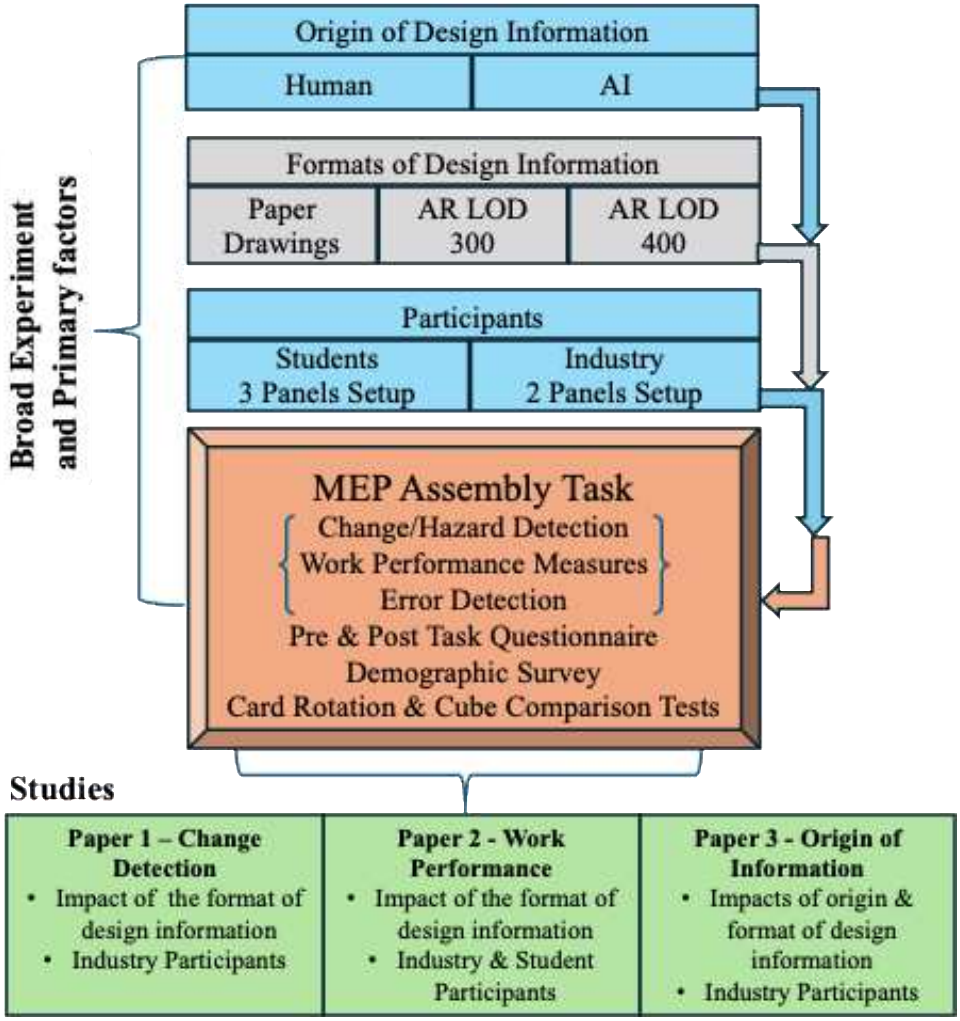


Figure 1.3 Experiment Overview

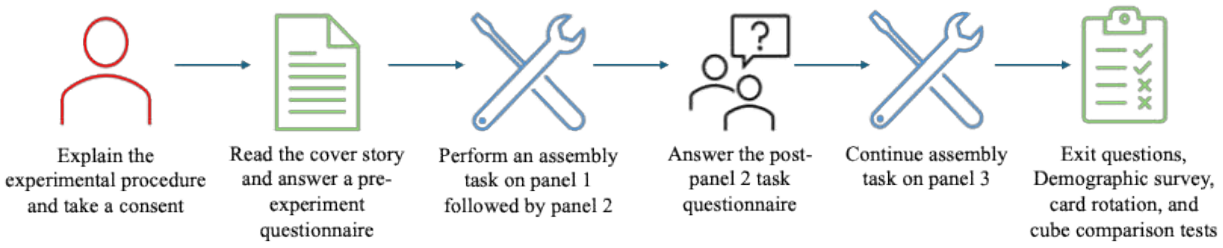
Table 1. 1 Industry Participants Control Groups

Group	Stage 1	Stage 2
A-1	Side 1, 2D only	Side 2, 2D + AR LOD 400
B-1	Side 1, 2D only	Side 2, 2D + AR LOD 300
C-1	Side 1, 2D + AR LOD 400	Side 2, 2D only
D-1	Side 1, 2D + AR LOD 300	Side 2, 2D only
A-2	Side 1, 2D only	Side 2, 2D + AR LOD 400
B-2	Side 1, 2D only	Side 2, 2D + AR LOD 300
C-2	Side 1, 2D + AR LOD 400	Side 2, 2D only
D-2	Side 1, 2D + AR LOD 300	Side 2, 2D only
Note: AI Design Cover Story – A-1, B-1, C-1 & D-1, Human Design Cover Story – A-2, B-2, C-2 & D-2		

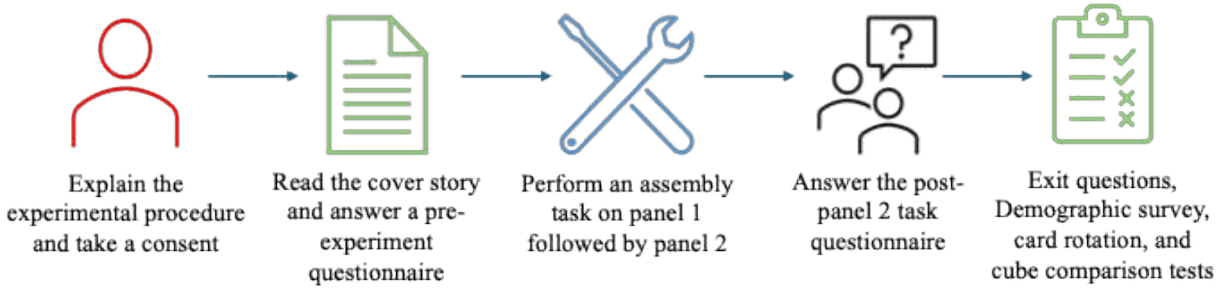
Participants followed a standard experimental procedure to perform the assembly task as shown in Figure 1.4. Throughout the assembly process, multiple performance metrics were systematically recorded, including task completion time, error rates, and rework instances per panel. In addition to the task-based metrics, participants completed questionnaires administered before and after the assembly task to capture subjective data on their experiences, perceptions, and confidence levels. After completing the task, participants were asked to complete demographic surveys and cognitive assessments designed to evaluate their spatial ability. To enable precise and targeted inquiry, the comprehensive dataset was later divided into subsets aligned with the specific parameters and goals of each study within the larger research framework.

Table 1. 2 Student Participants Control Groups

Group	Stage 1	Stage 2	Stage 3
A-1	Side 1, 2D only	Side 2, 2D + AR LOD 300	Side 3, 2D + AR LOD 400
B-1	Side 1, 2D+ AR LOD 300	Side 2, 2D + AR LOD 400	Side 3, 2D only
C-1	Side 1, 2D + AR LOD 400	Side 2, 2D only	Side 3, 2D + AR LOD 300
A-2	Side 1, 2D only	Side 2, 2D + AR LOD 300	Side 3, 2D + AR LOD 400
B-2	Side 1, 2D + AR LOD 300	Side 2, 2D + AR LOD 400	Side 3, 2D only
C-2	Side 1, 2D + AR LOD 400	Side 2, 2D only	Side 3, 2D + AR LOD 300
Note: AI Cover Story – A-1, B-1, and C-2, Human Design Cover Story – A-2, B-2, and C-2.			



Student Participants



Industry Participants

Figure 1.4 Standard Experimental Procedure for Student and Industry Participants

1.5 Dissertation Outline

The dissertation is divided into five chapters. Chapter 1 introduces the research, including the background and context, a review of relevant literature, the research objectives, questions, and the overall outline of the dissertation. Chapters 2, 3, and 4 are presented in the format of scholarly papers, each comprising an abstract, introduction, literature review, methodology, results, discussion, conclusion, and references. While these chapters address distinct research questions, some overlap is expected since they derive from the same comprehensive experimental procedure. The final chapter, Chapter 5, synthesizes the key findings from the preceding studies, discusses their contributions to the body of knowledge, acknowledges the limitations encountered, and proposes directions for future research.

The core research objectives are addressed through three empirical studies, detailed as follows. The titles, scope, and specific research questions of each study are subsequently outlined to clarify their individual foci and contributions within the overall framework of the dissertation.

1.5.1 Chapter 2 (Paper 1) How Does Augmented Reality Head-Mounted Display Impact the Ability to Detect Safety Hazards While Performing Piping Assembly?

This study focused solely on examining the impact of AR HMDs on the ability of industry craft workers to detect change in an AR-assisted environment. Participants were assigned to the control groups based on the format of information they used for the assembly task. The effect of design origin was not accounted for in the analysis, as shown in Figure 1.5, and the paper addressed the following research questions.

1. What impact do AR HMDs have on change detection on construction job sites that may pose safety risks among industry craft workers?

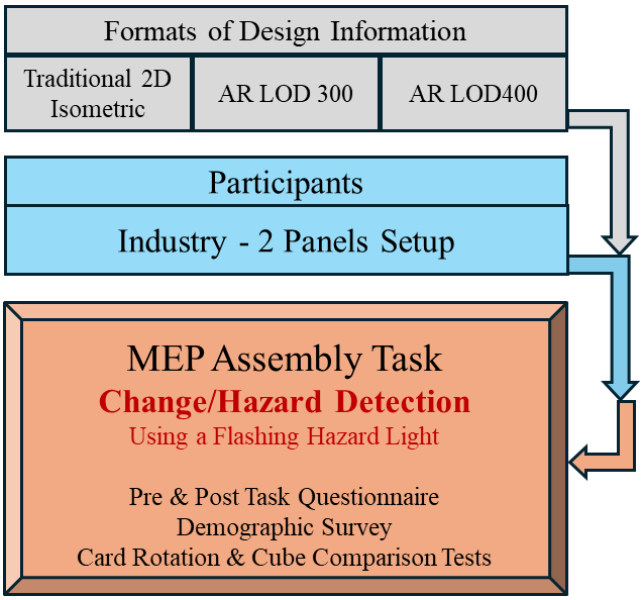


Figure 1.5 Chapter 2 – Experimental Overview

2. What is the correlation between craft workers' spatial cognitive ability and their response time to detect the change in an augmented reality-assisted construction environment?
3. What is the correlation between craft workers' age and their response time to detect the change in an augmented reality-assisted construction environment?

1.5.2 Chapter 3 (Paper 2) Exploring the Impact of Augmented Reality on Work Performance in a Full-Scale MEP Assembly Task: A Study of Industry and Novice Populations

In this study, the objective was to examine and compare the impact of information formats (paper drawings and AR models at LOD 300 and 400) on the work performance of both industry and novice populations. Here, the effects of information format, participants' age, and spatial cognition on the dependent variables —task completion time, rework rate, and error rate —were studied. Like Chapter 2, participants were assigned to the control groups based on the information format used, and the effect of the design origin was not taken into account as shown in Figure 1.6.

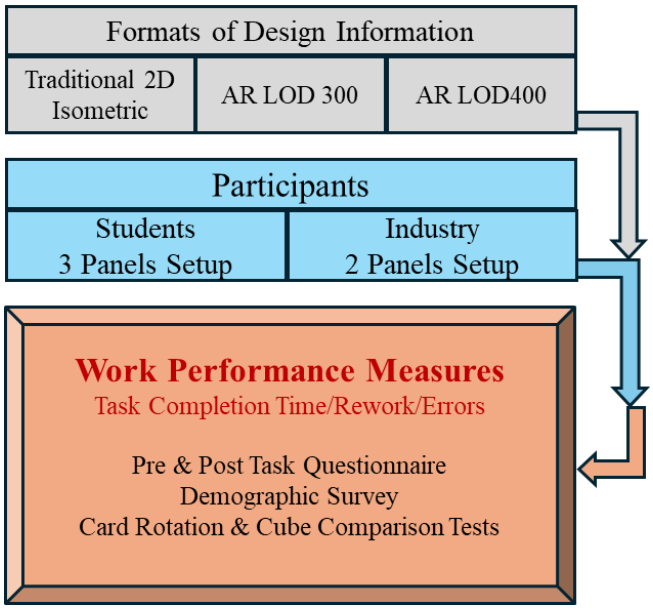


Figure 1.6 Chapter 3 – Experimental Overview

This chapter aimed to address the following research questions.

1. What impact does AR HMDD have on the work performance of the construction industry craft workers and novice population when used as a design information visualization tool at different LODs compared to traditional delivery methods?

2. What impact does the spatial cognitive ability of an individual have on work performance when design information is delivered through AR HMDD at different LODs compared to traditional delivery methods?
3. What impact does the age of an individual have on work performance when design information is delivered through AR HMDD at different LODs compared to traditional delivery methods?

1.5.3 Chapter 4 (Paper 3) Human Vs AI: Assessing Trust and Efficiency in Augmented Reality Assembly Tasks Among Construction Industry Professionals

This study expanded on the findings of Chapter 3 to explore more nuanced human factors. It included the 'design origin' (AI vs. Human), another key variable, along with the information format for the analysis, which focused on industry participants, as shown in Figure 1.7.

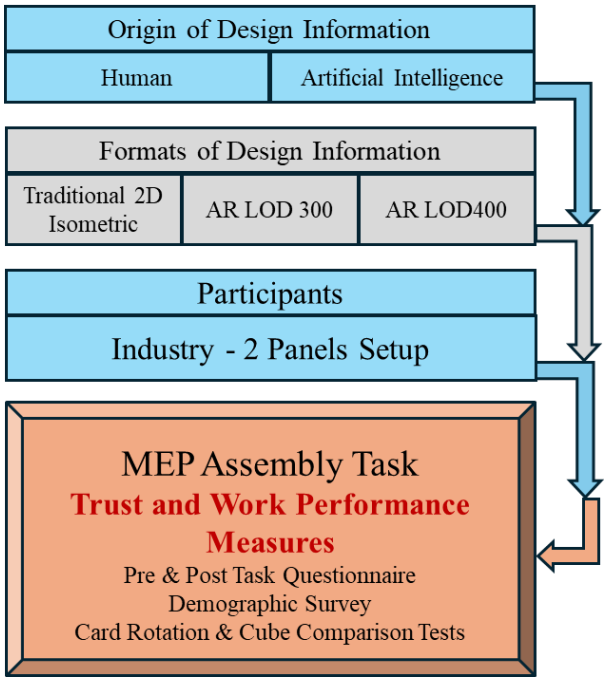


Figure 1.7 Chapter 4 – Experimental Overview

To the best of the candidate's knowledge, this study was the first of its kind to empirically examine the complex interplay between the origin of design information, trust, format of design

information, and work performance in the context of a real-world construction task, and aimed to answer the following research questions,

1. How does the origin of design information, particularly when identified as Human VS AI-generated, influence workers' trust, moderated by participants' detection of intentional error in the task?
2. How does the interplay between design origin and design information formats affect distinct aspects of user performance?
3. How does the effect of the origin of design information on workers' trust and performance in an AR-assisted environment vary when the age and spatial cognitive ability of the participants are controlled?

In this dissertation, the selection of study populations was guided by the imperative to maximize ecological validity and applicability to real-world construction practice. The first and third studies were restricted to industry professionals, recognizing the pioneering nature of research on augmented reality (AR) in safety hazard detection and trust in AI versus human-origin design within AR-assisted environments. Although data were concurrently collected from student participants, analyses and reporting were confined to industry samples to ensure the generalizability of the findings and avoid unnecessary expansion of the scope. Methodological considerations also justified the exclusion of student data for these studies, as students, typically younger and more technologically adept, often possess prior experience with related technologies, such as virtual reality, in gaming contexts. This demographic characteristic may introduce bias by inflating estimates of usability, engagement, and performance benefits in studies limited to student populations, potentially obscuring context-specific barriers and safety concerns relevant to the construction workforce.

Consistent with established literature, the second study incorporated both student and industry participants, leveraging this comparative design to elucidate differences and commonalities in AR technology adoption. The inclusion of both populations allowed for a direct evaluation of AR's potential to bridge the performance divide between novices and experienced practitioners. Notably, results indicated that AR adoption is not significantly associated with age, underscoring the technology's applicability across a demographically diverse workforce. The analyses of student data collected in the first and third studies are reserved for future publications and are beyond the scope of this dissertation.

Taken together, these methodological choices underscore the importance of rigor in experimental design and reporting, particularly when introducing novel technologies to operational domains. The findings substantiate that scientific inquiry into human-technology interaction in construction should prioritize practitioner validation while contextualizing conclusions drawn from student samples within their inherent limitations.

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CHAPTER 2 – HOW DOES AUGMENTED REALITY HEAD-MOUNTED DISPLAY IMPACT THE ABILITY TO DETECT SAFETY HAZARDS WHILE PERFORMING PIPING ASSEMBLY?[1]

Abstract: Augmented Reality (AR) Head Mounted Display Devices (HMDDs) have the potential to revolutionize information delivery during the construction phase. However, concerns remain about whether AR HMDDs impact workers' ability to detect changes in their surroundings, which could pose safety risks. In this controlled experiment, one hundred industry craft workers participated in an assembly task on a full-scale Mechanical, Electrical, and Plumbing (MEP) model using three information formats: traditional isometric paper drawings and two AR models at levels of detail (LOD) 300 and 400 that vary based on the density of information provided. A safety hazard scenario was introduced, and the response time to detect the change was recorded. Findings revealed a significant difference in response times, with non-AR HMDD users detecting changes more quickly than AR HMDD users. Further investigation examined the correlation between workers' age, spatial cognition, and response time to detect changes. This study is one of the first in the construction domain to introduce hazards (referred to as change) and examine AR HMDDs' impact on individuals' ability to detect them.

Author Keywords: Augmented reality; Head-mounted display devices; Change detection; Construction assembly; Situational awareness.

[1] This chapter is based on the published study.
Chaudhari, R., Goodrum, P., Bhandari, S., Hallowell, M., Jones, M., Brady, N., and Yeh, T. (2025). "How does augmented reality head-mounted display impact the ability to detect safety hazards while performing piping assembly?" International Journal of Industrial Ergonomics, 107, 103751. https://doi.org/10.1016/j.ergon.2025.103751

2.1 Introduction

In recent years, the construction sector has begun integrating emerging technologies to enhance communication, productivity, and safety. Augmented Reality (AR) is one such technology that has gained considerable attention in the last decade. Industry stakeholders are increasingly recognizing these technologies' potential applications across different project stages. AR is a powerful tool that can overlay information onto reality, allowing for improved performance and decision-making. For instance, it assists designers in enhancing visualization (Alsafouri and Ayer, 2019), which can improve the communication of design intent. It allows safety managers on the job site to perform safety audits and activities by allowing real-time visualization of potential hazards and monitoring activities and tasks (Heinzel et al., 2017; Olsen et al., 2019). Facility management personnel can access crucial information (Irizarry et al., 2013) and support maintenance evaluations (Ammari and Hammad, 2014) and overall facility management (Rankohi and Waugh, 2013).

AR Head Mounted Display Devices (HMDD) such as Microsoft HoloLens, Google Glasses, Magic Leap, Vuzix Glasses, etc. can offer promising solutions for field applications. For example, AR HMDDs are becoming popular, especially for assembly-based tasks in the construction industry, as traditional approaches are often quite costly and time-consuming (Alkan and Basaga, 2023). In Bartuska et al. (2023), the researchers built prefabricated timber wall elements using AR assistance with improved efficiency and accuracy. Similarly, Qin et al. (2021) found that workers using AR to assemble wood frame walls were more efficient than workers using traditional design modalities, even when the tasks were performed in differing conditions, created with a combination of frame sizes and types of information display. Chalhoub and Ayer (2018) utilized AR to communicate design information for constructing electrical conduit assemblies and found

it more efficient than the traditional method. Cuperschmid et al. (2016) focused on assembling precast wood-frame walls, while Hou et al. (2015) used AR to facilitate piping assemblies.

However, there is some preliminary evidence to support the idea that AR HMDDs can also reduce workers' awareness while performing assembly tasks (Abbas et al., 2020; Hasanzadeh et al., 2018; Jung et al., 2018; Qin et al., 2023) . These studies proposed that AR HMDDs can impact the situational awareness of workers by increasing their cognitive load (Aromaa et al., 2020), reducing attention levels (Hasanzadeh et al., 2018), and restricting field of view (FOV), which could potentially impair work and safety performance (Qin et al., 2023b). This is a major concern in work environments like construction, where multiple trades and equipment function in tandem, creating dangerous and changing working conditions. If the usage of AR HMDD reduces awareness of the overall environment among workers as they perform their primary tasks, it can yield significant safety concerns in practice. Studies in the past have explored the impact of HMDDs on the situational awareness of construction workers. However, they have largely ignored the role of perceptual limitations such as change blindness due to AR HMDDs. Additionally, these investigations lack the requisite ecological and external validity because they were performed in controlled laboratory environments, and not all the simulated tasks were scaled appropriately to reflect the complexity of real-world construction tasks accurately. The participants recruited for these studies were predominantly university undergraduates or graduate students, often in small sample sizes. Although some studies included industry professionals, the sample sizes remained insufficient to draw definitive conclusions.

This study aims to address gaps in the body of knowledge by investigating AR HMDD's impact on detecting the change among experienced craft workers on industrial job sites. Academically, this is the first effort to examine the effect of AR HMDD on the ability of an individual to detect

change that may pose risks of safety hazards in the construction domain. Additionally, considering the issue of an aging workforce in the construction industry and findings from previous studies (Dadi et al., 2014; Goodrum et al., 2016a; Sweany et al., 2016) that show a significant relationship between cognitive ability and age of construction craftworkers with work performance, this study aims to explore these relationships in terms of hazard detection in an AR-assisted environment. In this experiment, the participants performed a realistic piping assembly task where design information was delivered in different formats: traditional isometric paper drawings and AR models with levels of details (LOD) 300 and 400 that vary based on the density of information provided. During the experiment, a hazard scenario was introduced (i.e., referred to as "change" in this paper), and the authors aimed to determine whether using AR HMDD to complete a primary task could compromise workers' ability to detect changes in their surroundings and pose safety hazards to them.

Overall, the objective of this study is to answer the following research questions:

1. What impact do AR HMDDs have on change detection on construction job sites that may pose safety risks among industry craft workers?
2. What is the correlation between craft workers' spatial cognitive ability and their response time to detect the change in an augmented reality-assisted construction environment?
3. What is the correlation between craft workers' age and their response time to detect the change in an augmented reality-assisted construction environment?

2.2 Literature Review

2.2.1 Augmented Reality

Augmented Reality (AR) is defined as a technology where computer-generated graphical information is superimposed onto the user's view of the real world (Wang and Dunston, 2006).

Simply put, it involves enhancing the real environment with virtual information (Cleveland, 2011). AR can be delivered through various platforms such as smartphones, tablets, computers, and Head Mounted Display Devices (HMDDs). These platforms are categorized into handheld devices (e.g., smartphones, tablets) and wearable devices (e.g., HMDDs, smart glasses). Comparatively, AR HMDDs provide mobility and hands-free capabilities, making them ideal for fieldwork. Modern AR devices can augment reality using visuals, sound, touch, and even smell (Woodward and Ruiz, 2023); however, this study focuses on AR through visual displays. AR technology is considered a promising technology to enable Industry 4.0 concepts in various sectors (Nassereddine et al., 2022) as it efficiently connects the physical world of employees with a digital environment.

AR technology has been used successfully within different industries. For instance, Michalos et al. (2018) used AR glasses and smartwatches to collaborate with humans and robots for assembly in the automotive industry. Stoltz et al. (2017) investigated the potential of Google Glasses to facilitate miscellaneous warehouse operations, like package locating and sorting. Another study in the logistics industry (Hanson et al., 2017) used AR to convey labor-picking information on all the necessary components, parts, tools, and materials required for an assembly operation, known as kit preparation. The results showed that AR information was time-efficient and more accurate than traditional printed paper lists for kit preparation. The other prominent fields include quality assurance (Segovia et al., 2015) and manufacturing (Nee et al., 2012).

Over the past decade, AR HMDDs have also gained popularity in construction assembly for accelerating digitalization and enhancing labor productivity (Alkan and Basaga, 2023). Kwiatek et al. (2019) conducted a study involving the installation of a complex pipe model using AR, revealing faster task completion and improved spatial cognition among participants. Similarly, studies by Ahn et al. (2019), Bartuska et al. (2023) and Qin et al. (2021) on a projection-based

wood wall assembly showed that participants completed tasks more quickly and with fewer errors using AR models compared to traditional methods. Chalhoub and Ayer (2018) confirmed AR's effectiveness in improving the accuracy and reducing assembly time for electrical equipment tasks. Additionally, Hou et al. (2015) and Syberfeldt et al. (2015) conducted research on LEGO assembly, Wu et al. (2023) and Abbas et al. (2020) developed applications for rebar assembly, Kim et al. (2012) used AR for bridge construction, Deshpande and Kim, (2018) used it to assemble furniture, and Fazel and Izadi, (2018) experimented with AR in a bricklaying task. However, very few studies have focused on understanding the impact of these devices on environmental awareness or detecting changes in the environment.

2.2.2 Situational Awareness (SA) and AR HMDD

Situational awareness is defined as "the detection of elements in the environment within a volume of space and time, the comprehension of their meaning, and the projection of their status in the near future" (Endsley et al., 1998). SA is a comprehensive concept involving the perception, comprehension, and projection of elements in the environment over time and space (Endsley, 1988). Perception involves detecting the relevant cues; comprehension is understanding the meaning of the cues, while projection is predicting the future state of the cues (Endsley, 1988). These three levels of SA are essential for hazard identification, effective decision-making, accident prevention, and overall risk management in dynamic industrial environments (Endsley, 2021).

SA, in the context of AR, has been extensively explored in different sectors. Some studies have proven that AR HMDD or smart glasses improve user awareness and safety. For example, Park and Park (2019) stated that HMDD in the automotive sector can improve driver's SA and safety. Borgmann et al. (2017) showed that smart glass-assisted urological surgery improves SA and is safe for surgeons. However, other studies indicated that AR systems can impact SA and increase

cognitive load. According to Kerr et al. (2012), divided attention between the AR display and the environment raised safety concerns for four out of nine participants, who had to be warned in a task as they approached a road junction in an augmented environment. Baumeister et al. (2017) evaluated the impact on cognitive load by three AR displays (Samsung Gear VR, projector-based AR, and Microsoft HoloLens) and found that restrictions of HMDDs like FOV, vergence, and resolution increased users' cognitive load and impacted SA negatively. In a study by Abbas et al. (2020), forty-five PhD students were randomly divided into three groups to perform rebar inspections using paper plans, a tablet AR model, and a HoloLens AR model. The task included identifying rebar errors, such as spacing between rebars, missing rebars, and insufficient rebar covers, using the given formats. They reported that the limited FOV in AR HMDDs negatively influenced SA during rebar inspection tasks.

Most of the studies mentioned above used self-reporting tools like the Situation Awareness Global Assessment Technique (SAGAT) and Situation Awareness Rating Technique (SART) to measure high-level overall SA. While these tools provide valuable insights into comprehension and projection, they overlook the nuances of the foundational level of SA, i.e., perception (Endsley et al., 1998). Perception involves recognizing and interpreting critical information from the surrounding environment. When perception is compromised, the subsequent levels of SA, i.e., comprehension and projection, are also negatively impacted. Therefore, it is essential to investigate perception in AR-assisted environments objectively because, on the one hand, AR HMDDs enhance the visibility of task-relevant information by overlaying virtual cues in the real-world environment. But on the other hand, they can introduce visual clutter, attention biases, or occlusions, which may hinder the user's ability to detect critical changes in their surroundings, compromising their perception. This research focuses specifically on exploring this phenomenon

of failure to detect changes (change blindness) in the users' surroundings in an AR-assisted environment.

2.2.3 Change Blindness (CB)

CB occurs when individuals fail to notice unexpected but important changes, objects, or events while their attention is on a primary task (Simons and Chabris, 1999). In a famous Invisible Gorilla Test by Simons and Chabris, (1999), subjects were tasked with counting the number of ball passes between several participants in a video. After watching the video, when asked, 46% of the subjects did not report seeing a person in a full gorilla suit walking through the scene. This proves that when individuals concentrate on the primary task, secondary tasks, objects, or changes in surroundings receive less attention, are ignored, or go completely unnoticed. In an AR-assisted environment, particularly with AR HMDDs, if an AR interface inadvertently occludes key environmental cues or directs attention too narrowly to virtual elements, users may fail to notice critical changes, resulting in errors or safety risks.

Previous studies (Bhandari et al., 2018; J. Chen et al., 2016; Hasanzadeh et al., 2017; S. Park et al., 2021) have mentioned that CB, along with the psychological and emotional conditions of craft workers, is a major cause of unexpected human-related accidents in the construction sector. These studies have addressed the concept of CB in construction, primarily in hazard detection, but almost none have explored it in the context of AR HMDDs. In this study, we aim to understand how AR HMDDs may impact users' ability to detect changes in their surroundings while primarily focusing on completing an assembly task with various information formats.

2.2.4 Information Delivery and Cognitive Load

The mode of information delivery in many streams of the construction sector has greatly changed over the past few years, transitioning from paper-based blueprints to BIM 3D models (Qin

et al., 2021). Despite this shift, isometric engineering drawings have served as the primary information format for pipefitters for at least the past four decades (Goodrum and Miller, 2015). Isometric drawings are images with horizontal lines drawn at a 30° angle to the horizontal, while vertical lines remain vertical. This allows for a clear directional distinction of the design's geometric properties. However, these drawings are often not to scale, requiring craft workers to read both the drawing and the accompanying text to create a mental image of the components. This process can increase cognitive load and affect work performance.

In contrast, AR devices, regarded as tools for delivering future design information, present 3D models or 2D images within the user's existing environment, making the interpretation of design information more intuitive. BIM 3D models can be developed at different levels of details (LOD), for example, LOD 100, 200, 300, 400, and 500, where LOD 100 provides conceptual representation, LOD 200 offers approximate geometry, LOD 300 provides more precise geometry, LOD 400 projects detailed fabrication level geometry and LOD 500 is a fully as-built model (Latiffi et al., 2015). Previous studies present varying perspectives on AR devices. Some studies report positive effects of AR HMDD, noting its ability to reduce cognitive load and enhance task performance. Conversely, other studies, citing the limitations of HMDD, highlight negative effects, indicating that the use of AR HMDD may lead to increased cognitive load, decreased task performance, and potentially contribute to change blindness.

Apart from the restrictions of the HMDD, another reason that might restrict the use of AR HMDD as a tool to deliver information could be the cognitive limitations of humans in processing the presented information effectively. Cognitive overload tends to occur when working memory is required to process a significant amount of information rapidly, leading to decreased performance and SA (Paas et al., 2004). According to Doswell and Skinner (2014), Cognitive Load Theory

(CLT), human working memory can typically manage an average of seven disconnected items simultaneously. If more information is presented, it may be overwhelming for the user to process. Sweller, (1994) explain that too little CL and too much CL could affect performance. Based on this theory, performance can be enhanced when the information provided through AR HMDD is optimal. However, if the information is too vague or overwhelming, it can impair performance and situational awareness, potentially leading to change blindness. Figure 2.1 effectively illustrates this concept by providing a clear visual representation. To understand this phenomenon in detail, this research investigates the impact of AR models at different LODs on users' ability to detect changes. Additionally, this study explores the correlation between the spatial ability and age of the users with the ability to detect changes in an AR-assisted environment.

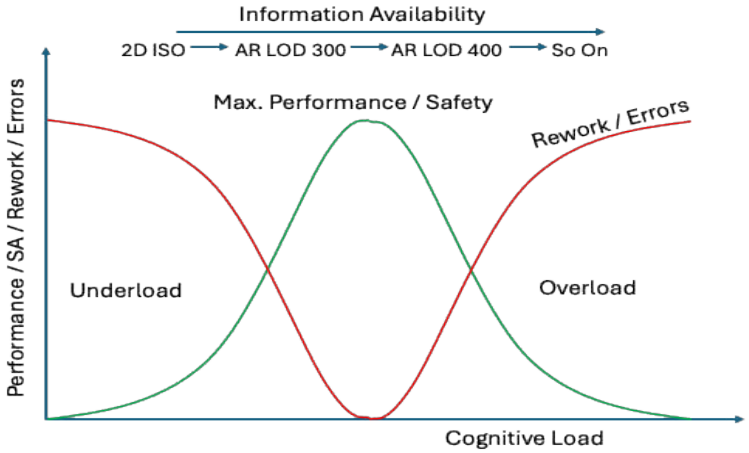


Figure 2.1 Relationship between Performance, Situational Awareness, and Cognitive Load (Abbas et al., 2020; Lyell et al., 2018; Paas et al., 2004)

2.2.5 Spatial Cognitive Ability

Cognitive ability is the capacity of an individual to understand and process spatial information (Ekstrom and Woods, 1976). Ekstrom and Woods (1976) suggested that the information format must be fully understood for a task to be successfully executed. They also discovered that individuals have a limited capacity to comprehend spatial information. Engineering information

formats are particularly complex, requiring individuals to utilize spatial cognition to encode, remember, transform, and match information (Lohman, 1979). People exhibit significant variation in their spatial cognition, which can affect their work performance and change detection. In a scale model assembly task, Goodrum et al. (2016) found that when participants were provided with 2D drawings supplemented by 3D information, those with lower spatial cognition performed as effectively as those with higher spatial cognition.

Similarly, Dadi et al. (2014) demonstrated that providing participants with 3D drawings or a 3D physical model in addition to 2D drawings significantly improved task performance. Endsley et al. (1998) highlighted that high spatial ability enhances situational awareness in domains such as the military and aviation, enabling individuals to evaluate and react to environmental changes swiftly. Numerous studies have explored the correlation between spatial cognition and performance. However, this study aimed to examine the correlation between spatial cognition and the ability to detect changes. Leveraging this understanding can help develop better strategies and environments that support individuals with lower spatial ability to perform their tasks more effectively and safely in AR-assisted environments.

2.2.6 Age and Safety Awareness

The construction industry faces a dilemma with the increasing average age of its workforce. According to an analysis by the National Association of Home Builders (NAHB) of the latest 2021 American Community Survey (ACS) data, the median age of construction workers is 42 years, which is one year older than the median age of workers in the national labor force (NAHB, 2023). The issue of an aging construction workforce adds complexity to occupational safety (Schwatka et al., 2012). In this context, change detection becomes increasingly important as it is the first step for workers to proactively reduce injuries or accidents when exposed to dangerous construction

sites filled with machinery and physical hazards (Hasanzadeh et al., 2017). Graham and Burke (2011) tested the relationship between age and CB based on the Invisible Gorilla Test and found that older adults were more likely to experience CB than young adults.

The impact of age on work performance and safety is a complex and intriguing area of study. Li et al. (2024) conducted the very first study to investigate the impact of age on early preattention and later attention with three types of hazards: falling from height, struck-by, and tripping on the same level, based on Electroencephalography (EEG) measurements. The results showed that older workers showed less change blindness to being struck than younger workers. However, they paid substantially less attention to nonfatal hazards, such as tripping on the same level, and this relationship was not influenced by experience. However, Kamardeen and Hasan, (2022) reported that construction workers over the age of 45 years are more likely to be injured or permanently disabled compared to their younger counterparts. Schwatka et al., (2012) demonstrated that injuries sustained by older workers tend to result in higher costs per injury compared to those of younger workers. Additionally, Varianou-Mikellidou et al., (2019) stated that older workers might experience more human errors when facing hazards, putting them at higher risk on job sites.

While relevant research underscores the relationship between age and safety performance, almost none of the studies have focused on examining the relationship between age and AR HMDD in relation to change blindness and its impact on situational awareness in the construction domain. Exploring this phenomenon is important because, as an industry, we need to be cognizant of developing technologies that support an aging workforce while also being aware that some technologies could potentially have an adverse effect on older workers. This study aims to underline the urgency and significance of understanding the correlation between age and users'

ability to detect changes in an AR-assisted environment and its potential impact on the safety of the construction industry.

2.3 Research Hypothesis

Based on the objective of the study, research questions, and literature review, the following hypotheses were proposed to examine the expected relationships.

H1 – There is a significant difference in the ability to detect changes between non-AR users (who use traditional paper drawings) and AR HMD users (who use AR models at LOD 300 and 400) during the assembly task.

H2 – A significant relationship exists between the spatial cognition ability of craft workers and their response time in detecting changes within an augmented reality-assisted environment, where response time decreases as spatial cognition ability increases.

H3 – There is a significant correlation between the age of craft workers and their response time to detect changes in an augmented reality-assisted environment, with response time increasing with the increase in participants' age.

2.4 Research Methodology

This study was a part of comprehensive research where a controlled experiment was designed to answer the aforementioned research questions and to test the hypothesis. Researchers followed a standard protocol that included developing an experimental setup, recruiting industry participants, performing experiments and data collection, and conducting statistical analysis, followed by results and discussion.

2.4.1 Experimental Setup

To enhance the ecological validity of the research procedures, we recruited subject matter experts (SMEs) for structured brainstorming sessions. The goal was to identify the major types of engineering deliverable displays currently used by SMEs, the associated problems and benefits of each display, and the construction tasks that need better display support. The SMEs were recruited from structural, mechanical, and electrical trades, each with at least five years of industry experience. Based on the discussion, a full-scale replica of a typical MEP system was built that can be found on many industrial construction job sites, featuring an array of mechanical pipes and electrical conduits mounted on panels. The model consisted of two metal panels of size 3 feet X 5 feet, as shown in Figure 2.2. Before recruiting participants from the industry domain, pilot tests with 40 undergraduate students were conducted to ensure the clarity and completeness of the experimental setup.

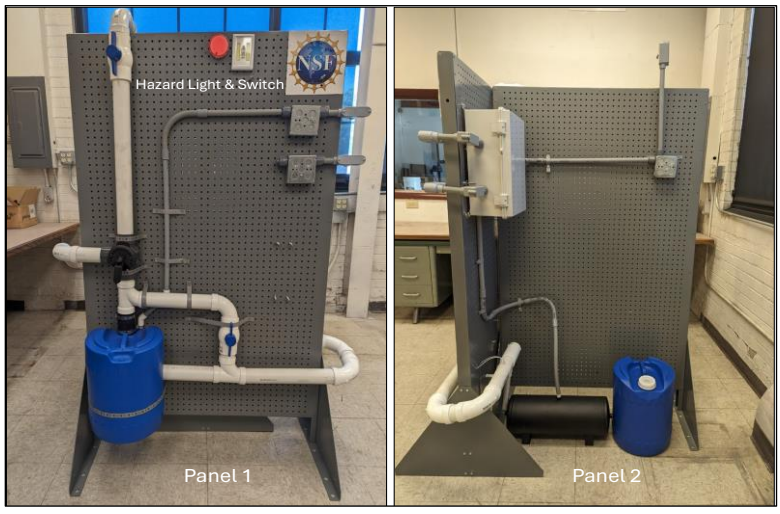


Figure 2.2 Experimental Set-Up (Panel 1 with safety hazard light and a switch, Panel 2)

The primary task of the participants was to install the missing pipe pieces and conduits using three information formats for guidance. Figure 2.3 shows the pieces that need to be installed on panel one.

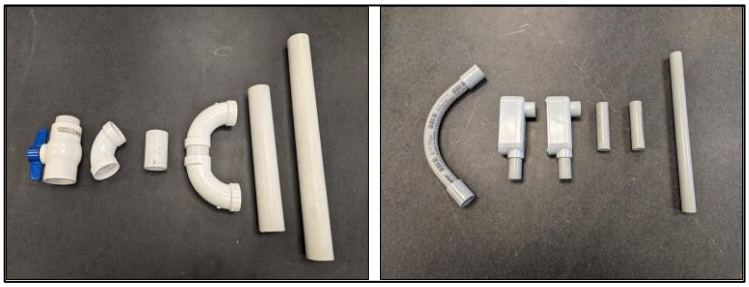


Figure 2.3 PVC Pipe Pieces and Electrical Conduits for Panel 1

The mechanical and electrical components to be installed were made of standard PVC material. There were six mechanical components with a diameter of 2 inches and six electrical components with a diameter of 0.5 inches. Participants did not have to cut, trim, bend, or file the pieces or use PVC cement to complete the assembly. Each piece could be connected simply by pushing and twisting into an existing piece. AR models were displayed through Microsoft HoloLens 2 HMDD. It has a display resolution of 2048 x 1080 pixels for each eye, a 52-degree field of view (43 degrees horizontally and 29 degrees vertically), and a 3:2 aspect ratio. The AR model displays were developed using the Unity3D game engine platform. Basically, the AR model through HoloLens was superimposed on the panels so participants could visualize and compare it with the existing incomplete assembly before installing the missing pieces. Figure 2.4 shows isometric paper drawings and snapshots of AR LOD 300 and 400 models from HoloLens.

A 2D image (NSF logo) of a tracking marker was placed on the panel's upper right corner, serving as a reference point to load and anchor the AR model on the panels. This tracking marker, always available on the panel, allowed the AR system to recalibrate its images if required during the task. The hazard light was integrated into panel one to introduce a change detection element

into the experiment. The decision to install it on panel one rather than panel two was arbitrary and did not follow a predefined rule. This placement does not affect the validity of the study, as the primary objective was to assess participants' ability to detect changes in the assembly task, regardless of which panel contained the element. According to the experimental protocol, the flashing light simulated a warning for a gas leakage scenario within the simulated unit. Participants were instructed to deactivate the light by switching off a corresponding control as promptly as they perceived the flashing signal, thus addressing change detection. The scope of this paper was to study the response time to detect the change during the assembly task. Other experimental measures and measures on panel two were out of scope for this study. Once the participant finished the task, post-experimental questions were asked, followed by the demographic survey and spatial cognition tests.

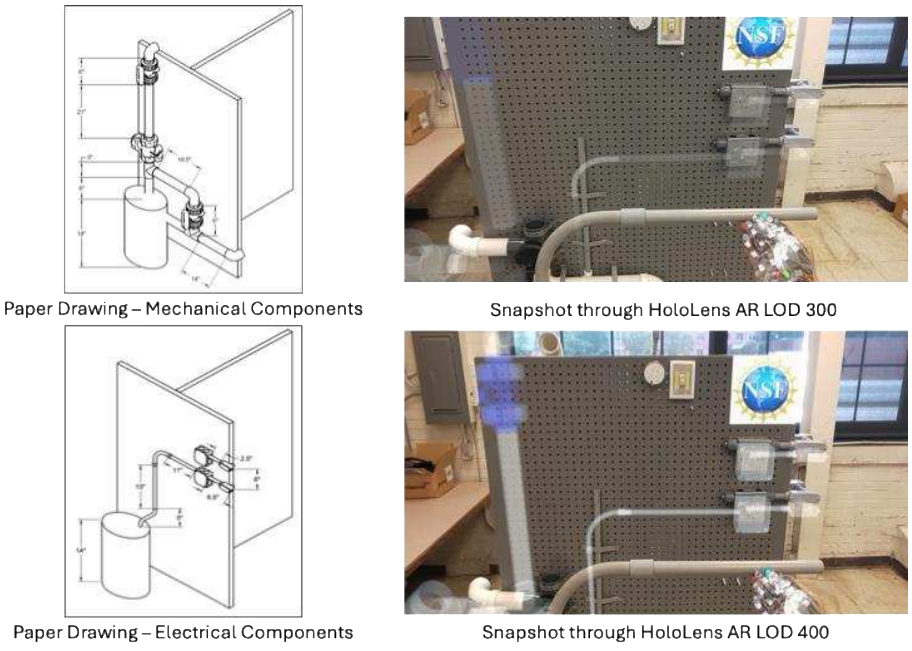


Figure 2.4 Isometric paper drawings and snapshots of AR models through HoloLens (LOD 300 and 400)

2.4.2 Participants

A total of 100 participants were recruited for this study. All participants were recruited from the construction industry, representing various trades such as plumbing, HVAC, maintenance, electrical, and prefabrication. Their positions included line workers, supervisors, project engineers, project managers, and industrial engineers. Initially, the experiments were conducted in a lab setting for the first 32 participants in a controlled, well-lit, and well-ventilated room. However, we developed a mobile test bed of the same scale to better understand the effects of an actual construction environment and enhance the data collection process. This mobile test bed was taken to three industrial job sites, where the remaining experiments were performed in an actual industrial environment. Even in the industrial setting, where the test bed was stationed on the shop floor, researchers ensured good light and ventilation. The participants ranged in age from 18 to 68 years. Their years of industry experience ranged from 6 months to 45 years, with an average of 10 years.

Participants were randomly divided into three groups based on the information format used (Paper, ARLOD300, and ARLOD400). Participants who felt uncomfortable or hesitant while performing the task were free to stop the experiment at any time. Each participant was compensated with a gift card for their time and contribution to the research study. Four participants were Spanish-speaking, so instructions were provided through a human translator, and all relevant documents were printed in Spanish. However, two of these participants were unable to complete the task. Additionally, two participants completed the task before activating the change detection scenario. Six participants did not notice the hazard light at all, while 12 participants noticed the flashing hazard light but, due to their focus on the assembly task, either ignored it or forgot to switch it off. Lastly, there were six participants for whom the LED light did not work due to a

technical issue. Hence, the final number of participants considered for direct analysis was 73 (Paper = 33, ARLOD300 = 17, ARLOD400 = 23), as shown in Table 2.1.

Table 2. 1 Participant Demographic

Demographic	Description
Number of participants	73
Age range	18 - 68
Average age	32.2 (SD = 11.8)
Years of experience	0.5 - 45
Average years of experience	10.2 (SD = 9.8)

SD = Standard Deviation

2.4.3 Experimental Procedure and Measures

The protocol was explained in detail upon the participant's arrival for the experiment, informed consent was obtained, and participants were asked about their prior experience with AR HMDDs or Virtual Reality (VR) HMDDs. Before the task began, they were given a cover story and instructions to understand the scenario. Per the cover story, participants acted as MEP craft workers and were tasked with finishing the mechanical piping and electrical conduit to install a physically simulated industrial unit (Experimental setup). Per the cover story, this specific unit was designed to convert natural gas to polypropylene to manufacture medical supplies such as syringes, medical vials, and specimen bottles. Since the proposed unit was to use natural gas, a red warning light would be activated if a hypothetical gas leak was detected.

Once the participants were ready to perform the task, they were provided with information in the form of drawings on paper or AR models through the HoloLens. The HoloLens was calibrated for each participant using the in-built application. After the task began and the participant was engaged, the researcher manually activated the LED flashlight using a remote sensor ninety seconds into the task. Participants were instructed to turn off the switch next to the LED light as soon as they noticed it, regardless of the information format they were using for the assembly. Once the switch was turned off, they could continue to complete the assembly task. With careful

observation, the time taken to turn off the switch was recorded for each participant using a stopwatch. After the task, participants were asked about their overall experience using the AR HMDD and any distractions they experienced during the assembly task. They then completed a demographic survey followed by spatial cognition tests.

Primary experimental measures were 1) Whether participants noticed the change or not, and 2) If the change was noticed, what was the time taken to turn off the switch next to the hazard light? The spatial cognition test scores were calculated later to understand the correlation.

Figure 2.5 Participants Performing the Assembly Task

2.4.4 Spatial Cognition Assessment

To assess the user's spatial ability skills, several tools are available like the Differential Aptitude Test: Space Relations (DAT:SR), the Mental Rotation Test (MRT), Card Rotation and Cube Comparison Tests, and the Mental Cutting Test (MCT). We used Card Rotation and Cube Comparison Test kits developed by Educational Test Services (ETS) for this study. Figure 2.6 shows the examples of both the tests. The Card Rotation Test measures the ability to mentally manipulate objects in two dimensions, while the Cube Comparison Test evaluates similar skills in three dimensions.

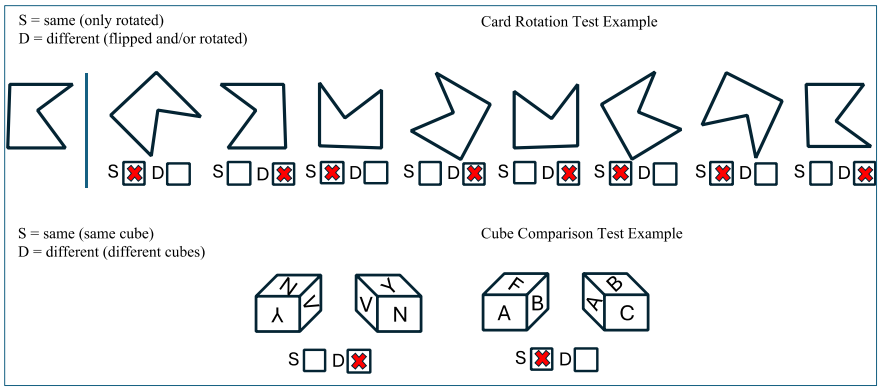


Figure 2.6 Examples of Card Rotation and Cube Comparison Tests

The card rotation test, with a maximum score of 40, and the cube comparison test, with a maximum score of 14, were designed to assess participants' spatial cognition. In the card rotation test, participants are tasked with identifying a rotated version of an image, not a flipped one. Similarly, the Cube Test requires participants to rotate 3D cubes to determine if they match mentally.

2.4.5 Statistical Methods

We recorded the data for each participant to compare the average time taken to turn off the hazard light switch across three groups. The control group was the Paper Plans group, while the test groups were ARLOD300 and ARLOD400. We obtained participants' age data from demographic questionnaires and recorded their spatial cognition test scores. Initially, we compared basic statistical measures, such as mean and standard deviation (SD), in a tabular format. We then used boxplots to visualize the data distribution across the groups and utilized scatter plots to understand the correlation between age, spatial cognition, and the time taken to detect the change.

While boxplots and scatter plots offered initial insights and visual summaries for statistical hypothesis testing, as well as for analyzing the effects and relationships between the dependent variable (response time) and the predictor variables (information format, age, and spatial cognition

test scores), researchers adhered to a standard methodology. The data was right-skewed with some outliers, so researchers assessed and confirmed the normality using the Shapiro-Wilk test. A non-parametric Kruskal-Wallis test and pairwise comparisons were employed to compare the differences in response times across the three groups. Spearman's rank correlation tests were conducted to explore the relationships between the variables. Furthermore, the impacts of older and younger age groups and test scores were examined in depth. This structured approach ensured a thorough and trustworthy analysis, contributing valuable insights.

2.5 Results and Analysis

2.5.1 Descriptive Analysis

In a pre-experiment questionnaire, thirteen out of one hundred participants reported using Virtual Reality (VR) head-mounted display devices (HMDD) for gaming. None of the participants had prior experience with Augmented Reality (AR) HMDD. Due to time constraints, participants were not given training on how to use the AR HMDD. However, eye calibration was performed for each participant on the HoloLens to ensure optimal performance and a customized experience. Before comparing the mean response times between the groups, we examined the percentage of participants who either did not notice the hazard light at all or noticed it but ignored or forgot to turn off the switch, as shown in Table 2.2. The percentage of participants using paper drawings who did not notice the hazard light was 6% less than those using AR HMDD. The percentage of participants using the AR 400 LOD model who noticed the hazard light but ignored or forgot to turn it off was 7% higher than the other two groups.

Table 2. 2 Groupwise percentage of participants who didn't notice and noticed but ignored or forgot to turn off the hazard light.

Group	Did not notice the hazard light at all (%)	Noticed but ignored or forgot to turn off (%)
Paper Plans	2.70	10.81
ARLOD300	9.52	9.52
ARLOD400	8.57	17.14

Table 2.3 presents the mean and standard deviation of age, card rotation test, and cube comparison test for each group. The boxplot in Figure 2.7 indicates that participants using paper plans or not utilizing AR HMDD took less time to turn off the switch compared to the other two groups using AR LOD 300 and AR LOD 400. Participants using the LOD 400 model were the slowest to notice and deactivate the hazard light.

Table 2. 3 Groupwise mean and SD for age, card rotation, and cube comparison test scores

Group	Age		Card Rotation Test		Cube Comparison Test	
	Mean	SD	Mean	SD	Mean	SD
Paper Plans	34	12.3	28.6	10	8.4	3
ARLOD300	37	10.9	29.9	8.8	10.5	2.7
ARLOD400	35	11.9	27.9	8.4	9.3	2.7

Scatterplots were created to understand the correlation and effect of age and spatial cognition test scores, as shown in Figures 2.8, 2.9, and 2.10. One of the objectives of the study was to examine the correlation between age and response time. Since age and years of work experience were highly correlated (Pearson's correlation coefficient = 0.74), work experience was not included in the analysis to avoid multicollinearity and ensure the independent effect of age on response time could be accurately assessed. Across all three formats, a positive linear relationship between response time and age appeared particularly significant for the AR LOD 400 group.

However, no clear relationship existed between response time and spatial cognition test scores for any group in the scatter plots.

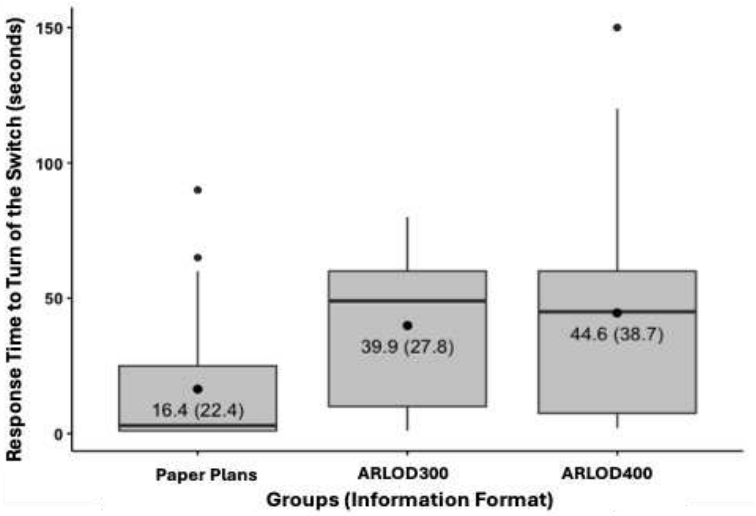


Figure 2.7 Boxplot for response time to turn off the switch by group with mean and SD

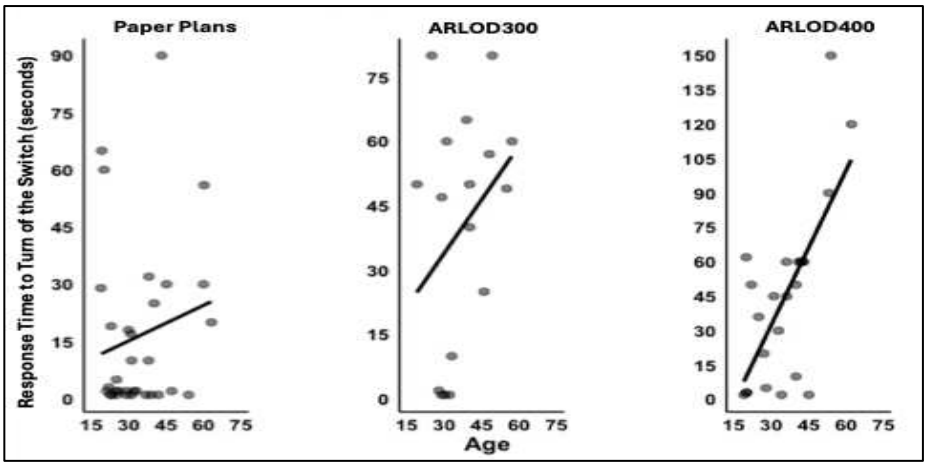


Figure 2.8 Scatterplot of time to turn off the switch by age for each group

2.5.2 Hypothesis Testing

As the data was skewed to the right, we first checked the normality of the data using the Shapiro-Wilk test before conducting statistical analyses.

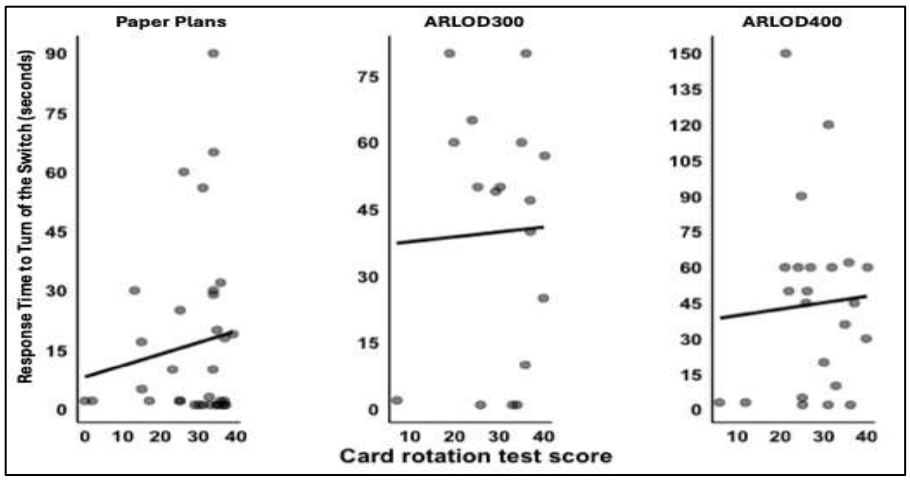


Figure 2.9 Scatterplot of time to turn off the switch by card rotation test score for each group

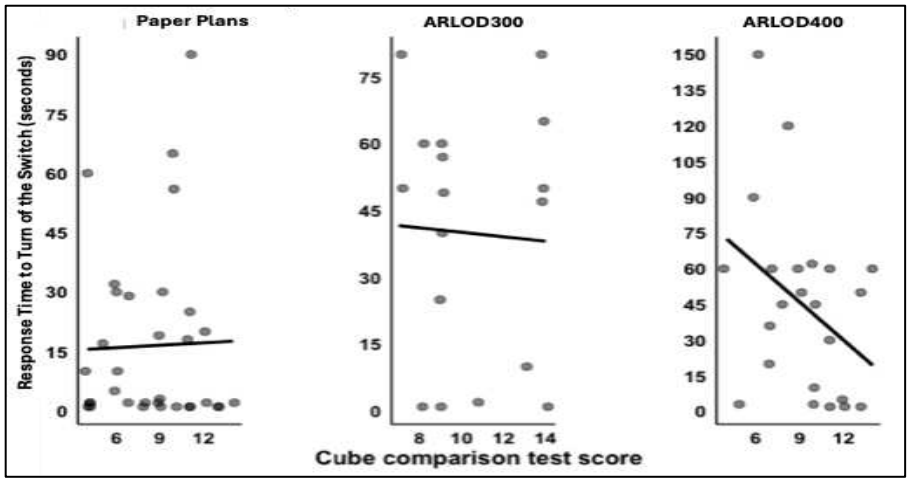


Figure 2.10 Scatterplot of time to turn off the switch by cube comparison test score for each group

We used a standard alpha value of 0.05 for all statistical tests to determine significance at the 95% confidence level. For the Shapiro-Wilk test, if the p-value produced by the test is less than the alpha value, the data is not normally distributed (Abbas et al., 2020). As shown in Table 2.4, the p-values produced by the test for each group were less than 0.05, indicating that data was not normally distributed.

Table 2. 4 Results of Shapiro-Wilk test for normality

Group	statistics	p-value
Paper Plans	0.73	0.001*
ARLOD300	0.89	0.044*
ARLOD400	0.88	0.010*

Note. * = significant difference ($p < 0.05$)

Further, we used a non-parametric Kruskal-Wallis H test to assess the statistical significance of the response time for the three groups. The p-value produced by the test was $0.00126 < 0.05$, indicating statistically significant differences in response time between the groups. After finding a significant overall effect with the Kruskal-Wallis test, post-hoc pairwise comparisons using the Bonferroni correction were used to determine which groups significantly differed. The result of the pairwise comparison is shown in Table 2.5.

Table 2. 5 Pairwise comparison for different groups

Paired Groups	z -ratio	p-value
Paper Plans - ARLOD300	2.57	0.0151 *
Paper Plans - ARLOD400	3.36	0.0011 *
ARLOD300 - ARLOD 400	-0.46	0.9688

Note. * = significant difference ($p < 0.05$)

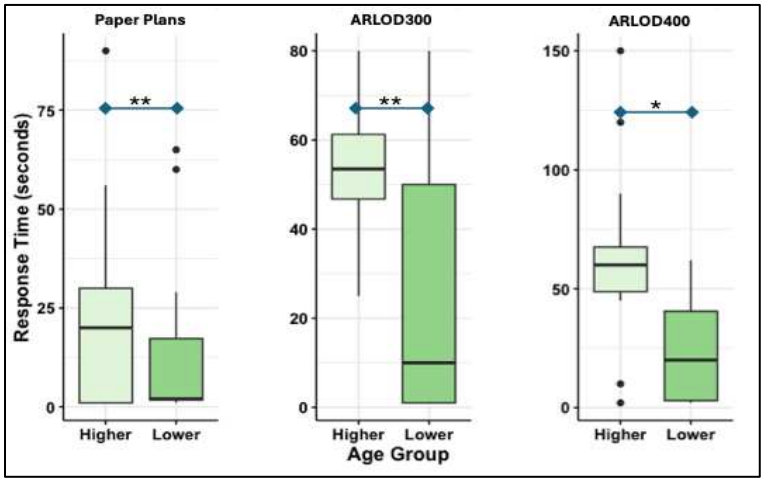
The post-hoc test revealed significant differences between the groups using Paper Plans and both ARLOD300 and ARLOD400, but no significant difference was found between ARLOD300 and ARLOD400. This indicates that non-AR HMDD users took significantly less time to notice and turn off the hazard light than AR HMDD users. As expected, the analysis supported the first hypothesis (H1), concluding that there was a significant difference in the response time to detect changes between the group using traditional isometric drawings (non-AR users) and the groups using AR LOD 300 and AR LOD 400 for the assembly task. Furthermore, Spearman's rank tests were conducted to examine the correlation between age, spatial cognition tests, and response time. The results are presented in Table 2.6.

Table 2. 6 Results of Spearman's rank correlation tests

Predictor	rho	p-value
Age	0.29	0.012 *
Card rotation test score	-0.033	0.781
Cube comparison test score	-0.046	0.695

Note. * = significant correlation ($p < 0.05$)

The positive value of the correlation coefficient rho for the variable age indicated a moderate correlation between age and response time, suggesting that response time also tended to increase as age increased. The p-value ($0.012 < 0.05$) confirmed the statistical significance of this correlation. In contrast, the very small negative rho values for the card rotation and the cube comparison test scores indicated a weak correlation with response time, confirmed by the p-values. It was important to test the correlation for both tests separately as these tests measure different aspects of spatial cognition (Goodrum et al., 2016a). Furthermore, the Wilcoxon rank-sum test investigated the effect of higher and lower age in detail within each group. We found that the effect of age was statistically significant within the AR LOD 400 group; that is, the response time increased significantly as the age increased, but it was not significant within the Paper or AR LOD 300 groups, as shown in Figure 2.11.



Note. * = significant difference ($p < 0.05$); ** = no significant difference ($p > 0.05$)

Figure 2.11 Boxplot for the effect of higher and lower age on response time for each group

Like age, the effect of high and low spatial cognition test scores on response time was investigated, but there was no significant effect within any group. This analysis did not support the second hypothesis (H2), concluding that there was no significant correlation between the spatial cognition ability of craft workers and their response time to detect change in either AR-assisted or non-AR-assisted construction environments. However, the analysis supported the third hypothesis (H3), and we concluded that there was a significant correlation between the age of craft workers and their response time to detect change in AR-assisted environments where the response time increased with the increased age. With reference to Figure 1, it can further be concluded that as the richness of the AR environment increases beyond a certain point, it negatively affects the change detection of the older craft workers.

2.6 Discussion

The purpose of this study was to understand the impact of AR HMDD on change detection. Participants' responsiveness to change detection was compared with AR models (LOD 300 and 400) and traditional information delivery methods, i.e., isometric paper drawings. Additionally, the correlation between spatial ability and age with the ability to detect change in an AR-assisted environment was investigated.

2.6.1 AR HMDD negatively impacts change detection

The findings highlight a significant drawback of AR HMDDs on change detection in construction environments compared to traditional paper drawings. HoloLens HMD is a see-through technology where participants can see superimposed digital content within their environment. AR HMDD was anticipated to maintain real-world awareness to support AR applications in an industrial environment. However, the evidence suggests that there may be contexts and occupational environments wherein AR HMDD may interfere with the ability of

individuals to detect changes. Based on the findings, the group that used paper drawings for the assembly task detected the change (flashing hazard light) significantly faster than those that used AR HMDD. Within the two AR levels, i.e., LOD 300 and LOD 400, the average response time of LOD 300 users was less than that of LOD 400 users; that might be because the density of information in LOD 400 model is more than LOD 300 model which engages user attention more on a primary task than the secondary information.

Researchers also observed that HoloLens users had to keep moving forward and backward to gaze at their environment and to get a full view of the AR models. Many participants reported that the AR model was distracting because it blocked their view of the experimental setup. Hence, they had to stand and focus more to look for the task information. These ergonomic challenges of constantly adjusting one's position to view AR models may detract from the ability to detect change. This finding was also confirmed by Abbas et al. (2020), as they found HMDD users focused narrowly on their tasks compared to natural human vision, which would make them less alert to changes in their surroundings. Non-HMD users did not have distractions like superimposed images or FOV restrictions, and normally, humans have a horizontal FOV of 104˚ to 94˚, which is much higher than HoloLens (Qin et al., 2023). As a result, users with paper drawings, which offered an unobstructed and comprehensive view of the surroundings, were better positioned to notice change.

AR HMDDs can lessen the cognitive load needed to process design information compared to isometric drawings. This enables participants to concentrate more on tasks that can enhance productivity. Most of the studies discussed reported improved work performance when information was conveyed through AR HMDDs, which also reduced gaze shifts between the real and augmented environments. Conversely, some studies noted SA issues arising from AR HMDDs.

However, this study takes a critical step forward by objectively examining the effect of AR HMDDs on users' perceptual awareness, specifically focusing on change detection and the risk of change blindness. This study explores the reduced ability to detect changes and the delayed responses to hazards associated with AR HMDDs, which could pose significant safety concerns in construction and industrial settings. In addition, the study's methodological approach, using real-world assembly tasks in controlled industrial settings with a significant sample size, enhances the ecological validity of the findings, making them highly applicable to actual construction environments.

2.6.2 No impact of spatial cognition on change detection

Spatial cognition refers to an individual's capacity to understand, comprehend, and process spatial information. This ability is closely linked to factors such as cognitive load, spatial memory, visual attention, and alertness (Mitolo et al., 2015). Individuals with high spatial ability demonstrate better alertness (Mitolo et al., 2015) and hence can detect changes in their surroundings quickly and accurately. However, the findings of this study challenged this expectation, revealing no significant relationship between spatial cognition and change detection in AR-assisted environments. This was true even when analyzed for the effect of high and low spatial cognitive ability within each group, showing no significant impact of spatial cognition on change detection.

Interestingly, AR HMDDs did not disproportionately hinder participants with lower spatial abilities, suggesting that the technology's interface complexity and information density may be equally challenging for all users. Conversely, participants with higher spatial abilities, who would typically excel in change detection tasks, may have experienced cognitive overload due to the mismatch between their natural spatial processing strategies and the constraints of AR

visualization. This phenomenon may be akin to the expertise reversal effect in instructional design, where tools that simplify tasks for novices can hinder experts by constraining their natural problem-solving approaches. Overall, these findings suggest that AR HMDDs may override natural cognitive advantages, raising questions about the effectiveness of AR in environments where change detection is critical and highlighting the need for interface designs that minimize cognitive interference.

2.6.3 The ability to detect change decreases as age increases

(Simons and Chabris, 1999) mentioned that noticing unexpected changes in surroundings depends on the availability of attention of an individual. Aging decreases attentional capacity; hence, relatively more attention of older adults is drawn toward the primary task, which leaves less attention available for processing the secondary tasks compared to their younger counterparts (Graham and Burke, 2011). MEP assemblies are complex, and experienced workers focus more on completing the task than other secondary issues. Also, when AR models are superimposed, the participant concentrates more on observing the model and installing the pieces, reducing their ability to detect change. In the near future, AR will become integral to construction technology; therefore, understanding the correlation between age and change detection while using AR HMDD is crucial as the workforce ages. To our knowledge, this is the first study to investigate the impact of AR HMDDs on age and the ability to detect change.

The findings of the study revealed a significant positive correlation between age and response time to detect change, with older participants generally taking longer. However, nuanced differences emerged when examining the impact of higher and lower age individually across different conditions. For the paper drawing group, the absence of AR HMDD distractions meant that age-related variations in response time were not statistically significant. Similarly, in the AR

LOD 300 group, the lower information density in the AR HMDD introduced variability in response times, neutralizing the differences between younger and older participants. In contrast, the higher information density for the AR LOD 400 group might have led to significantly longer response times for older participants, likely due to increased focus on the primary information. Another factor could be that younger participants were more likely to have prior experience with similar technology, such as Virtual Reality (VR) HMDDs, often used for gaming, while older participants encountered it for the first time. This familiarity with the technology among younger users could have contributed to their quicker adaptation and response times. These findings have significant implications for the design and implementation of AR technologies in construction and other industries, particularly in relation to the safety of older workers.

The impact of AR HMDD on an aging workforce is both significant and complex. As AR technologies become increasingly prevalent in construction and other industries, it is vital to understand how these tools uniquely affect the occupational safety of older workers. This study is a crucial step in this direction, but further research is needed to fully comprehend the implications and devise strategies to ensure the safety and productivity of older workers in the era of AR technologies.

2.7 Limitations and future work

Researchers acknowledged the following limitations in this study. All one hundred participants recruited for this study were experienced craftsmen from a construction background who were working full-time in various positions. None of the participants had prior experience using AR HMDDs or any type of AR device. While eye calibration was performed for each participant before the experiment, no training session was provided beforehand. Introducing a training session could have familiarized participants with the assembly task, potentially influencing the results. For

broader implications, future research studies may investigate the effects of prior training sessions on change detection. Incorporating training sessions could enhance participants' familiarity with AR systems, potentially improving their responsiveness to changes.

Secondly, in addition to visual adjustments, context-aware notifications and alerts can significantly improve users' responsiveness to environmental changes. The study discovered that participants often became overly focused on AR models, so incorporating peripheral alerts such as subtle visual cues, auditory signals, or haptic feedback can help redirect attention, when necessary, without causing major distractions. However, it is crucial to recognize that audio signals will serve as an external factor and won't inherently enhance the AR HMDD's built-in abilities to detect changes.

Addressing information overload through layered display techniques can further optimize user performance. The study highlighted that higher LOD in AR models, such as those at LOD 400, can significantly engage users' attention, making it challenging to process secondary environmental cues. Implementing a layered information hierarchy that allows users to switch between different levels of detail based on task requirements facilitates more manageable cognitive processing. This design approach would ensure that essential information is consistently accessible without overwhelming the user, thereby balancing efficiency with environmental awareness.

Finally, while researchers conducted experiments on-site in a real industrial setting, this experiment does not fully represent the use of AR HMDDs in actual projects. The main limitation is that conducting these experiments to fulfill real project objectives restricts the study's repeatability. Additionally, industrial safety protocols prohibit the implementation of new technologies without providing extensive training for users. Carrying out similar studies on actual

construction sites and involving real construction tasks could reveal many new aspects for further research.

2.8 Conclusion

AR HMDDs are considered to hold great potential to revolutionize the delivery of design information on construction job sites. While the impact of AR HMDDs on work performance has been extensively studied, this research specifically explored their effect on the ability to detect safety hazards in the craft worker's surroundings while they focused on the primary task. The outcomes of this study have significant implications, as researchers compared traditional information delivery methods with two types of AR models to assess construction professionals' change detection abilities while performing an assembly task on a full-scale MEP test bed. This study is among the first to investigate the correlation between age and spatial cognition with change detection in an AR-assisted environment. Participants were given three different information formats to complete an assembly task, during which a safety hazard scenario was introduced, and their response time to detect the safety hazard (referred to as "change") was recorded.

The findings indicated a significant difference in response times between AR HMDD users and non-AR HMDD users, with non-HMDD users being the quickest to respond. This suggests that AR HMDDs may impair users' ability to detect changes, potentially causing safety issues on job sites. Furthermore, the spatial cognition ability of individuals did not significantly impact response time under any conditions. However, older participants, particularly those using the AR model of LOD 400, showed significantly longer response times. This indicates that AR might reduce the ability of older workers to detect changes, making them more vulnerable compared to their younger counterparts.

These findings emphasize the need for careful ergonomic and safety-oriented design in AR HMDDs to mitigate potential risks. Participants reported discomfort due to the frequent repositioning needed to view AR models, underscoring the importance of user-centered ergonomic features such as automatic model scaling and adjustable positioning. Enhancing these aspects can reduce physical strain, improve comfort, and help users maintain better awareness of their surroundings. Additionally, tailoring AR interfaces to user demographics, including age and spatial ability, can enhance accessibility and performance. Adaptive interface complexity, customizable alerts, and personalized training modes can ensure that both younger and older workers effectively engage with the technology.

In conclusion, while AR HMDDs offer promising advancements in delivering design information on construction sites, their impacts on change detection and worker safety need careful consideration. Future research should aim to optimize AR systems to improve change detection capabilities while also implementing training programs and integrating multimodal feedback systems, such as audio cues, to enhance the effectiveness and safety of AR technologies in construction environments.

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Data Availability Statement

Some or all data that support the findings of this study are available from the corresponding author upon reasonable request.

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CHAPTER 3 – EXPLORING THE IMPACT OF AUGMENTED REALITY ON WORK PERFORMANCE IN A FULL-SCALE MEP ASSEMBLY TASK: A STUDY OF INDUSTRY AND NOVICE POPULATIONS[2]

Abstract: Building Information Modelling (BIM) has revolutionized the construction industry; however, field personnel still rely on traditional methods for design interpretation. Augmented Reality (AR) Head-Mounted Display Devices (HMDDs) offer a promising alternative for delivering 3D design information, yet their effectiveness must be validated across diverse populations with a significant sample size. This study examines the impact of AR HMDDs on Mechanical, Electrical, and Plumbing (MEP) assembly tasks, evaluating key performance metrics: task completion time, rework rate, and error rate. Both novice and experienced participants completed assembly tasks in industrial and laboratory settings, marking the first comparative analysis of AR models with different Levels of Detail (LOD 300 and LOD 400) against traditional isometric paper plans. Findings indicate that the AR LOD 400 model significantly improved all performance metrics across both populations, except for the error rate among industry professionals. The AR LOD 300 model notably reduced rework rates, while traditional paper plans were the least effective. Age did not significantly impact performance, whereas higher spatial cognition enhanced novices' efficiency. Participants acknowledged AR HMDDs, particularly the LOD 400 model, as beneficial for design comprehension; however some also reported distractions. These insights highlight the need for user-centered AR interface design and tailored training

[2] This chapter is based on the published study.
Chaudhari, R., Goodrum, P., Brady, N., Hallowell, M., Jones, M., Yeh, T., & Bhandari, S. (2025). "Exploring The Impact of Augmented Reality on Work Performance in A Full-Scale MEP Assembly Task: A Study of Industry and Novice Populations." Journal of Construction Engineering and Management. https://doi.org/10.1061/JCEMD4/COENG-16726

strategies to enhance usability and efficiency. As the first study to investigate the influence of AR model LODs on construction task performance with a robust sample size, the results provide valuable guidance for optimizing AR HMD technology, training protocols, and design information delivery in the construction industry.

Author Keywords: Augmented reality; Levels of Detail; Head-mounted display device; Construction assembly; Work performance.

3.1 Introduction

The construction industry significantly contributes to the global economy, employing approximately 7% of the world's workforce and generating an annual revenue of around $10 trillion (Barbosa et al., 2017). The United States itself employs more than 7.8 million workers, and based on governmental projections, it is projected to grow to approximately 8.3 million by 2032 (US Bureau of Labor Statistics, 2023). However, the sector faces significant challenges like decreased labor productivity, an aging workforce, a lack of skilled workforce recruitment, and an overall labor shortage (Ramadan et al., 2023). Alkan and Basaga (2023) highlighted that one of the primary factors contributing to low productivity in the construction sector is the inadequate adoption of digital technologies. This fact is supported by Barbosa et al. (2017) stating that a strong correlation exists between labor productivity and digitalization indices, and the construction sector ranks lowest in both among all sectors.

The architecture, engineering, and construction (AEC) industry is inherently complex, necessitating extensive information access for effective evaluation, communication, and collaboration. This complexity significantly heightens the industry's dependence on advanced information technologies. Over the past decade, Building Information Modeling (BIM) has been pivotal in driving the digitalization and modernization of the construction sector. BIM provides

design professionals with three-dimensional (3D) models presented at various Levels of Detail (LOD) (Latiffi et al., 2015). By offering accurate building information, these BIM models enhance interactions with customers and investors (Heinzel et al., 2017). As a result, there has been a steady increase in the use of BIM models, which support design processes, construction delivery, and facility management (Vilutiene et al., 2019).

Despite this progress, many construction projects, particularly within the Mechanical, Electrical, and Plumbing (MEP) trades, continue to rely heavily on traditional two-dimensional (2D) plans and written specifications to convey design information to field personnel. Craft workers, referring to 2D drawings during assembly tasks, engage in a series of physical operations such as observing, grasping, and installing components while also navigating the cognitive processes necessary to comprehend and translate the presented information based on their spatial abilities (Neumann and Majoros, 1998; Hou et al., 2015). This cognitive load can lead to mental fatigue, particularly among novice assemblers, ultimately increasing errors and rework, which negatively impacts productivity.

Emerging visualization methods, such as Augmented Reality (AR), may provide solutions to these challenges. AR technology, also referred to as Mixed Reality (MR), enables users to interact with both virtual and physical environments simultaneously. According to Kalawsky et al. (2000), AR is defined as the process of overlaying computer-generated graphical information onto the real-world environment, thereby enhancing user interaction. Thus, AR can provide craftworkers with real-time access to BIM 3D information. While AR technology is still in the innovation phase within the construction industry, it is anticipated to experience significant growth in the near future, as demonstrated by the increasing interest from numerous companies in incorporating it as a tool during the construction phase (Alkan and Basaga, 2023).

Research over the past decade confirms the potential of AR to improve labor productivity and reduce cognitive load. For instance, a study on electrical conduit assembly by Chalhoub and Ayer (2018) found substantial productivity improvements when BIM 3D design information was delivered through MR devices. Qin et al. (2021) demonstrated that participants using AR Head-Mounted Display Devices (HMDDs) obtained information more efficiently during wall frame assembly compared to traditional paper plans, effectively reducing measuring and framing issues. Additionally, Hou et al. (2015) found that AR visualization significantly lowered cognitive load while cutting assembly completion time and task errors by 50%.

While several studies have investigated AR technology, particularly the use of AR HMDDs as 3D information visualization tools, they share common limitations. For instance, many previous experiments were conducted in controlled laboratory settings using scaled-down models. The sample sizes were small, mainly involving university students as participants. Although researchers have compared groups utilizing traditional 2D drawings to those employing AR models projected through devices like HMDDs, smartphones, or tablets, no studies have addressed the impact of varying LODs in AR models. These factors limit the generalizability of findings to the actual construction workforce and the broader applications of this technology.

Additionally, the construction industry faces other challenges, such as an aging workforce, inadequate training, and negative public perception. To effectively address these issues, the industry must embrace modern technologies that can attract new skilled workers while also helping to retain those who are already employed (Ramadan et al., 2023). However, the successful implementation of these technologies requires careful testing and validation, particularly in dynamic construction environments that cater to diverse demographics. Specifically, in the AR domain, few studies have thoroughly examined the effects of AR on various skill levels and

demographics, such as age and the differences between experienced and novice workers. Research by Chalhoub et al. (2021) revealed that while novices and experienced participants had similar task completion times, novices showed lower accuracy, highlighting the need for tailored AR-based training. Research (Dadi et al., 2014; Goodrum et al., 2016a) also have demonstrated that age and spatial cognition significantly influence cognitive representation and task performance in non-AR environments. However, this correlation of age and spatial cognitive ability with task performance in AR environments remains largely unexplored.

We believe that as the industry adopts new technologies like AR, it is crucial to ensure that these innovations are easily adaptable for novice workers while supporting the aging workforce. Hence, our research aims to address the gaps mentioned by utilizing AR HMDDs to deliver 3D design information and compare their impacts with traditional delivery methods. Specifically, we have examined the impacts of conventional paper drawings, AR models (LOD 300 and 400), participant's age, and spatial cognitive ability on assembly task performance. Building on prior studies (Dadi et al., 2014; Goodrum et al., 2016; Sweany et al., 2016) and acknowledging that piping components, electrical conduits, and instrumentation constitute 50% of the total project cost in industrial construction (Goodrum et al., 2016), we developed comprehensive full-scale MEP models for the assembly task. These models represent typical MEP systems found on many industrial construction job sites.

For broader generalizability, we recruited 100 participants from the MEP industry (70%) and a university facilities management program (30%) who represented the experienced industry population. Additionally, we recruited more than 200 undergraduate students from the university to gain insights into a relatively inexperienced population.

3.2 Literature Review and Background

3.2.1 Design Information Format and Delivery

The mode of information delivery in the construction industry has significantly transitioned from paper-based blueprints to BIM 3D models over the last decade (Qin et al., 2021b). Despite this shift, pipefitting, plumbing, and electrical craftworkers still primarily rely on 2D isometric drawings as their primary source of information (Goodrum et al., 2016). Isometric drawings are representations where horizontal lines are drawn at a 30° angle to the horizontal, while vertical lines remain vertical. This technique provides a clear directional distinction of the design's geometric properties. 2D paper plans have long been recognized for their effectiveness in facilitating design and communication within the construction industry (Purcell and Gero, 1998). However, the research suggests that factors like missing information from drawings, errors in drawings, and ambiguous design representation may interfere with the standard linear communication process between the designer and the site worker (Chalhoub and Ayer, 2018c). When industry professionals were asked to rank the factors they commonly experienced as barriers to productivity, lack of required information to perform construction tasks was ranked eight out of 51 factors (Liberda et al., 2003). Additionally, O'Connor (1985) supported by stating that productivity decreases when the information is not conveyed correctly. 2D isometric drawings are often not to scale, requiring craft workers to interpret both the drawings and the accompanying text to construct a mental 3D image; hence, convenient access to this information would benefit task performance.

Goodrum et al. (2016) recruited 54 pipefitters to assemble a pipe spool using different information formats in a scale model assembly task. Participants were divided into three groups; researchers provided the first group with a traditional 2D isometric drawing, the second group

received a two-sided isometric drawing with a 2D isometric drawing on one side and a 2D projection of the corresponding 3D model on the other, and the third group was given a 2D drawing accompanied by a 3D-printed model of the assembly. They discovered that participants with lower spatial cognition performed just as effectively as those with higher spatial cognition when 2D drawings were supplemented with 3D information. Similarly, Dadi et al. (2014) showed that providing participants with 3D drawings or a physical 3D model in addition to 2D drawings significantly enhanced task performance. These findings highlight the value of integrating 3D visual aids to bridge the gap in spatial reasoning skills and improve overall efficiency in construction tasks.

AR technology can superimpose not only 2D images onto the workspace but also create a 3D environment within the user's field of view that encompasses the work unit. Wang and Dunston (2006) stated that by overlaying information onto the work unit in a spatially meaningful manner, the retrieval and display of information are seamlessly integrated with the views of the work unit. This integration reduces the time required for information searching within the instructional medium. A pipe assembly study by Kwiatek et al. (2019), confirmed that information delivered through handheld AR device improved user's task performance, resulting in shorter task time and reduced rework. Similarly, Deshpande and Kim (2018) found that when 14 participants used AR HMDD instead of paper plans to assemble furniture, their spatial problem-solving skills improved, particularly in complex assembly tasks.

Previous research has compared the AR models with traditional formats and AR models across different devices; however, the experimental setups used were scaled down, which does not reflect the complexities of the real world. Also, the sample size was not significant. This study addresses these gaps by using the full-scale model and conducting experiments with significant sample sizes.

3.2.2 AR and Head-Mounted Display Devices in Construction

AR technology enhances the user's natural environment with virtual information (Cleveland, 2011). AR has been mainly used in the construction sector to enhance safety measures, enable effective inspections, improve project modeling, and provide better training and education (Alkan and Basaga, 2023). However, over the last decade, research aimed at facilitating construction assemblies using AR has gained significant attention. Table 3.1 provides a list of recent studies that used AR as a visualization tool for construction assembly tasks.

In one of the studies Abbas et al. (2020) used AR technology to assist with rebar inspection tasks. They found it more efficient at detecting errors and missing rebars than traditional paper-based plans. Tavares et al. (2019) ensured a safer working environment by allowing human-robot interaction during welding tasks. They utilized AR visuals that helped the operator tack-weld the beams, which were later seam-welded by the industrial robots. Research by Ahn et al. (2019) and Bartuska et al. (2023) on projection-based wood wall assembly revealed that participants completed tasks faster and with fewer errors when using AR models than with traditional methods. Industries use various platforms, such as smartphones, tablets, computer screens, and head-mounted displays, to project AR information. HMDDs and smart glasses are categorized as wearable devices, whereas smartphones and tablets are referred to as handheld devices. Alkan and Basaga, (2023) revealed that though construction adopted AR initially through projection and screens, today, the most preferred AR visualization tool is HMDDs, followed by smartphones and tablets. The mobility and hands-free capabilities of HMDDs have made them the most suitable and widely used visualization tool in this sector.

Looking at the substantial growth of AR research and HMD users in recent years, multiple companies are investing in technology.

Table 3. 1 Recent studies in construction assembly with AR environment

Research Studies	Assembly Experiment	Sample Size	Environment
Dallasega et al. (2023)	AR to support MEP marking	4 foremen	Onsite
Wu et al. (2023)	Rebar tying task	16 students	Controlled lab
Kim et al. (2022)	Architectural landscape fabrication and installation	12 students	Controlled lab
Chalhoub et al. (2021)	Electrical conduit assembly and point layout	18-28 Industry, 39-42 Students	Controlled lab
Qin et al. (2021)	Wood frame wall assembly	18 students	Controlled lab
Moghaddam et al. (2021)	Simple pipe assembly	20 students	Controlled lab
Wen et al. (2021)	Steel sculpture plan reading	34 students	Controlled lab
Chu et al. (2020)	Dougong structure assembly	48 students	Controlled lab
Abbas et al. (2020)	Rebar assembly and inspection	45 PhD Students	Controlled lab
Kwiatek et al. (2019)	Pipe spool assembly	21 pipe fitters and 40 engineers and students	Controlled lab
Chalhoub and Ayer (2018)	Electrical conduit assembly	18 Electrical personal	Controlled lab
A. Deshpande and kim (2018)	Furniture assembly	14 Students	Controlled lab
Wang et al. (2018)	Steel installation	40 students	Controlled lab
Cuperschmid et al. (2016)	Wood Frame wall assembly	28 Students	Controlled lab
Shirazi and Behzaden (2015)	Building structure model assembly	60 students	Controlled lab
Hou et al. (2015)	Construction piping assembly	unknown	Controlled lab

Microsoft developed HoloLens. Facebook, now known as “Meta,” believes visualization technology will create a new virtual universe in the future called the metaverse and has developed Meta glasses. Google has its smart glasses, and recently, Apple launched its Vision Pro devices in the market. All these advancements and the increased number of research in construction with AR HMDDs can enhance the sectors’ digitalization efforts. This study has used MS HoloLens HMDD to display 3D information and to evaluate work performance in an AR environment.

3.2.3 Building Information Modeling (BIM) and Levels of Detail (LOD)

Vilutiene et al. (2019) stated that BIM is a set of technologies designed to enhance inter-organizational and cross-disciplinary collaboration within the AEC industries. It is a 3D representation of construction projects that provides detailed information on schedule, costs, and

lifecycles, referred to as BIM's 4th, 5th and 6th dimensions (Kwiatek et al., 2019). Among other benefits, BIM is intended to improve productivity and elevate the quality of a building's design, construction, and maintenance stages. Hwang et al. (2009) claimed that projects that utilize BIM models can reduce design errors, increase productivity by 30%, and ultimately reduce the cost of industrial projects significantly.

For the past four decades, isometric engineering drawings have served as the primary information format for pipefitters (Goodrum and Miller, 2015). Hou et al. (2015) believed that failing to adopt a new model could increase the cost of piping projects by 10%. BIM information projected through AR HMDD could serve as this new, cost-effective model. However, it is equally important to identify what information to include in these models and how much to include, particularly for the assembly tasks. Based on cognitive load theory, performance can be maximized when the information is optimal; however, too vague or overwhelming information can impair work performance (Paas et al., 2004). Figure 3.1 effectively illustrates this concept.

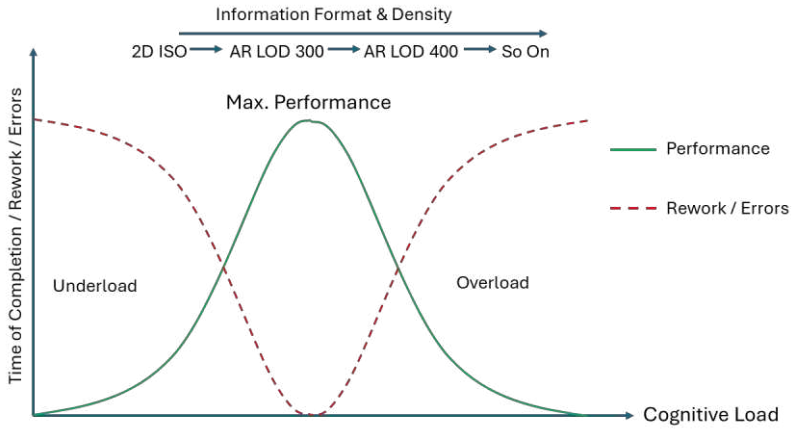

Figure 3.1 Relationship between Performance, Information Density, and Cognitive Load

Based on the richness of data, LOD is a critical criterion to consider while developing BIM 3D models (Leite et al., 2011). LOD is associated with the levels of detail of information included in the building model elements, and its use depends on the scope and requirement of work. LOD

levels range from 100 to 500, each representing different stages of model details. LOD 100 provides a conceptual representation, LOD 200 offers approximate geometry, LOD 300 includes more precise geometry, LOD 400 features detailed fabrication-level geometry, and LOD 500 is a fully accurate as-built model (Latiffi et al., 2015; Leite et al., 2011). Precise geometry LODs represent the components' precise shape and size, while fabrication LODs represent specific, as-is objects with detailed orientation.

Given their suitability for assembly tasks, we included LOD 300 and 400 in this research study. Figure 3.2 below shows the basic difference between these two models. For example, a valve in LOD 300 is represented by a rectangular box, while the valve in LOD 400 is shown as is in a 3D format.

Snapshot through HoloLens AR LOD 300 Snapshot through HoloLens AR LOD 400

Figure 3.2 A Comparison of LOD 300 and 400

This is the first study in the construction domain to compare the impact of traditional paper plans and AR models at varying LODs on task performance. Investigating this phenomenon was crucial to identify the optimal model for maximizing performance. Also, if both LODs yield similar results, using high-LOD models becomes unnecessary, avoiding the need for expensive, high-performance devices and allowing users to opt for smaller, more affordable, and comfortable devices, ultimately enhancing the adoption of this technology.

3.2.4 Spatial cognition

Spatial cognition ability is the capacity of a person to understand and process information (Ekstrom and Woods, 1976). It does not consider a single factor but encompasses a range of factors that work together, including spatial perception, spatial visualization, and mental rotation (Tartre, 1990). Individuals demonstrate significant variation in their spatial cognition ability because of the relative capacity each of us has to comprehend the information (Ekstrom and Woods, 1976). This aspect is crucial in the piping industry as 2D plans are complex and require high spatial cognition to encode, remember, transform, and match the information (Lohman, 1979). A study by Uttal et al. (2013) found a positive correlation between above-average spatial abilities and achievements in STEM (science, technology, engineering, and mathematics) fields. They stated that the students with below-average spatial ability first struggled in STEM foundation courses but later overcame the challenges when the curriculum was designed based on their specific engineering fields.

Similarly, as discussed in the previous section, a study by Goodrum et al. (2016) proved that participants with lower spatial cognition performed just as effectively as those with higher spatial cognition when 2D drawings were supplemented with 3D information. This is an ideal research outcome when an information format helps lower-performing individuals perform as well as higher-ability users (Quarles et al., 2008). In unfamiliar or complex environments, an AR system can assist users by creating a lasting cognitive map and improving their ability to understand spatial relationships (Wang and Dunston, 2006).

In this research, we aimed to examine the unexplored phenomenon in the construction domain: the correlation between participants' spatial abilities and work performance while using different information formats to complete the assembly task. To assess spatial ability, various institutions have developed tools that utilize questions applied to 2D and 3D environments to assess

participants' spatial skills. Some of them include the Mental Rotation Test (MRT), Card Rotation and Cube Comparison Tests, Mental Cutting Test (MCT), and the Differential Aptitude Test: Space Relations (DAT: SR). For this study, the standardized Card Rotation and Cube Comparison Test kits developed by the Educational Testing Service (ETS) were used to evaluate the spatial abilities of the participants.

3.2.5 Workforce in Construction and Technology

The construction sector must balance incorporating new technologies with addressing workforce challenges. The industry is experiencing an aging workforce while struggling to attract younger generations. To sustain future labor demands, the sector must appeal to new demographics. The literature suggests that integrating modern technologies can help address these issues. A pilot study with 54 high school students Buckner and Bender, (2020) revealed that the construction sector is often perceived as a low-paying, non-technical field with limited career growth compared to other industries. The study found that, beyond wages, low exposure to technology discourages young people from pursuing careers in construction. According to Herzberg's motivation theory, technology serves as an intrinsic motivator, as workers find it engaging and satisfying, ultimately influencing productivity (Hashiguchi et al., 2020). As younger generations shift from hands-on to technology-based learning, the construction industry must integrate advanced tools to attract and retain skilled workers.

The adoption of on-site technologies also impacts worker performance. In a survey of 2,780 construction workers, Ramadan et al. (2023) assessed self-reported performance and ease of accessing information from technologies such as barcode scanning, BIM, drones, AR/VR, robotics, AI, and RFID chips. The results indicated that nine out of thirteen technologies, including AR, had a statistically positive impact on worker performance, while seven technologies enhanced

access to essential information. While modern technologies are great at attracting younger craftsmen and improving work performance, it is equally important to consider their impact on the existing workforce.

Today's workforce includes four generations working simultaneously, each with distinct learning styles, work execution methods, and communication preferences (Barrios and Reyes, 2015). According to the US Department of Labor, workers above 55 are classified as older employees (Loeppke et al., 2013). Older workers contribute valuable experience, knowledge, and efficiency to the industry; however, some studies highlight challenges associated with aging. Kamardeen and Hasan (2022) reported that aging is linked to declining physical strength and cognitive abilities, potentially affecting task execution. Tams and Hill (2017) found that older workers often struggle with adapting to modern technologies, experiencing stress and anxiety that can impact productivity. Conversely, Zimmer et al. (2015) found that age is not a significant factor in technology-related errors, suggesting that older workers can effectively adapt to digital tools with proper training. Given these insights, it is essential to assess how emerging technologies like AR impact both older and novice workers. In this research study, like spatial cognition from the previous section, we aimed to investigate the correlation between participants' age and work performance in an AR-assisted environment.

3.3 Research Questions

To address gaps in previous research and contribute to the body of knowledge, this study explored the impact of AR HMDDs on the work performance of both industry professionals and novice participants. Additionally, the study examined how AR HMDs influence performance while controlling for participants' age and spatial cognition. To achieve these objectives, the following research questions were investigated for both populations,

1. What impact does AR HMDD have on the work performance of the construction industry craft workers and novice population when used as a design information visualization tool at different LODs compared to traditional delivery methods?
2. What impact does the spatial cognitive ability of an individual have on work performance when design information is delivered through AR HMDD at different LODs compared to traditional delivery methods?
3. What impact does the age of an individual have on work performance when design information is delivered through AR HMDD at different LODs compared to traditional delivery methods?

3.4 Methodology

We performed controlled experiments in the laboratory and industrial environments to achieve the research objective. As illustrated in Figure 3.3, the study was carried out in different phases, starting from developing an experimental setup, participant recruitment, and conducting the experiments, followed by performing statistical analysis and discussing the results.

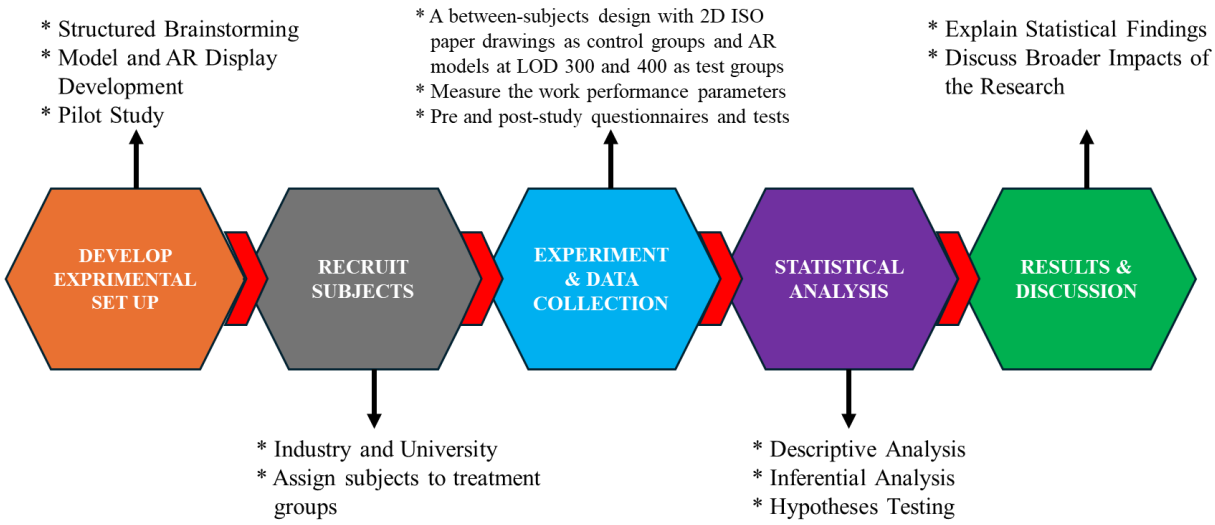

Figure 3.3 Research Methodology

3.4.1 Experimental Setup

To gain a better understanding of the construction tasks that need enhanced display support, we recruited around 20 subject matter experts (SMEs) from structural, mechanical, and electrical trades, each with at least five years of industry experience, for organized brainstorming sessions. This process helped us develop an experimental test bed and identify the primary deliverable displays currently utilized by SMEs and any associated problems or benefits. The test bed developed was a full-scale replica of a typical MEP system commonly found on many industrial construction job sites. It consisted of two metal pegboards, each measuring 3 feet by 5 feet, with an array of mechanical pipes and electrical conduits mounted on three sides formed by connecting the peg boards, as shown in Figure 3.4. The rationale for formulating and selecting three panels was that participants should be able to utilize all three information formats (isometric drawings and AR models: LOD 300 and LOD 400) during the assembly task to facilitate analyses "between subjects" and "within subjects." A safety hazard light was placed on one of the panels for other study purposes, which falls outside the scope of this paper.

Figure 3.4 Experimental Test Bed with Three Panel Sides

A pilot study was conducted with 40 undergraduate students to ensure completeness and clarity of the experimental setup. Further, to enhance the data collection process and to recruit the maximum number of industry participants, we developed another testbed of the exact same scale, referred to as the "mobile test bed." Unlike the original setup, which consisted of three panel sides, the mobile test bed included two sides of the panels, closely resembling the original setup, as shown in Figure 3.5. We did not include the third-panel side in the mobile test bed because of the limited time available for the industry participants and the complex structure of panel three, which led to logistical issues.

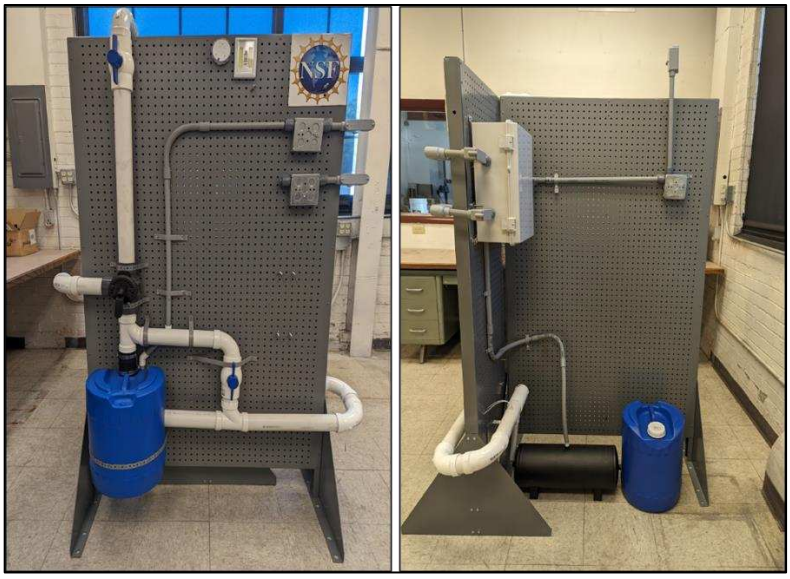

Figure 3.5 Mobile Test Bed with Two Panels

The experiments with student participants were conducted in a controlled lab environment using the stationary three-panel setup. The experiments with industry participants were performed on the mobile test bed. The mobile test bed was stationed on the industry floor, which provided an actual industrial environment for the experiments. The environment for the experiments, in both lab and industry settings, was well-lit and ventilated. Participants were tasked with installing the

missing mechanical pipe pieces and electrical conduits placed in bins in random order, using the three information formats. Traditional ISO paper drawings were used as a control group, while AR models at LOD 300 and 400 were used as test groups. The mechanical and electrical components were made of standard PVC material, as shown in Figure 3.6. The number of components required to be installed on each panel side and their dimensions are listed in Table 3.2.

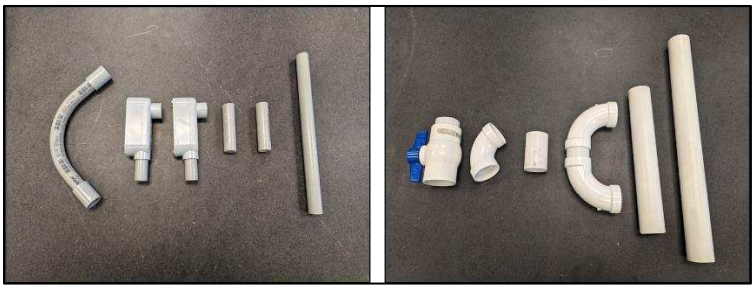

Figure 3.6 Mechanical and Electrical PVC components for Panel 1

Table 3. 2 List of components to be installed in the assembly task

Panel	Number of Components		Total	Dimensions
	Mechanical	Electrical		
1	6	6	12	Diameter: 0.5 - 2 inches Length: 2.5 - 21 inches
2	0	9	9	Diameter: 0.5 inches Length: 1.5-13.5 inches
3	8	5	13	Diameter: 0.5 - 2 inches Length: 2.5-15.5 inches

The complexity of the assembly task for each panel was determined based on the sizes and the number of components that needed to be installed. For student participants, panel side three was the most complex as it required the installation of a total of thirteen components, followed by panel one and then panel two. For industry participants, panel side one was the most complex, with twelve components to install, compared to panel two. Overall, the setup used for student participants was more complicated, with thirty-four components to install on three panels. However, the use of a more complex setup for the inexperienced population (students) allowed us

to test the ability of untrained individuals to perform complex tasks using AR. AR display models were created using the Unity 3D game engine platform. An interface integrated into Unity3D allows for the creation of an application for Microsoft HoloLens, facilitated by the Mixed Reality Toolkit (MRTK) (Deshpande and Kim, 2018). We used the HoloLens 2, featuring a display resolution of 2048 x 1080 pixels for each eye, to visualize the AR models. The superimposed 3D AR models displayed all the components, allowing the participants to compare and install the missing pieces. Figure 3.7 below shows the isometric drawings and snapshots of AR LOD 300 and 400 models from HoloLens.

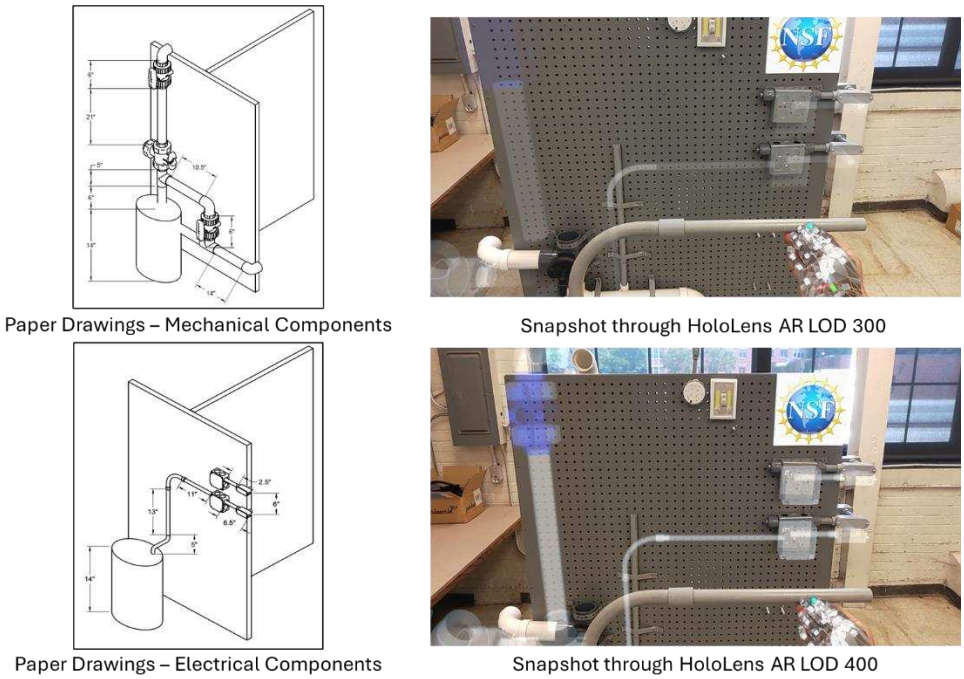

Figure 3.7 Isometric drawings and snapshots of AR models through HoloLens for panel one

We placed a 2D image of the NSF logo, a tracking marker, in the upper right corner of the panel. This image acted as a reference point for loading and anchoring the AR model onto the panels. The tracking marker always remained on the panel, enabling the AR system to recalibrate its images, if needed, during the task.

3.4.2 Participants

We recruited 219 students from psychology, civil engineering, and computer science at the University of Colorado, Boulder, representing a novice population. Including students from multiple disciplines strengthened the generalizability of the findings by capturing a diverse range of cognitive and perceptual abilities, learning styles, and prior experiences with visual-spatial tasks. This approach ensured that the results were not solely influenced by individuals with formal engineering training but were applicable to a broader population, reflecting the varied backgrounds of potential AR technology users in construction and related fields. One hundred craft workers were recruited from MEP manufacturing industries (70%) and the university facilities management program (30%). Industry participants represented various construction trades such as HVAC, plumbing, electrical, manufacturing, and maintenance, with work positions ranging from line workers to supervisors, project managers, project engineers, and industrial engineers. The goal was to involve as many craftsmen as possible who are working in a real construction setting, whom we have referred to as the experienced population. The age of the industry participants ranged from 18 to 36 years, with relative industry experience ranging from 6 months to 45 years, as shown in Table 3.3. Two out of 100 participants were unable to complete the assembly task and were, therefore, excluded from the analysis. There was minimal variation in the age of the student participants, except for a few outliers, and their average years of industry experience were negligible. Hence, these parameters are excluded from the analysis for student participants.

Table 3. 3 Participant Demographic

Demographic	Industry	Student
Number of participants	98	219
Age range	19 - 68	NA
Average age	36.3 (SD = 12.2)	19.8 (SD = 3.4)
Years of work experience	0.5 - 45	NA
Average years of experience	10.5 (SD = 10.2)	NA

SD = Standard Deviation

All participants were randomly assigned to control groups based on the panel and information format they would use to perform the assembly task (Tables 3.4 and 3.5). For industry participants, because there were only two sides in the experimental setup, the ISO paper drawings were included at least once for each participant as they served as the control group.

Table 3. 4 Industry Participants Control Groups

Group	Panel 1	Panel 2
A	ISO only	ISO + AR LOD 400
B	ISO only	ISO + AR LOD 300
C	ISO + AR LOD 400	ISO only
D	ISO + AR LOD 300	ISO only

Table 3. 5 Student Participants Control Groups

Group	Panel 1	Panel 2	Panel 3
A	ISO only	ISO + AR LOD 300	ISO + AR LOD 400
B	ISO + AR LOD 300	ISO + AR LOD 400	ISO only
C	ISO + AR LOD 400	ISO only	ISO + AR LOD 300

Before the experiment session, the experimental protocol was explained to each participant, informed consent was obtained, and participants were asked about their prior experience of using AR HMDDs or Virtual Reality (VR) HMDDs. Participants were informed that they were free to stop the experiment at any time if they felt uncomfortable or hesitant. Pre-experiment and post-experiment questions were made concise to minimize potential biases, and participants were informed that their data would be used solely for research purposes on an anonymous basis.

3.4.3 Assembly Task Overview and Measures

All participants were provided with a cover story to contextualize the assembly task. According to the cover story, they played the role of MEP craft workers who were required to complete the installation of mechanical pipes and electrical conduits left unfinished by the previous craft worker. The experimental setup represented an ethylene cracker unit that converts natural gas to polypropylene to manufacture medical supplies such as syringes, medical vials, and specimen bottles. After reading the cover story, the procedure was explained again, and pre-experimental questions were asked. Depending on the control group assigned, participants were given the corresponding information format and instructed to begin the task when ready. Even if participants were using AR-based information, they were allowed to refer to ISO paper drawings. This flexibility to use the best possible information source supported the task and captured the realistic scenario of using AR applications during construction.

Before loading the AR model, the HoloLens was calibrated for each participant using the built-in application to ensure personalized user comfort and hologram alignment. Once the participant was ready, the task start time was recorded. Participants were keenly observed from a distance to avoid disturbing them or making them aware of the observation. Researchers ensured that all activities of the participants were recorded on the data collection sheets. During the task, each component could be easily connected by simply pushing and twisting it into place with the existing pieces. Participants did not need to cut, trim, bend, or file the components or require PVC cement to complete the assembly. If a participant installed a component incorrectly and then reinstalled it correctly after noticing the mistake, it was counted as a rework. If a component was installed incorrectly and was not corrected until the end of the task, it was counted as an error in the assembly. After installing all the components for a particular panel and signaling completion, the

task end time was noted. Once the task was finished on one panel, the participant was guided to proceed to the next panel with the required information format, and the same procedure was repeated.

After completing the assembly task, each participant answered the post-experiment questions and filled out a demographic survey. They concluded the experiment by taking the card rotation and cube comparison tests. Figure 8 shows examples of both tests. The card rotation test measures the mental ability to manipulate objects in two dimensions. In this test, participants are shown images of cards with different orientations. One card is a reference card, and the other several images are rotated versions of the same card. As a response, participants must determine whether the rotated version is the same card (only rotated) or different (flipped or flipped and then rotated). The cube comparison test evaluates similar skills in three dimensions. Here, participants are shown pairs of images of cubes with different orientations. Each face of the cube may have different markings, letters, patterns, or colors to distinguish it. Participants must determine if the two cubes are the same or different by mentally rotating them to see if they can match the faces of one cube to the other. The card rotation test was worth 40 points, and the cube comparison was worth 14 points. These tests helped us assess the participant's spatial cognition ability.

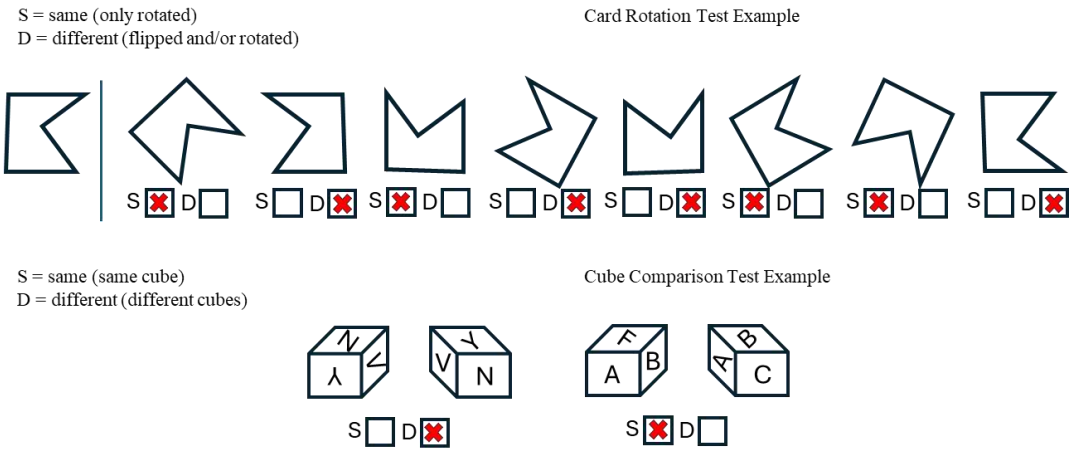

Figure 3.8 Examples of Card Rotation and Cube Comparison Tests

Figure 3.9 presents an overview of the experimental procedures for both industry and student participants, while Figure 3.10 displays a participant performing the task. The total time allocated to complete the experiment was 45-50 minutes for student participants and 30-35 minutes for industry participants. The time to complete the task and the quality of work in each trial were measured during the task. The time to completion was calculated as the difference between the task's end and start times. The quality of work was assessed based on the rework rate and the number of errors that occurred during each trial.

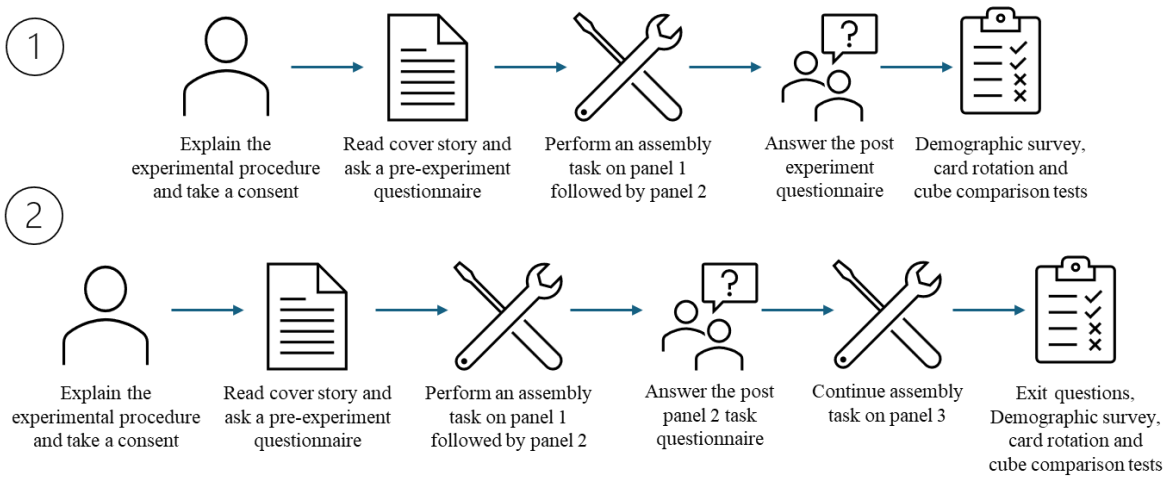

Figure 3.9 Overview of the Experimental Procedure 1) Industry Participants 2) Student Participants

3.4.4 Research Hypothesis

Guided by our research questions and objectives, we aimed to statistically test the following set of null hypotheses regarding task performance, spatial cognitive ability, and the participants' age. We conducted these hypothesis tests comparatively, evaluating AR models against the control of traditional 2D paper drawings. All hypotheses were tested for both populations separately, except the age factor, which was not considered for student participants, as the variability was minimal.

Figure 3.10 Industry Craft Performing the Assembly Task

- $H1_0$: AR displays do not reduce the assembly task time.
- $H2_0$: AR displays do not reduce the rework rate during the assembly task.
- $H3_0$: AR displays do not reduce the error rate during the assembly task.
- $H4_0$: The spatial cognitive ability of an individual has no significant impact on work performance when design information is delivered through AR display compared to traditional delivery methods.
- $H5_0$: An individual's age has no significant impact on work performance when design information is delivered through AR display compared to traditional delivery methods.

3.4.5 Statistical Methods

Based on the number of panels and the number of treatments (information formats), the researchers initially planned a three-group, three-period crossover design. Student subjects performed the task on each panel and received all treatments. For industry crafts, a similar design was used with modifications: subjects performed the task on two panels and used two of the three treatments, with 2D paper drawings used for at least one panel. This design is also known as a

partial crossover design. The control groups for students and industry participants are shown in Tables 4 and 5. This design approach helps control for individual differences by having each participant serve as their own control (Hou et al., 2015b). Mixed-effects regression models were used to analyze this design statistically. A mixed-effects model, also called a mixed model or hierarchical linear model, is a statistical approach that includes both fixed and random effects.

This model is particularly effective for analyzing data where observations are not independent and are organized into groups or clusters (Faraway, 2016). Fixed effects are the effects of interest that are assumed to be the same across all observations. In this study, information format, age, and spatial cognition test scores were the fixed effects predictors, which provided estimates of the overall impact on response variables, i.e., task time, rework, and error. While the random effects of the model account for the variability within groups, here, subjects and panels associate with the random effects. Mixed-effects models can account for the inherent variability within groups or clusters by including random effects, leading to more robust and generalizable results. Mixed-effects models allow for more accurate modeling of data that exhibit grouping, repeated measures, or hierarchical structures, making them widely applicable in many fields (Faraway, 2016).

3.5 Results

3.5.1 Statistical Analysis

The initial descriptive analysis summarized and described the main features of the response variables. Tables 3.6 -3.11 show the panel-wise metrics of task completion time, rework, and errors for students and industry participants.

Table 3. 6 Industry Task Completion Time Metrics

Information Format	Panel 1			Panel 2		
	N	Mean (SD) (seconds)	Min - Max	N	Mean (SD) (seconds)	Min - Max
ISO Paper	40	264.1 (83)	72 - 425	34	161.21	0.26
AR LOD 300	23	237.9 (53)	147 - 335	14	175.07	0.29
AR LOD 400	35	214.1 (59)	90 - 380	18	169.22	0.29

Table 3. 7 Industry Rework Metrics

Information Format	Panel 1			Panel 2		
	N	Mean (SD)	Min - Max	N	Mean (SD)	Min - Max
ISO Paper	40	2.5 (3.4)	0 - 14	34	2.32 (2.6)	0 - 12
AR LOD 300	23	1.04 (1.4)	0 - 6	14	0.36 (0.6)	0 - 2
AR LOD 400	35	0.97 (2)	0 - 11	18	0.83 (1)	0 - 3

Table 3. 8 Industry Error Metrics

Information Format	Panel 1			Panel 2		
	N	Mean (SD)	Min - Max	N	Mean (SD)	Min - Max
ISO Paper	40	0.28 (0.6)	0 - 2	34	0.26 (0.7)	0 - 2
AR LOD 300	23	0.48 (0.8)	0 - 2	14	0.29 (0.8)	0 - 3
AR LOD 400	35	0.34 (0.7)	0 - 2	18	0.29 (0.8)	0 - 3

Table 3. 9 Students Task Completion Time Metrics

Information Format	Panel 1			Panel 2			Panel 3		
	N	Mean (SD) (seconds)	Min - Max	N	Mean (SD) (seconds)	Min - Max	N	Mean (SD) (seconds)	Min - Max
ISO Paper	74	292.5 (138)	107 - 900	71	303 (139)	60 - 900	74	309.5 (99)	101 - 674
AR LOD 300	74	305.1 (122)	117 - 762	74	228.5 (120)	60 - 766	71	368.1 (170)	147 - 900
AR LOD 400	71	254.2 (105)	100 - 535	74	226.5 (108)	60 - 579	74	297.5 (128)	119 - 738

Table 3. 10 Students Rework Metrics

Information Format	Panel 1			Panel 2			Panel 3		
	N	Mean (SD)	Min - Max	N	Mean (SD)	Min - Max	N	Mean (SD)	Min - Max
ISO Paper	74	1.8 (3.2)	0 - 23	71	1.8 (1.9)	0 - 9	74	1.9 (1.8)	0 - 9
AR LOD 300	74	1.2 (1.4)	0 - 6	74	0.8 (1.2)	0 - 5	71	2.3 (1.8)	0 - 8
AR LOD 400	71	1.2 (1.7)	0 - 8	74	1.3 (1.6)	0 - 9	74	1.7 (1.7)	0 - 7

Table 3. 11 Students Error Metrics

Information Format	Panel 1			Panel 2			Panel 3		
	N	Mean (SD)	Min - Max	N	Mean (SD)	Min - Max	N	Mean (SD)	Min - Max
ISO Paper	74	0.8 (1.2)	0 - 5	71	0.6 (0.9)	0 - 4	74	0.2 (0.5)	0 - 2
AR LOD 300	74	1 (1.3)	0 - 4	74	0.4 (0.8)	0 - 5	71	0.4 (0.7)	0 - 3
AR LOD 400	71	0.3 (0.8)	0 - 4	74	0.4 (0.8)	0 - 3	74	0.1 (0.5)	0 - 2

Numbers in the tables provide important insights into the data. The AR LOD 400 model looked efficient for most factors compared to the ISO paper drawings and the AR LOD 300 model. Overall, the average task time, rework, and errors were decreased for the participants who used the AR LOD 400 model, which was true for both populations. Regression analysis was performed to gain a deeper understanding of statistical significance and hypothesis testing, followed by a pairwise comparison. The collective results of generalized mixed-effect models for student and industry populations are presented in Tables 3.12 and 3.13. Six different models were run to examine the impacts of predictor variables (information format, age, and spatial cognition test scores) on response variables (task time, rework, and error), considering the random effects of subjects and panels. The results show the overall impact of treatments on all three panels, considering the ISO paper drawings as a control group while AR LOD 300 and 400 as test groups.

For each regression model, assumptions were examined through residual plots, Q-Q plots, and checks for overdispersion. The use of a negative Binomial model for task time and Poisson models for count data (rework and error) appropriately addressed the data distribution. No major violations of normality, linearity, or homoscedasticity were observed in residual diagnostics. Verifying model assumptions is critical to ensure the validity of statistical inference, as violations can lead to biased estimates, incorrect standard errors, and misleading conclusions. By confirming that assumptions were met, the robustness and credibility of the regression results were strengthened.

In addition to coefficient estimates, we have reported marginal and conditional R^2 values for each model using the Nakagawa and Schielzeth (2013) method, which quantifies the proportion of variance explained by fixed effects (R^2m) and by the full model, including random effects (R^2c). For example, in Table 13, for the industry participants, the task completion time model showed an R^2m of 0.198 and an R^2c of 0.631, indicating that fixed predictors explained 19.8% of the variance while the full model accounted for 63.1%. The rework model demonstrated higher explanatory power, with $R^2m = 0.185$ and $R^2c = 0.637$. The error model had limited fixed-effect explanatory power ($R^2m = 0.011$), though random effects explained 68.7% of the variance (R^2c).

These results suggest that while individual predictors had moderate effects, the overall models accounted for meaningful variance in the outcomes. While the marginal R^2 values of the final models may appear modest, such values are common and acceptable in behavioral research and real-world field studies, where substantial inter-individual variability and unmeasured contextual influences are present (Chicco et al., 2021). Notably, the selected models demonstrated strong predictive value through statistically significant fixed effects, practically meaningful improvements (e.g., reduction in task time and rework), and favorable Akaike Information Criterion (AIC) / Bayesian Information Criterion (BIC) model fit criteria. These factors collectively support the robustness and utility of the models despite modest explained variance. To further substantiate these findings, 95% confidence intervals were reported for all estimated coefficients, enhancing the interpretation and credibility of the fixed effects.

Table 3. 12 Results of Regression Analysis for Student Participants

Predictor	Task Time (R^2m = 0.148, R^2c = 0.569)			Rework (R^2m = 0.135, R^2c = 0.567)			Error (R^2m = 0.149, R^2c = 0.558)		
	Estimate	p-value	(β) [CI]	Estimate	p-value	(β) [CI]	Estimate	p-value	(β) [CI]
Intercept (2D ISO)	390	-		2.59	-		0.63	-	
AR LOD 300	-14	0.255	(-0.019) [–0.097, 0.026]	-0.54	0.0019 *	(-0.238) [–0.389, –0.088]	0.05	0.566	(0.076) [–0.185, 0.338]
AR LOD 400	-61	0.0001*	(-0.168) [–0.230, –0.106]	-0.62	0.0006 *	(-0.264) [–0.415, –0.112]	-0.26	0.0005*	(-0.541) [–0.850, –0.233]
Card_R Test	-5	0.0001*	(-0.011) [–0.017, –0.006]	-0.05	0.003 *	(-0.020) [–0.034, –0.006]	-0.01	0.044 *	(-0.022) [–0.043, –0.005]
Cube_C Test	-4	0.0019 *	(-0.023) [–0.038, –0.008]	-0.02	0.012 *	(-0.048) [–0.085, –0.010]	-0.02	0.017 *	(-0.071) [–0.129, –0.012]

Note. * = significant difference ($p < 0.05$). For rework and error (Poisson Model), β indicates log count difference.

Table 3. 13 Results of Regression Analysis for Industry Participants

Predictor	Task Time (R^2m = 0.198, R^2c = 0.631)			Rework (R^2m = 0.185, R^2c = 0.637)			Error (R^2m = 0.011, R^2c = 0.687)		
	Estimate	p-value	(β) [CI]	Estimate	p-value	(β) [CI]	Estimate	p-value	(β) [CI]
Intercept (2D ISO)	240	-		4.62	-		0.48	-	
AR LOD 300	-10	0.55	(-0.019) [–0.162, 0.086]	-3.10	0.0001*	(-1.13) [–1.567, –0.673]	0.35	0.203	(0.526) [–0.278, 1.382]
AR LOD 400	-27	0.047*	(-0.114) [–0.226, –0.001]	-2.59	0.0001*	(-0.835) [–1.183, –0.478]	0.04	0.72	(0.136) [–0.664, 0.850]
Age	0.62	0.206	(0.002) [–0.001, 0.006]	-0.09	0.066	(-0.018) [–0.038, 0.001]	-0.01	0.6	(-0.012) [–0.057, 0.040]
Card_R Test	-3	0.002*	(-0.008) [–0.013, –0.002]	-0.07	0.07	(-0.019) [–0.039, 0.010]	-0.03	0.06	(-0.056) [–0.115, 0.002]
Cube_C Test	-4	0.091	(-0.001) [–0.030, 0.002]	-0.005	0.99	(-0.0001) [–0.079, 0.079]	-0.005	0.79	(-0.024) [–0.166, 0.216]

Note. * = significant difference ($p < 0.05$). For rework and error (Poisson Model), β indicates log count difference

3.5.2 Effect of Treatments on Time of Completion

The statistical significance testing shows that the task completion time was significantly less for the participants who used the AR LOD 400 model. For student participants, time was reduced

by 17% and for industry by 11%, compared to the ISO paper drawing group, which was statistically significant. This was supported by 95% CI for students [–0.230, –0.106] (β= -0.168) and industry populations [–0.226, –0.001] (β= -0.114). Further, the pairwise comparison showed a significant difference between AR LOD 300 and AR LOD 400 groups, where AR LOD 400 reduced time significantly for student participants but not for industry crafts. The effect of age on completion time was not significant, showing no strong correlation for any of the treatments. However, the impact of spatial cognition test scores was significant for both populations. It indicated a reduction in task time for each unit increase in the test score. This shows that the participants with higher spatial cognition ability performed the task more efficiently. When analyzing the interaction between information format and test scores, we found this relationship significant for both AR LOD groups in student participants and for the AR LOD 400 group in industry participants. Hence, for these groups, the correlation of reduced completion time with increasing test scores was significantly robust compared to the other two groups.

3.5.3 Effect of Treatments on Mean Rework and Error

Rework numbers revealed that participants using AR treatments significantly reduced the rework compared to the ISO paper group; interestingly, it was valid for both novice and experienced populations. For students, rework was decreased by 21% and 24% when using AR 300 and AR 400 models, respectively, while the percentages for industry crafts were 67% and 56 %. These findings suggested that AR models provided substantial benefits in terms of accuracy and efficiency, regardless of the user's prior experience level. Age and spatial cognition had no significant effect on rework for industry crafts. However, rework was reduced significantly for student participants as the spatial cognitive ability score increased.

Compared to rework, the overall error rate was much less, regardless of the information formats, but for industry participants, AR treatments increased the error rate. Although the difference was not statistically significant, the error rate increased with AR models. Additionally, age or spatial cognitive ability did not influence the error rate. However, errors decreased significantly for novice participants when they used the AR LOD 400 model with a percentage of 42%. Also, errors were reduced significantly with the increase in spatial cognition ability. Therefore, AR models reflected an advantage in lowering assembly errors for the novice population.

3.5.4 Responses to the Questionnaire

In a pre-task questionnaire, participants were asked about their prior experience with AR HMD devices. None had experience with AR technology, but a few, mostly younger participants, reported using VR HMDDs for gaming purposes. After completing the task, participants answered the following open-ended questions about their experience with AR:

a. How was the experience of using the AR model compared to 2D plans?
b. Was there anything confusing about the AR models?
c. Do you recommend using AR technology on construction sites?

Based on the responses, almost all participants indicated that AR HMDD was a helpful medium for communicating design information. It was noted that AR facilitated the alternation between plans, with most participants not referring to paper plans while using AR models. Some participants suggested that while AR is beneficial, it should not completely replace paper plans but be used alongside them. Approximately seventy percent of participants reported no confusion with AR models, although some mentioned that AR holograms occasionally blocked the actual model. Participants overwhelmingly suggested that AR technology would be very supportive of

construction job sites, reducing the time required to understand 2D information by presenting 3D information directly in the field of view. Some experienced participants still preferred using paper plans but acknowledged that AR would be useful for training novices. However, there were concerns about potential safety issues, such as distractions or the stress of using the device for extended periods. Overall, the feedback highlighted the promise of AR in enhancing efficiency and comprehension on construction sites while also pointing out areas for improvement and the need for cautious implementation.

3.6 Discussion

Cost, time, and quality are essential indicators for evaluating the success of construction projects, and both work performance and productivity are crucial for achieving these goals (Pekuri et al., 2011). High work performance, marked by accuracy and adherence to standards, ensures tasks are completed correctly the first time, reducing errors, rework, and associated costs while also adhering to schedules and maintaining quality standards. Productivity, defined as the efficiency of output relative to input, directly impacts project timelines by accelerating task completion and increasing throughput, thus shortening project durations.

This study examined the impact of emerging AR HMD technology on work performance indicators, namely time to completion, rework rate, and error rate. The participants were asked to complete the MEP assembly task using AR models at various LODs, and their performance was compared to the traditional paper plans. The focus was on novice and experienced populations. For both populations, results indicated that the AR model with LOD 400 significantly reduced the task time, while the AR LOD 300 did not produce similar improvements. AR 300 models provide a general reference for users. In contrast, AR 400 models offer detailed, accurate images that show components as they are, making it easier for users to comprehend and interpret the information,

which might have improved the task completion time. This demonstrates that the density and clarity of design information delivered through AR models play a crucial role in influencing work performance. Consequently, our findings led us to reject the null hypothesis $H1_0$, and we stated that in this study, AR models reduce task completion time compared to traditional plans. However, this effect is contingent upon the level of detail provided in the AR models.

Rework is a crucial indicator of work performance. It is defined as the unnecessary effort of redoing a process or activity due to errors made during the initial attempt (Chalhoub et al., 2021). Rework has been shown to have a severe and direct impact on the total cost of projects (Hwang et al., 2009). In this study, both novice and experienced populations showed a very significant reduction in rework when using AR models. The differences were significant for both AR LODs when compared with paper plans, leading us to reject the null hypothesis $H2_0$, which stated that AR does not reduce the rate of rework during the assembly task. This implies that AR facilitates a better understanding of the assembly process for the assembler.

Furthermore, although there was no direct comparison, the rework rate of the novice population was less than that of the experienced population, even with the complex setup. This indicates that AR may help new generations adapt to new technologies and comprehend design information more quickly. This finding is particularly significant as all student participants were first- or second-year undergraduates and 72% of them were not from a civil engineering background. This suggests that AR technology can be a powerful tool in training and education, helping novices perform at levels comparable to experienced workers despite their lack of industry-specific background.

Mistakes made during work, if noticed, necessitate rework. However, if these mistakes go unnoticed, they become errors, which can be more damaging than rework. Undetected errors can cause severe issues related to cost overruns, project delays, and safety risks. Hence, the impact of

technology on errors plays an important role. For industry participants, the rate of errors was greatest among participants using traditional paper plans, but it was not statistically significant, while for students, errors were reduced significantly with AR LOD 400. The results showed mixed responses for both populations with no clear indication to generalize the results. However, we rejected the null hypothesis $H3_0$ for the novice population, stating that AR with greater LOD reduces the number of errors for the novice population. Meanwhile, we failed to reject $H3_0$ for the experienced population.

Upon investigating the impact of age on industrial participants, we found no significant effect on task completion time, rework rate, or error rate. Therefore, we failed to reject the null hypothesis $H4_0$, stating that an individual's age has no significant impact on work performance when design information is delivered through AR displays compared to traditional delivery methods. This finding indicates that participants from the lower age group performed at the same level as those from the higher age group. In other words, participants with less experience performed as well as those with more experience. Additionally, Hashiguchi et al. (2020) mentioned that increasing age impacts the motivation of workers and decreases their ability to adapt to modern technologies, which affects their work performance. However, our results indicate that AR HMDDs did not significantly impact work performance based on age. Overall, AR HMDDs helped less experienced and more experienced participants perform at the same level, making it an ideal technology that can be easily adapted by an aging workforce while beneficial for novice users. This suggests that AR HMDDs may bridge the gap between different age groups and experience levels, enhancing productivity and performance across the board.

Conversely to age, the spatial cognition ability of participants revealed exciting findings. For industry participants, task completion time increased significantly with higher spatial ability, but

there was no impact on rework and errors. However, for students, spatial ability significantly impacted all three factors, reducing task completion time, rework, and errors. This suggests students with higher spatial cognition could more effectively visualize and understand the assembly process, leading to faster completion times, reduced errors, and less rework. As a result, we rejected the null hypothesis $H5_0$ for students but failed to reject it for industry craftsmen.

Overall, the findings from this AR study make several significant contributions to the field of construction and provide valuable insights for future researchers and construction information designers. This research highlights the transformative potential of AR HMDDs in enhancing work performance by reducing rework and task completion times. Specifically, the study demonstrates that AR models with higher levels of detail, such as AR LOD 400, significantly improve performance metrics, underscoring the importance of detailed and precise AR designs in construction settings. While the AR LOD 400 improved performance, some participants reported it to be distracting at times. This issue can be addressed by allowing participants to switch between AR models. Models with greater detail can help observe and comprehend design information initially, and then participants can switch to a lower LOD model while performing tasks as needed. This flexibility will allow users to benefit from detailed visualizations when necessary while minimizing distractions during task execution. Additionally, it will help future designers develop AR interfaces that are both informative and intuitive, ensuring that users can fully leverage the technology's capabilities without feeling overwhelmed.

3.7 Limitations

Despite the valuable insights provided by this study, we have acknowledged the following limitations. Firstly, the study's controlled experimental setting may not fully capture real-world construction environments' complexities and dynamic nature. Although the experiments with

industry craftsmen were conducted on the industry shop floor, the tasks were not performed on actual construction projects. The non-repeatability of experimental procedures is a significant limitation, as it prevents the execution of research experiments in real-world scenarios. Also, the stringent safety protocols in the construction industry pose challenges that do not permit the use of new technologies on production lines without comprehensive training programs. This restriction limits the immediate applicability of the study's findings to active construction sites.

Secondly, though eye calibration was performed for each participant, the participants were not formally introduced to the AR HMD technology before the task. Additionally, in crossover designs, carryover effects can occur when participants perform two or more consecutive trials without sufficient cool-down periods in between. In our study, we did not incorporate adequate cool-down periods, which might have influenced the performance of the participants. Furthermore, the performances of both populations were not directly compared due to the different experimental setups and environments. This limitation suggests that future researchers should design studies that allow for direct comparisons between different experience levels and age groups. Addressing this limitation would provide a clearer understanding of the impact of AR technologies on various demographics.

Lastly, the study did not extensively investigate safety issues like situational awareness while using HMDDs and the cognitive load imposed by different levels of detail in AR models. While AR LOD 400 was shown to improve performance, its reported distractions could contribute to mental fatigue over prolonged use and may impact users' ability to detect change, aspects that require further examination. Future research should address these limitations to provide a more holistic understanding of the implications of AR in construction.

3.8 Conclusion

This study evaluated the impact of AR HMDDs on MEP assembly performance by comparing traditional ISO paper drawings with AR models presented at different levels of detail (LOD 300 and LOD 400). We examined three critical performance indicators, task completion time, rework rate, and error rate, across both novice and experienced populations. Unlike previous research that often relied on scaled-down or simplified tasks, our investigation employed a full-scale MEP assembly model. It involved a significant number of participants from industry as well as university. This comprehensive approach enhanced both the internal validity and ecological relevance of our findings by closely simulating realistic construction scenarios.

Our findings make several contributions to the body of knowledge. First, the AR model with LOD 400 significantly reduced task completion time and rework rates for both novice and industry participants compared to traditional paper plans. This improvement can be attributed to the detailed and well-defined representation offered by the high-LOD AR models, which facilitated better comprehension of complex design information. In contrast, the AR LOD 300 model yielded more moderate improvements; while it did not significantly affect task time relative to paper plans, it did produce a significant reduction in rework. These results underscore that the density and clarity of design information delivered through AR systems play a critical role in enhancing work performance. For error rates, the AR LOD 400 model significantly benefited student participants by reducing errors, whereas no statistically significant improvement was observed for industry professionals. This differential outcome suggests that while experienced workers may have developed compensatory strategies for interpreting traditional drawings, novices can benefit substantially from the enhanced detail and clarity offered by AR.

A further contribution of this study is its investigation into the role of demographic and cognitive factors. Our analysis showed that age did not significantly impact work performance in an AR-assisted environment. This finding is particularly encouraging given the aging workforce in the construction industry, as it suggests that AR HMDDs may serve as an equalizer by enabling both older and younger workers to perform at similar levels. Moreover, spatial cognition emerged as a significant predictor of performance, particularly among students, indicating that higher spatial ability is associated with faster task completion, fewer errors, and less rework.

To our knowledge, this study is the first to examine the effect of the level of detail in AR models on full-scale construction assembly tasks, thereby extending the existing literature on AR in construction. Our comparison between AR LOD 300 and AR LOD 400 demonstrates that not all AR presentations are equally effective, providing crucial empirical evidence that informs the design and implementation of AR interfaces. Moreover, by exploring the interplay between spatial cognition, age, and technology performance, the study deepens our theoretical understanding of how these factors influence the adoption and effectiveness of emerging technologies in complex work environments.

From a practical perspective, the findings carry significant implications for the construction industry. The performance improvements observed with AR HMDDs, particularly when using high-detail models, suggest that these technologies could drive substantial productivity gains. However, such benefits come with important considerations: high-detail AR models require advanced and potentially expensive hardware. If similar performance outcomes can be achieved with lower-detail models, the industry may opt for more cost-effective and ergonomically friendly solutions. Furthermore, unlike similar studies, this research was conducted both in an industrial environment with industry craft workers and in a lab setting with student participants with a

significant sample size. The inclusion of both industry professionals and students adds robustness to the findings and enhances their generalizability to actual construction settings. Also, the positive reception among novice users indicates that AR technology can play a pivotal role in training and skill development, thereby equipping a new generation of construction professionals with the tools needed to excel in modern work environments.

These findings can guide the creation of best practices for using AR HMDDs effectively to deliver design information for construction assembly tasks and other on-site activities. Future research should focus on integrating the AR system into real construction projects, allowing for the measurement and quantification of performance and productivity improvements during actual site assembly activities. Additionally, it is crucial that future studies continue to include industry professionals alongside students to ensure that the results are relevant to the complexities of real-world construction environments.

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Data Availability Statement

Some or all data that support the findings of this study are available from the corresponding author upon reasonable request.

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CHAPTER 4 – HUMAN VS AI: ASSESSING TRUST AND EFFICIENCY IN AUGMENTED REALITY ASSEMBLY TASKS AMONG CONSTRUCTION INDUSTRY PROFESSIONALS

Abstract: As the construction industry accelerates its digital transformation, it is essential to investigate the value proposition of emerging technologies thoroughly. This study examined the intricate relationship between the perceived origin of a design (AI vs. Human), the information format (AR vs. Paper), user trust, and work performance. The objective was to understand how user trust is affected by the perceived origin of a design and whether it influences user work performance in an AR-assisted environment. To explore this, we conducted a controlled experiment with ninety-eight experienced industry craft workers performing a full-scale Mechanical, Electrical, and Plumbing (MEP) assembly task. The perceived origin of the design was manipulated as either AI or human-generated. Participants used traditional paper drawings or one of two AR models to complete the task. We recorded self-reported trust both before and after the task, as well as work performance factors such as task time, rework, and errors. The findings revealed that user trust is not uniform; participants' perceptions of design accuracy remained stable despite errors, while trust in the design's safety decreased significantly when it was attributed to AI. Regarding performance, the AR interface notably enhanced accuracy by reducing rework, regardless of the design's perceived origin. Task speed, however, was mainly influenced by the user's innate spatial cognitive ability. These outcomes suggest that successful integration of AI into construction will not depend just on the capabilities of the algorithms but on the entire sociotechnical system, with the user interface playing a crucial mediating role. Therefore, to unlock

the full potential of these technologies, experts must address underlying human factors such as trust and user perception.

Author Keywords: Human-AI Trust; Augmented Reality; Construction Technology; Human-Factors; Design Perception; Work Performance

4.1 Introduction

The foremost digital technology, Artificial Intelligence (AI), plays a vital role in digitization, effectively bridging the physical and digital worlds across various science, technology, and engineering domains. The global market size of AI in 2023 was US$196 billion and is expected to reach US$1.81 trillion by 2030 (Howarth, 2024). AI has been crucial in promoting Industry 4.0 worldwide among manufacturing, healthcare, e-commerce, automotive, finance, and agriculture (Bitkina et al., 2020). Although construction is one of the fastest-growing industries, it remains among the least digitized. It is also grappling with persistent challenges, including stagnant productivity, declining work performance, an aging workforce, and labor shortages (Chen et al., 2022). While digital technologies offer promising solutions to some of these issues, the integration of advanced tools, such as AI, Virtual Reality (VR), and Augmented Reality (AR), in the workplace is still in its early stages (Abioye et al., 2021; Rafsanjani and Nabizadeh, 2023).

While the use of AI is currently limited, a growing body of research has demonstrated the potential of AI to transform the architecture, engineering, and construction (AEC) industry, marking a critical step toward the sector's digital transformation. For example, the use of AI in the design and planning phases of buildings and structures is gaining significant attention nowadays. Nikitin and Sinenko (2024) highlights that AI-driven Generative Design (GD) can improve the quality of design documentation by minimizing mechanical and technical errors while equipping designers with vast amounts of analytical data. Furthermore, when integrated with Building

Information Modeling (BIM), generative AI can produce numerous design alternatives based on user-defined parameters, enhancing both creativity and efficiency in architectural and engineering workflows (Rane et al., 2023). These advancements have fueled increased investment in AI technologies, with indications that AI may be capable of fully automating the design process in the near future (Pan et al., 2022). However, even when automation is effective, its integration is not a straightforward matter of application. Integrating automation into human-operated decision systems raises critical questions about the origin and trustworthiness of information as AI systems begin to replace or augment traditional human-generated content. Prior studies (Uusitalo et al., 2021) suggest that uncertainty surrounding the origin of information, whether human or machine-generated, may impact the credibility, i.e., users' trust in the information.

Trust is a critical factor in the successful adoption and effective utilization of emerging technologies (Emaminejad et al., 2022). When users lack trust in the data source, they are less likely to rely on it for decision-making. For AI systems, this skepticism is particularly high and can stem from various sources, including a lack of transparency in AI algorithms, concerns over data accuracy, and the potential for unintentional biases embedded within the AI models (Regona et al., 2022). Saremi and Bayrak, (2021) argue that trust in intelligent systems directly impacts both their acceptance and the degree to which they improve human decision-making. They further state that high-performing AI tools may fail to deliver meaningful value if users perceive them as unreliable. Conversely, even moderately performing AI tools can deliver meaningful value if users perceive them as reliable and trustworthy.

Trust becomes even a more critical factor when the design information is visualized through a technology like AR. Augmented Reality (AR) has shown great promise in enhancing user interaction with digital content by seamlessly integrating it into real-world contexts. AR

applications have been successfully deployed in other industries, including aerospace, gaming, healthcare, manufacturing, education, and entertainment (Chu et al., 2020). In construction, AR has been primarily applied to areas such as worker training, project visualization, safety planning, inspections, and task guidance (Alkan and Basaga, 2023). However, its use for direct construction operations, such as real-time assembly, remains underexplored.

Recent studies (Chalhoub and Ayer, 2018b; Chu et al., 2020; Cuperschmid et al., 2016; Dallasega et al., 2023; Qin et al., 2021) suggest that AR technology has the ability to deliver 3D BIM content to onsite personnel, reducing their cognitive load and improving work performance significantly. But, Sahu et al. (2021) suggests that their full potential can be realized by integrating diverse AI strategies, such as deep learning and expert systems, to adapt to broader scene variations and user preferences. They further state that this integration can bring a paradigm shift in the performance of AI models and tasks related to AR. However, as mentioned earlier, trust in AI-generated design content becomes a critical dependency. If workers distrust the accuracy of information, they may also be skeptical of the AR systems that visualize it, potentially undermining the benefits of both technologies (Kaplan et al., 2023). Also, excessive trust in AI-generated information can be problematic, as it may lead users to overlook potential errors or hazards embedded in the design, resulting in overreliance on the technology (Araujo et al., 2020). Therefore, understanding the interplay of human trust in AI-driven design data is fundamental not only for AI adoption but also for ensuring the successful application of AR in the construction industry.

In this research study, we conducted a controlled experiment with ninety-eight industry craft workers performing Mechanical, Electrical, and Plumbing (MEP) assembly tasks on a full-scale experimental setup. We first manipulated the perceived origin of design information as either AI-

generated or human-generated. In a pre-/post-experimental design, each participant was then randomly given two of the three information formats: traditional paper drawings, an AR model at Level of Detail (LOD) 300, and an AR model at LOD 400. The assembly task was broken into different panels. Participants were given different information formats for different panels, and the assignment of information to the panel was randomized. To further assess changes in trust, the experiment included an intentionally embedded design error. This allowed us to observe how trust scores varied after the participants noticed the error based on their original perception of the design's origin.

This study was built directly upon our prior study (Chaudhari et al., 2025) to explore more nuanced human factors by introducing the 'design origin' (AI vs. Human) as another key variable, along with the information format. To our knowledge, this study is the first of its kind to empirically examine the complex interplay between the origin of design information, trust, format of design information, and work performance in the context of a real-world construction task, and we aimed to answer the following research questions,

1. How does the origin of design information, particularly when identified as Human VS AI-generated, influence workers' trust, moderated by participants' detection of intentional error in the task?
2. How does the interplay between design origin and design information formats affect distinct aspects of user performance?
3. How does the effect of the origin of design information on workers' trust and performance in an AR-assisted environment vary when the age and spatial cognitive ability of the participants are controlled?

4.2 Literature Review

4.2.1 Information Delivery with AR Systems

AR is an advanced form of reality where technology is used to superimpose digital information onto a real-world environment, creating an enriched and interactive experience (Aromaa et al., 2020). The overlay can include text, graphics, audio, and other virtual elements seamlessly integrated with the physical world, enhancing the user's perception and interaction with their surroundings (Alkan and Basaga, 2023). AR systems and Head-Mounted Display Devices (HMDDs) have proven helpful across various sectors, as they provide information that would otherwise not be available or visible in users' environments. For instance, in a driving simulator study, with eighty participants, Schwarz and Fastenmeier (2018) concluded that AR, in warning situations while driving a car, provides the opportunity to increase the amount of information conveyed without distracting the driver. Borgmann et al. (2017) used Google Glass for urological surgery and found it safe and feasible, providing additional useful functions for surgeons. Another study (Rowen et al., 2019) used Google Glass when navigating marine vessels. They concluded that AR displays improved operators' performance and situational awareness in safety-critical systems.

In the construction sector, field personnel primarily rely on two-dimensional (2D) drawings and blueprints to perform construction tasks (Chalhoub and Ayer, 2018b). Previous studies have shown that different design information formats impact the productivity and quality of work of construction craftsmen. For example, in a study by Dadi et al. (2014), participants were tasked with assembling a 3D structure. Researchers divided participants into three groups based on the information format provided to perform the task: 2D drawings, 3D computer models, and 3D printed models. The results showed that the 3D printed model increased direct work and reduced

workload compared to the other two groups. In another study, (Hou et al., 2015) worked with student participants to assemble a PVC pipe system with two information formats. Researchers provided traditional 2D drawings to one group and a 3D AR model to another group. The results showed that the 3D AR group completed the assembly task 50% faster than the other groups. Similarly, in wall frame assembly tasks (Bartuska et al., 2023; Cuperschmid et al., 2016; Qin et al., 2021b), researchers reported improved work performance when information was delivered through AR HMDDs. Additionally, Chaudhari et al. (2025) showed how the Level of Detail (LOD) of 3D models, when used with AR devices, can affect key performance factors in construction. The researchers found that between the two LOD models, LOD 300 and LOD 400, the LOD 400 model was more efficient because it displayed more details than LOD 300.

Thus, AR devices, particularly HMDDs, hold substantial promise for the construction industry and are emerging as a transformative tool for delivering design information to the future workforce (Alkan and Basaga, 2023). The existing literature strongly anticipates that AR can enhance productivity and improve work performance on job sites. However, this exploration becomes critical when the perceived origin of design information is compromised, because although humans traditionally create design information, the future of design generation is expected to be increasingly shaped by Generative AI (GAI) (Rane et al., 2023). Therefore, this research aimed to evaluate whether variations in the perceived origin of design information affect users' trust and, hence, their performance in an AR-assisted environment, compared to when the same information is presented in traditional formats.

4.2.2 Artificial Intelligence in Construction

Definitions of AI vary based on usage and applications (Saremi and Bayrak, 2021). In general, AI is defined as the ability of a system to interpret external data accurately, learn from it, and apply

that knowledge to achieve specific goals and tasks autonomously (Chen et al., 2024). AI is a sophisticated technology encompassing several subfields relevant to the construction industry, including machine learning, computer vision, robotics, natural language processing, knowledge-based systems, generative design, optimization, and automated planning and scheduling (Regona et al., 2022). Most AI algorithms require large volumes of high-quality data for effective training, making the implementation process both costly and time-consuming for construction firms. Furthermore, the lack of skilled personnel and domain-specific expertise has contributed to the slow adoption of AI in construction (Pan and Zhang, 2021). Despite these challenges, the proven success of AI applications in industries such as pharmaceuticals, retail supply chain management, healthcare, and manufacturing has sparked growing interest and investment in adapting AI for construction purposes (Hatami et al., 2019).

Today, applications of AI in the building and construction industry can be seen in the areas of smart building operations, construction management and safety, offsite manufacturing and automation, material design and optimization, structural design and analysis, sustainability, life cycle analysis and circularity, and architectural design and visualization (Baduge et al., 2022). Though the exploration of AI in all these areas is still in the early stages, researchers are investing more in using AI in architectural design and visualization, specifically, integrating AI with the Generative Design (GD) process (Rane et al., 2023). GD is an iterative design process that can automatically explore and iterate on possible designs and provide the best solution to designers (Chew et al., 2024). Nikitin and Sinenko, (2024) suggest that integrating Machine Learning (ML) algorithms with the GD process can analyze a wide range of datasets, predict performance outcomes, and recommend designs. This integration empowers designers to tackle complex

designs with greater precision as AI algorithms continuously learn, adapt, and refine their approaches over time (Chew et al., 2024).

Generative deep learning models, a subfield of ML, such as Generative Adversarial Networks (GANs) and Variational Autoencoders (VAEs), have demonstrated remarkable capabilities in generating innovative architectural designs in both 2D and 3D (Baduge et al., 2022). For instance, based on GANs, Chaillou (2019) developed a model called 'ArchiGAN' which was trained using an image dataset. This model generates fully furnished architectural plans of a building when the shape of the land is given as input. An algorithm, 'House-GAN' proposed by Nauata et al. (2020), generated layouts of houses when bubble diagrams with specific constraints such as the number of rooms, room connectivity, type of rooms, etc., were provided as input. Wu et al., (2019) proposed another algorithm based on VAEs that generates residential floor plans when the perimeter of the house is provided as input.

These advancements are rapidly progressing, and as technology matures, AI is expected to play a significant role in automating the design process in the near future. However, the credibility of information generated by AI algorithms requires critical examination. Ensuring the reliability and accuracy of AI-generated designs is crucial, as errors or biases in the data or algorithms can lead to flawed outcomes (Rane et al., 2023). Furthermore, integrating AI in design requires transparency and explainability to build trust among designers and stakeholders. Establishing trust and robust verification processes is essential for successfully adopting and integrating AI or other technologies in the construction design process.

4.2.3 Augmented Reality and Trust in AI

Trust is a cornerstone of effective human-AI collaboration, and its existence is predicated on the presence of risk. Researchers define trust as the willingness to depend on another party or

source of information in a risky situation, based on beliefs about their competence, integrity, and predictability (Gefen et al., 2003; Hoffman, 2017). In essence, trust becomes necessary to perform correctly and safely in uncertain conditions, particularly when it comes to the use of information generated by AI platforms (Jacovi et al., 2021). Understanding the relationship between users' trust and AI is, therefore, critical, as improper calibration can lead to misuse, dangerous over-reliance (abuse), or rejection of beneficial technology, all of which can negatively impact performance and lead to unfair or incorrect outcomes (Jacovi et al., 2021; Lakkaraju and Bastani, 2020).

Trustworthiness in AI-enabled systems can be achieved by effectively managing risks associated with AI-specific characteristics and human interaction with the technology. Bach et al. (2024) mentioned that AI characteristics like being opaque, biased, and uninterpretable have raised concerns about establishing trust in the AI systems. They further explain that opaqueness makes it challenging to predict AI behavior, backtrack errors, and understand the logic behind output production, leading to greater trust in human origin than AI. Emaminejad et al. (2022) conducted a comprehensive literature analysis to explore the interplay between AEC projects' unique aspects and the sociotechnical concepts that lead to trust in AI. They reported that transparency and explainability are the primary AI trust dimensions across various AEC subcategories, including preconstruction, construction, and post-construction, followed by safety and reliability, privacy and security, and ethics and fairness. These inherent AI qualities help build intrinsic trust in technology among users.

In contrast, extrinsic trust stems from external validations and human attitudes or influences, such as the reputation and trustworthiness of AI models (Jacovi et al., 2021), which may yield contradictory results. For example, research has shown that people tend to trust decisions made by AI more than those made by humans, possibly because they perceive AI as more objective (Klein

et al., 2024). However, trust is not absolute. Humans tend to perceive AI as lacking emotional capability and differentiate between tasks they deem "human" versus those they see as "mechanical," adjusting their trust in the information source accordingly (M. K. Lee, 2018). This demonstrates a critical inconsistency, emphasizing that trust in AI is not uniform but may depend heavily on the user's perception of the task and the perceived strengths and weaknesses of AI compared to human intelligence.

This highlights the crucial role that human judgment and validation play in establishing trust in AI systems. As the user's trust increases, so does their acceptance of technology. In contrast, increased perceived risk contributes to its rejection, or a preference for trusting other sources over the technology (Crockett et al., 2020). In the last few years, the significance of the interplay between humans and AI-based processes has been overshadowed by a predominant focus on technical advancements within the field (Hatami et al., 2019). However, experts argue that trust is crucial for the adoption of AI (Küper and Krämer, 2025). Therefore, it is imperative to incorporate human needs, perceptions, and behaviors into the design of AI systems to facilitate successful integration and acceptance.

This phenomenon becomes particularly crucial in the construction sector, specifically when using AI in GD, as project teams often rely on traditional, trusted methods and are hesitant to experiment, given the limited established performance of AI systems in this area. This is where the interface through which information is delivered becomes a critical mediating factor. While AI serves as the generative "brain" creating the design, Augmented Reality (AR) can act as the interactive "eyes and hands" that present the information (Sahu et al., 2021). A highly usable AR interface can serve as a cognitive bridge, potentially mitigating the negative performance effects of low trust, such as user hesitation and efficiency loss from excessive verification (W. Li, 2024).

By reducing the primary cognitive load of the task and making instructions intuitive, AR may shift the user's focus from the source of the information to the immediate action, thereby buffering or overcoming the hesitation that stems from skepticism towards the AI.

In this research, we aimed to investigate a complex phenomenon, such as how people trust information when the origin of the design is manipulated as either human-generated or AI-generated. How does their perception about the origin of information change after noticing an intentional error introduced during the task, and how does it impact their performance in AR-assisted assembly tasks?

4.2.4 Trust in technology, age, and spatial cognition

The construction industry also faces other challenges with an aging workforce, as the average age of construction workers is 42 years (US Bureau of Labor Statistics, 2023). This demographic trend has raised concerns regarding adopting new technologies in the sector, with several studies highlighting a significant correlation between age and technological proficiency. According to Tams and Hill (2017), older workers often encounter challenges when utilizing and adapting to modern technologies, leading to increased stress, anxiety, and reduced productivity. These difficulties are attributed to cognitive and biological changes associated with aging, potentially hindering the work performance of older construction workers. However, contrary findings by Zimmer et al. (2015) did not establish age as a significant factor when utilizing information technology to detect errors.

Furthermore, Dermott (2019) underscores the importance of the construction industry embracing technological advancements not only for its own growth but also to attract a younger demographic to the sector. Research by Buckner and Bender (2020) also points to the lack of technological progress as a deterrent for the younger generation when considering careers in

skilled construction work. Saremi and Bayrak (2021) shed light on the fact that older adults tend to exhibit greater trust in intelligent systems than young adults, mainly due to the situational trust calibration of the latter. Interestingly, they also observed that improved visualization engendered greater trust in young adults toward intelligent systems than in older adults. All these examples reveal a highly conflicting relationship between age and technology adoption and therefore require ongoing investigation by including the age factor in various studies.

In addition to age, individual spatial cognition also plays a pivotal role in work performance and productivity, especially when information is presented through diverse media and formats. Goodrum et al. (2016) conducted a study involving 54 pipefitters tasked with assembling a pipe spool using various information formats. Their findings revealed that participants with lower spatial cognition performed just as effectively as those with higher spatial cognition when 2D drawings were enhanced with 3D information. Among the various demographics, users' age and spatial cognitive ability have been relatively underexplored in the context of trust in AI and visualization through AR HMDDs, warranting further investigation. This research aimed to explore how trust in AI-generated design varies with age and whether it impacts their work performance in an AR-assisted environment. Additionally, we investigated whether there is a correlation between individuals' spatial ability and their trust in AI-generated design, as well as its impact on work performance.

4.3 Methodology

4.3.1 Experimental Setup

We conducted a controlled experiment with a crossover design to achieve the research objectives. Each step of the experimental design was designed in collaboration with subject matter experts (SMEs) with at least five years of industry experience with structural, mechanical, and

electrical trades to heighten the ecological validity of the findings shared. To begin with, SMEs shared strengths and weaknesses associated with the primary types of engineering deliverable displays. Based on the inputs, we developed a full-scale replica of a typical Mechanical, Electrical, and Plumbing (MEP) system found on industrial construction sites. The experimental setup consisted of arrays of mechanical pipes and electrical conduits mounted on the metal panels measuring 3 feet by 5 feet, as shown in Figure 4.1.

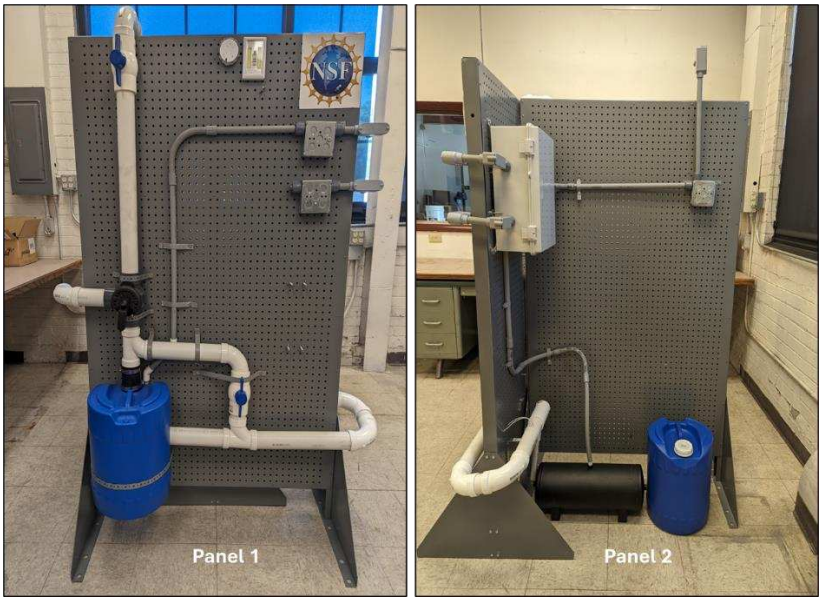

Figure 4.1 Experimental Set-Up

To manipulate the origin of design information, before the assembly task began, one group of participants was informed that an AI application developed the design, while the other group was told that a certified human engineer had created it. Further, participants were asked to install the missing pipe pieces and conduits using three different formats for guidance. Figure 4.2 illustrates the components required for installation on panels one and two.

The mechanical and electrical components were made from standard PVC material. Table 4.1 provides the number of pieces to be installed on each panel, along with the dimensions. Participants were not required to cut, trim, bend, or file the pieces and did not need to use PVC cement to

complete the assembly. Each piece could be connected simply by pushing and twisting the new piece into an existing one.

Figure 4.2 Panel 1: A. Mechanical Components, B. Electrical Components, Panel 2: C. Electrical Components

Table 4. 1 Number of Components to be Installed in an Assembly Task

Panel	Number of components to be installed		Total	Dimensions
	Mechanical	Electrical		
1	6	6	12	Diameter: 0.5 - 2 inches Length: 2.5 - 21 inches
2	0	9	9	Diameter: 0.5 inches Length: 1.5 -13.5 inches

AR models were presented via Microsoft HoloLens 2 HMDD. It features a display resolution of 2048 x 1080 pixels for each eye, a 52-degree field of view (43 degrees horizontally and 29 degrees vertically), and a 3:2 aspect ratio. The AR model displays were created using the Unity3D game engine platform. Basically, the 3D AR model was overlaid on the panels to allow participants to visualize and compare it with the incomplete assembly before installing the missing pieces. Figure 4.3 illustrates the paper drawings and snapshots of AR LOD 300 and 400 models from HoloLens. Given the suitability of the assembly task, we used LOD 300 and 400 models in this study. Where LOD 300 features precise geometry of the models that represent the components' precise shape and size, and LOD 400 features detailed fabrication-level geometry that represents specific, as-is objects with detailed orientation. A 2D image of the NSF logo, designated as a

tracking marker, was positioned in the upper right corner of the panel. This image served as a reference point to load and anchor the AR models on the panels. The tracking marker remained present on the panel, enabling the AR system to recalibrate its images, if necessary, during the task.

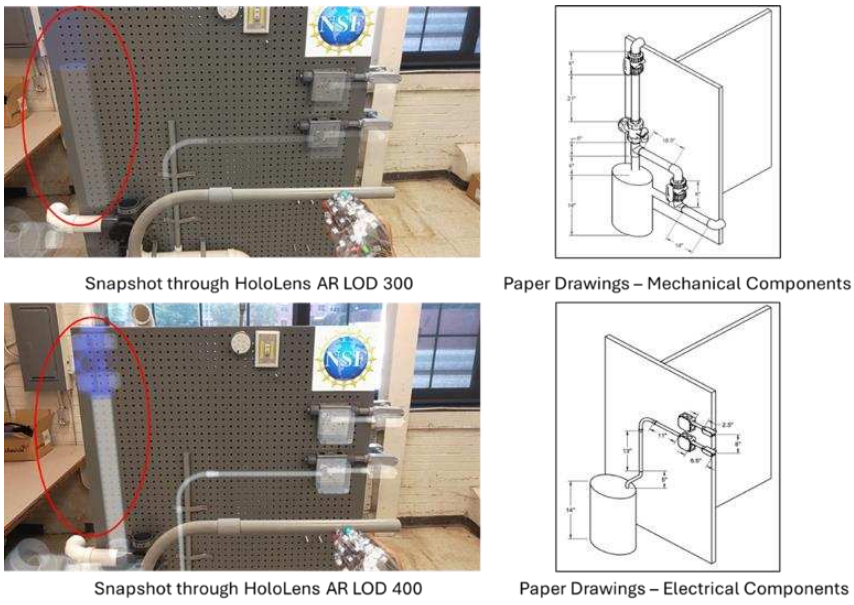

Figure 4.3 Snapshots of AR Models through HoloLens and 2D Isometric Drawings for Panel One

So, initially, they might trust AI as much as a human designer, exhibiting more trust as the design appears error-free and safe. However, they might lose trust rapidly when they discover errors in the design information, inferring that AI in GD is incompetent and may impact safety in dynamic construction environments. To examine the detailed dynamics of this phenomenon, we introduced an intentional error in the experiment without notifying the participants, measured work performance factors, and asked participants to self-report their trust in design information before and after the task. High and low trust levels may lead participants to become either insensitive or hypervigilant about mistakes in design, ultimately affecting their overall work performance.

The details of an intentional error are discussed further. The traditional paper drawing and AR model in Figure 4.4 show that electrical components “a and b” should ideally be connected to the

metal box one. However, in the experimental setup, we adjusted the height of the conduit so that components “a and b” would connect to the metal box instead of just one. As participants were instructed that they could not cut or trim the pipe, they considered this a design error impacting the design credibility.

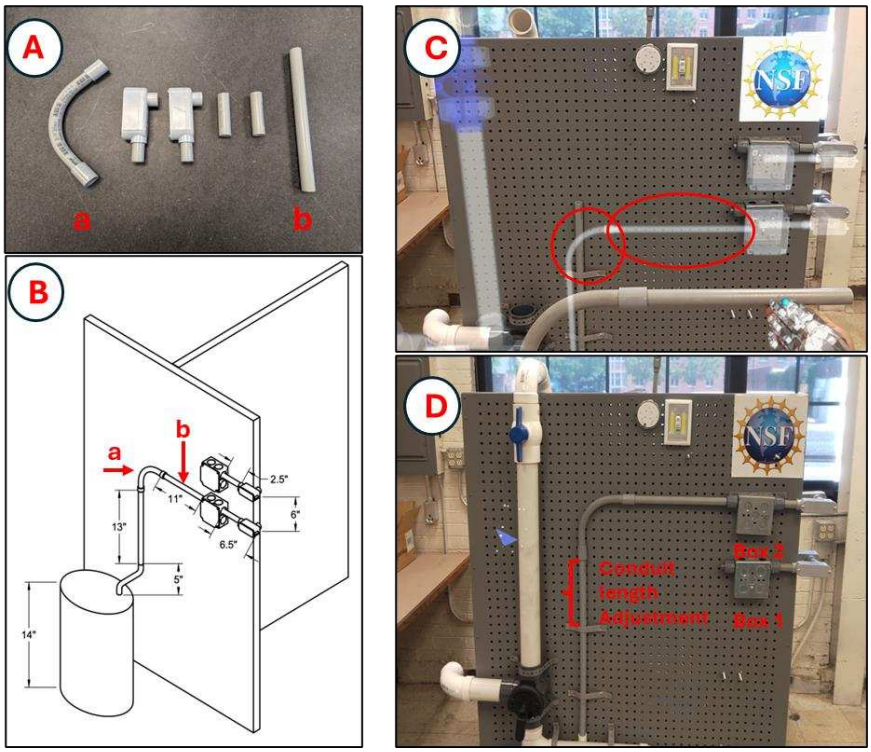

Figure 4.4 A) Components a & b; B & C) 2D drawing and AR model showing components a & b to connect with metal box 1; D) Adjusted conduit length on the actual panel so that components a & b, when installed, connect to box 2, instead of box 1.

4.3.2 Experimental Procedure and Measures

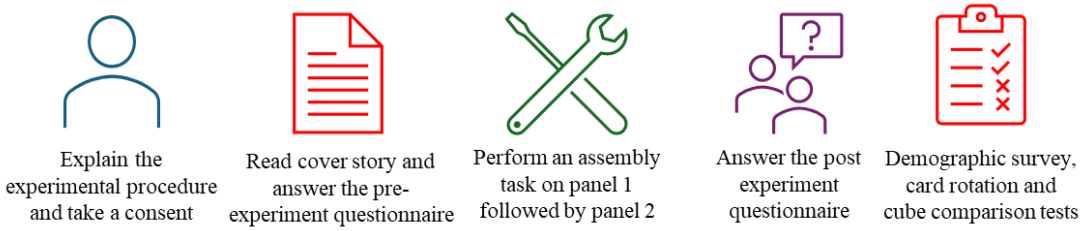

Figure 4.5 Overview of the Experimental Procedure

When the participants arrived for the experiment, they were given a detailed explanation of the protocol, and informed consent was obtained. Participants were asked about their previous experience with AR or VR HMDs. Before starting the task, they were given a cover story and instructions to comprehend the scenario. According to the cover story, participants were required to act as MEP craft workers and were given the task of completing mechanical piping and electrical conduit for the installation of a simulated MEP unit. To manipulate the perceived origin of the design, participants were randomly assigned to a cover story. One story attributed the design to an AI application, while the other attributed it to a human engineer.

Before the task began, we orally asked participants the following trust questions and asked them to report trust in the origin of design information (Human VS AI) on a scale from 1 to 7, with 1 being the lowest and 7 being the highest trust level.

Q1 (Question on Design Accuracy): On a scale from 1 (no trust) to 7 (complete trust), how much do you trust that the plans created by artificial intelligence / human engineers are free of errors?

Q2 (Question on Design Safety): On a scale from 1 (no trust) to 7 (complete trust), how much do you trust that the plans created by artificial intelligence / human engineers are free of any safety hazard?

After the pre-experiment questionnaire, participants were provided with the corresponding information format based on their group assignment and were instructed to begin the task. Even if they were using AR-based information, participants had the option to refer to paper drawings, offering flexibility and mirroring the real-world scenario of AR applications in construction. Before loading the AR model, each participant's HoloLens was calibrated using the built-in

application to ensure personalized user comfort and hologram alignment. The task start time was recorded when the participant was ready.

While performing the task on panel one, researchers observed if participants noticed the intentional error. When the intentional error was noticed, most of the participants were a bit confused and asked about the error. Without giving a hint, we asked them to follow their instinct and complete the task. As anticipated, the intentional error led participants to believe that the design was flawed. Later, the task end time, number of errors, and rework made during the task were recorded. If a participant installed a component incorrectly and then reinstalled it correctly upon realizing the mistake, it was considered rework. However, if the component was installed incorrectly and not corrected until the task was completed, it was classified as an assembly error.

After completing the task on panel one, participants were instructed to proceed with the task on panel two. There was no intentional error on panel two; however, due to the error on panel one, participants may have been more vigilant for other potential errors. Then, like panel one, the work performance factors were noted for panel two. Once the assembly task was completed, we again asked the same trust questions, "Q1 and Q2," to examine if there was any significant change in the trust level after noticing the intentional error, regardless of the origin of the design information. Later, each participant completed a demographic survey, and the experiment concluded with the card rotation and cube comparison tests. These tests are spatial cognitive ability measurement tools developed by Educational Test Services (ETS). The Card Rotation Test measures the ability to mentally manipulate objects in two dimensions, while the Cube Comparison Test evaluates similar skills in three dimensions.

4.3.3 Participants

In this study, 100 participants from the construction industry were recruited across various trades, including plumbing, HVAC, maintenance, electrical, and manufacturing. They held positions ranging from line workers to engineers. A mobile test bed was utilized at three industrial job sites for the experiments better to understand the impacts in an actual construction environment. These sites ensured good lighting and ventilation. The participants' ages ranged from 18 to 68, with an average age of 36 years. Their industry experience spanned from 6 months to 45 years, with an average of 10.5 years, as shown in Table 4.2.

Table 4. 2 Participant Demographics

Demographic	Industry
Number of participants	100
Age range	19 - 68
Average age	36.3 (SD = 12.2)
Years of work experience	0.5 - 45
Average years of experience	10.5 (SD = 10.2)

Participants were randomly divided into eight control groups based on the origin of design information, type of information format used, and the panel, as shown in Table 4.3. The traditional paper drawing served as the control variable and was therefore included at least once in each group. Any participant who felt uneasy or hesitant during the task could withdraw from the experiment at any point. Each participant received a gift card as compensation for their time and contribution to the research. Four participants spoke only Spanish, so they were given instructions through a human translator, and all relevant documents were provided in Spanish. Two participants were unable to complete the task. Consequently, the final number of participants considered for direct analysis was ninety-eight.

Table 4. 3 Participants Control Groups

Group (N)	Panel 1	Panel 2
A1 (10)	2D ISO only	2D ISO + AR LOD 400
B1 (10)	2D ISO only	2D ISO + AR LOD 300
C1 (18)	2D ISO + AR LOD 400	2D ISO only
D1 (12)	2D ISO + AR LOD 300	2D ISO only
A2 (9)	2D ISO only	2D ISO + AR LOD 400
B2 (11)	2D ISO only	2D ISO + AR LOD 300
C2 (17)	2D ISO + AR LOD 400	2D ISO only
D2 (11)	2D ISO + AR LOD 300	2D ISO only

Note: Origin of Design Information – AI (A1, B1, C1, D1), Human Engineer (A2, B2, C2, D2)

4.4 Results

4.4.1 Analytical Plan

The data collected went through two main stages of analysis: examining the subjective trust ratings and modeling the objective work performance metrics. All statistical tests were performed with a significance level of 95%.

4.4.1.1 Trust Analysis

Participant trust was measured using survey questions that targeted two key factors: the perceived accuracy and safety of the design information. The analysis proceeded in a structured sequence to test our hypotheses. First, to confirm the efficacy of the experimental manipulation, a paired-samples t-test was conducted for each question on the full dataset to determine if trust scores changed significantly from pre-task to post-task after the intentional error was discovered. Following this, an independent samples t-test was used to compare the baseline (pre-task) trust levels between participants in the AI-origin group and the Human-origin group. To examine the change in trust within each condition, additional paired-samples t-tests were performed for each origin group. To further explore the influence of individual characteristics on trust, a series of

Pearson correlation analyses was conducted to investigate the relationship between participant demographics (age and spatial ability) and their reported trust scores.

4.4.1.2 Work Performance Analysis

To analyze work performance, we aimed to understand the impact of the competing influences of potential user skepticism towards AI-generated designs and the known performance benefits of AR technology. Our prior work (Chaudhari et al., 2025) established that AR interfaces can significantly improve performance over traditional formats by reducing task time and rework rate. Therefore, to test the interplay of these factors in the current study, a series of mixed-effects models was constructed. Mixed-effects models enable more accurate modeling of data that exhibit grouping, repeated measures, or hierarchical structures, making them widely applicable across various fields (Faraway, 2016). This approach was chosen to robustly examine the combined effect of information format and design origin, as well as their interaction, on key performance metrics.

Three separate models were developed, one for each of our primary dependent variables: task completion time (in seconds), rework frequency (a count of corrected actions), and final error count. However, the error count analysis was removed from the discussion because the number was very minimal, and hence, performance was primarily measured based on task time and rework rate. The models specified the following fixed effects: Information Format (Paper vs. AR), Design Origin (AI vs. Human), with a two-way interaction between them and the participant's age and spatial cognitive ability scores as key covariates. To control for non-independence of observations, participants and panels were included as random effects. Given the different nature of the outcome variables, task time and rework rate were analyzed using Generalized Linear Mixed-Effects Models (GLMMs) to account for the overdispersion commonly found in such data. This

multifaceted modeling approach enabled a robust and nuanced examination of how various factors contributed to both the speed and accuracy of work performance.

4.4.2 Impact on Trust

To assess the overall impact of error discovery on user trust, a paired t-test was conducted on the pre- and post-task survey responses, collapsing the data across both design origin conditions as in Table 4.4. The analysis revealed a differential impact on the two dimensions of trust. Regarding the question of accuracy (Q1) in the design information, no statistically significant change was observed ($t = 0.316$, $p = 0.752$) in trust scores after the error was noticed. In contrast, the discovery of the error related to the safety of the design (Q2) led to a statistically significant reduction in participant trust ($t = 3.53$, $p = 0.001$). This finding indicates that while perceptions of accuracy were resilient, perceptions of safety were significantly more sensitive to the presence of a design flaw.

Table 4. 4 Paired t-Test Results for Trust Questions (Regardless of the Design Origin)

Questions	Mean Difference	t-statistic	p-value
Q1 (Accuracy)	0.031	0.316	0.752
Q2 (Safety)	0.464	3.533	< 0.001*

Note: * = significant difference ($p < 0.05$)

Further, to determine if the impact of the error on trust was dependent on the design's perceived origin, the analysis was stratified by group, and the results are presented in Table 4.5.

Table 4. 5 Paired t-Test Results for Trust Questions by Design Origin

Questions	Design Origin	Mean Difference	t-statistic	p-value
Q1 (Accuracy)	AI	0.030	0.2	0.845
	Human	0.061	0.43	0.665
Q2 (Safety)	AI	0.592	3.533	< 0.001*
	Human	0.337	2.36	0.103

Note: * = significant difference ($p < 0.05$)

For the question concerning accuracy (Q1), trust was dropped; however, the change was not statistically significant for either group (AI: $t = 0.20$, $p = 0.845$, and Human: $t = 0.43$, $p = 0.665$). In contrast, similar to the overall effect, a reduction in trust was observed for the safety question (Q2). This effect was particularly pronounced in the AI group, where the drop in perceived safety was highly significant ($t = 3.53$, $p < 0.001$). However, the effect was not significant in the Human group ($t = 2.36$, $p = 0.103$). These findings suggest that while accuracy perceptions were resilient, the error triggered safety concerns, with the effect being significant when the design was attributed to an AI, as shown in Figure 4.6.

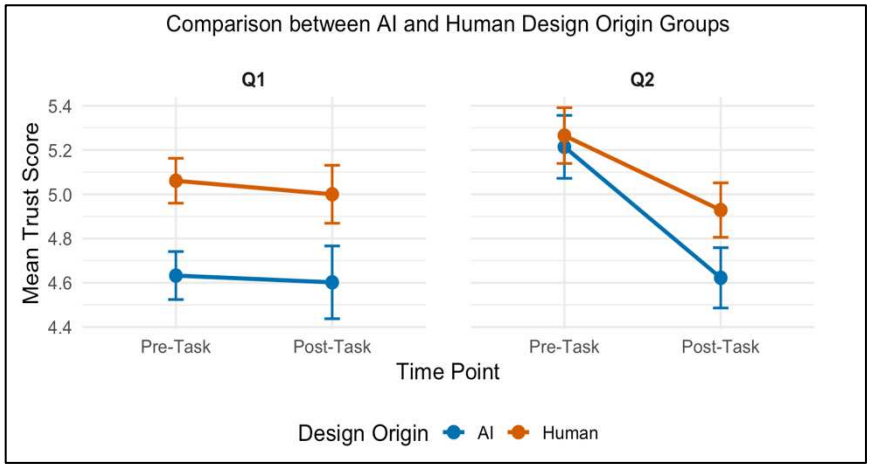

Figure 4.6 Change in Trust Before and After Noticing an Intentional Error

Lastly, to explore the influence of individual characteristics on trust, a series of Pearson correlation analyses was conducted. While participant age showed no clear, consistent relationship with trust scores, spatial cognitive ability showed a compelling, divergent pattern that depended on the design's perceived origin. When the design was attributed to an AI, participants with higher spatial ability exhibited significantly lower trust from the outset (r for Q1 = -0.364, $p < 0.001$; r for Q2 = -0.205, $p = 0.042$). This suggests that users with greater spatial skills were inherently more skeptical of a non-human design source. In contrast, when the design was attributed to a human, a significant positive relationship emerged, where participants with higher spatial ability

reported significantly higher trust (r for Q1 = 0.243, p = 0.016; r for Q2 = 0.235, p = 0.020). This inverse relationship suggested that individuals with high spatial ability perceive errors differently depending on their source.

4.4.3 Impact on Work Performance

The results from our previous study (Chaudhari et al., 2025) are presented in Table 4.6. In this study, the impact of AR models was compared to traditional paper drawings, and it was found that AR models, specifically the AR model at LOD 400, were very efficient, significantly reducing task completion time (p = 0.047) and rework rate (p = 0.0001) for users. In this study, we examined the impact of information format with another primary variable, i.e., the origin of design information, and the combined model results are presented in Table 4.7. To ensure the validity of the statistical inferences, a diagnostic assessment was conducted for each regression model. Key assumptions were examined using residual plots, Q-Q plots, and checks for overdispersion. The selection of a negative Binomial model for task time and a Poisson model for the count data (rework) was chosen to address the data's distribution appropriately. The diagnostic checks revealed no major violations of normality, linearity, or homoscedasticity. By confirming that these foundational assumptions were met, the robustness and credibility of the regression results are thereby strengthened, minimizing the risk of biased estimates or misleading conclusions.

Table 4. 6 Impact of Information Format on Work Performance

Predictor	Task Time			Rework		
	Estimate	p-value	CI	Estimate	p-value	CI
Intercept (Paper Dwgs)	240	-		4.62	-	
AR LOD 300	-10	0.55	[–0.162, 0.086]	-3.10	0.0001*	[–1.567, –0.673]
AR LOD 400	-27	0.047*	[–0.226, –0.001]	-2.59	0.0001*	[–1.183, –0.478]
Age	0.62	0.206	[–0.001, 0.006]	-0.09	0.066	[–0.038, 0.001]
Card_R Test	-3	0.002*	[–0.013, –0.002]	-0.07	0.07	[–0.039, 0.010]
Cube_C Test	-4	0.091	[–0.030, 0.002]	-0.005	0.99	[–0.079, 0.079]

Note: * = significant difference (p < 0.05)

Table 4. 7 Impact of Information Format and Origin of Design Information on Work Performance

Predictor	Task Time			Rework		
	Estimate	p-value	CI	Estimate	p-value	CI
Intercept (Format - Paper Dwgs, Origin - AI)	233	-		3.84	-	
AR LOD 300	-5.13	0.79	[–0.193, 0.148]	-2.23	0.043*	[-1.071, -0.015]
AR LOD 400	-2.33	0.9	[–0.163, 0.145]	-2.33	0.033*	[–0.958, –0.037]
Design Origin_Human	11.18	0.52	[-0.097, 0.192]	0.38	0.718	[-0.432, 0.627]
Age	0.70	0.22	[–0.001, 0.006]	-0.06	0.117	[–0.035, 0.004]
Card_R Test	-2.8	0.004*	[–0.012, –0.002]	-0.06	0.278	[–0.039, 0.011]
Cube_C Test	-4.19	0.048*	[–0.226, –0.003]	-0.038	0.89	[–0.025, 0.001]
AR_300:D_originHuman	-14.68	0.61	[-0.313, 0.184]	-2.054	0.142	[-1.453, 0.210]
AR_400:D_originHuman	-42.64	0.077	[-0.421, 0.022]	-2.104	0.101	[-1.341, 0.119]

Note: * = significant difference ($p < 0.05$)

The analysis of Rework indicated that the primary driver of task accuracy was the information format. Both the AR LOD 300 ($p = 0.043$) and AR LOD 400 ($p = 0.033$) models led to a statistically significant reduction in the number of reworks compared to the baseline 2D drawings and AI origin. Crucially, the perceived origin of the design (Design Origin_Human) had no significant main effect ($p = 0.718$), nor were there any significant interactions. This strongly suggests that the use of AR technology itself was the key factor in helping participants make fewer mistakes, overpowering any potential influence of user trust in the design's source.

In contrast, the analysis for Task Time revealed a more complex narrative that refined our preliminary findings. While our initial analysis suggested that both the AR 400 interface and spatial ability were significant predictors of speed, the current, more comprehensive model clarifies this relationship. After accounting for all factors simultaneously, the direct effect of the AR interface became less significant. Instead, the model showed that the participants' innate cognitive abilities, specifically the Card Rotation Test (Card_R Test) ($p = 0.004$) and Cube Comparison Test (Cube_C

Test) ($p = 0.068$), were the primary drivers of performance speed (i.e., Task Time). This indicates that the speed benefit previously attributed to the technology was likely a confounding effect of user skill, which the current model accounts for. While the main effect of design origin (Design Origin_Human) was not significant on its own ($p = 0.52$), a marginally significant interaction was observed between the AR LOD 400 format and a Human design origin (AR_400:D_originHuman) ($p = 0.077$). This trend suggests that within the most advanced AR condition, participants may have worked slightly faster when they believed the design was from a human, hinting that the streamlined interface was sensitive enough to reveal subtle performance effects related to user trust.

Overall, task accuracy was driven by the quality of the technology, while task speed was primarily determined by the user's innate skill, with a minor, conditional influence from the design's origin.

4.4.4 Analysis of Qualitative Data

While this study was primarily a quantitative experiment, an embedded qualitative component was included to provide essential explanatory context for the statistical findings. At the end of the experiment, participants were asked four open-ended questions designed to elicit the reasoning behind their quantitative ratings and user experience. The primary purpose of this data was to contextualize and add explanatory depth to the pre-defined variables of trust and performance. This descriptive analysis helped illuminate why certain quantitative results were observed, providing a richer, more holistic understanding of user perceptions.

4.4.4.1 How did you choose your trust ratings? What considerations did you make?

Participant responses revealed a nuanced and experience-based approach to assigning trust. Many noted that encountering errors in human-engineered designs was not uncommon, which

tempered their reaction to the intentional error. This perspective explains why trust in the design's accuracy (Q1) was not significantly impacted; fallibility was viewed as a universal trait of any design process. As one experienced participant stated, "I've seen plenty of drawings from senior engineers with mistakes. It happens. To me, the AI is no different in that regard." However, participants drew a sharp distinction when considering safety (Q2). A strong preference for human oversight emerged, rooted in the belief that human judgment incorporates a broader, more holistic set of considerations than an AI might. One participant's comment was particularly telling: "For safety, you need a person. A human thinks about the crew, the 'what-ifs.' I don't trust a program to have that kind of common-sense judgment." This directly supports the quantitative finding where trust in the AI group's design dropped significantly after an error on the safety-related question.

4.4.4.2 How was the experience of using AR models compared to paper drawings?

Feedback on the AR experience was overwhelmingly positive. The principal benefit identified was the reduction in cognitive load, as the 3D AR models eliminated the need to mentally map 2D information onto the 3D physical workspace. One user described this as, "a game-changer. You just see it right there. There are no mental gymnastics trying to match a flat drawing to the real world." While some experienced participants still expressed a preference for the familiarity of paper drawings for their primary work, they widely acknowledged the technology's value in specific contexts, particularly for training. As one veteran worker noted, "I wouldn't throw out my paper plans, but having this to double-check complex areas or to train a new guy is incredibly powerful."

4.4.4.3 Was there anything confusing about the AR models?

The majority of participants reported no significant confusion when using the AR models. The issues that were mentioned were minor and typically related to the physical hardware. For instance,

a few participants noted that holograms could occasionally obstruct their direct line of sight to the physical model, requiring them to shift their position to see around the digital overlay.

4.4.4.4 Do you recommend using AR technology on construction sites?

Participants broadly recommended the use of AR on construction sites, but with important caveats. The consensus was that AR should be implemented as a powerful supplementary tool to aid in visualization and verification, rather than as a complete replacement for traditional plans. Furthermore, participants raised pragmatic concerns about sustained, real-world deployment. These included potential safety issues stemming from distraction and the physical strain of wearing HMD for an entire workday. This feedback underscores the need for thoughtful implementation strategies, a point supported by previous research indicating that AR HMDs may impact worker's ability to detect safety hazards (Chaudhari et al., 2025).

4.5 Discussion

This study investigated the effects of the perceived origin of a design (AI vs. human) and the information format (AR vs. paper drawings) on user trust and performance during a full-scale MEP assembly task. The findings highlighted the interaction between how users perceive trust in the information source, how trust and source dynamics operate when a user detects an error in the information, and how this influences the user's work performance in an AR-assisted environment. The results of this study indicate that people's perception of trust in the origin of information is influenced by the level of risk associated with using the generated data. As mentioned in Section 4.3.1.1, we considered two possibilities when asked about trust in the origin of the design. The first scenario was simple, reflecting natural skepticism, where participants would have less confidence in AI compared to human engineers, resulting in consistently lower trust scores for AI than for human-origin systems. The second, more complex scenario was that of conditional trust,

where users might initially trust both AI and human designers equally due to uncertainty about the capabilities of AI. However, after discovering an error, trust would quickly erode, causing users to view AI as systemically incompetent.

For both questions, participants reported less trust in AI origins compared to human origins, but this difference was not statistically significant. This led us to consider a second possibility, concluding that initially, participants trusted AI as much as they trusted human origins. The next step was to examine what happens after noticing an intentional error. For the design accuracy question, their trust did not change significantly even after they noticed an error in the design, indicating that users believed there is always a chance of error in design documents, regardless of who creates them. This result was supported by answers to open-ended questions from many participants, who reported that throughout their careers, they have often observed mistakes or errors in designs generated by engineers, and they would not be surprised if an AI algorithm repeated the same pattern. However, this perception changed when participants were asked about the safety of design information. Their trust in both AI and human origins decreased, but this effect was statistically significant for the AI origin. This suggests that trust in the origin is proportional to the perceived level of risk. Participants also noted that when it comes to safety, they would rely more on humans because they doubt AI would consider all safety factors in design, which they believe humans would do. This aligns with literature suggesting that humans perceive AI as less capable of tasks requiring holistic, "human" judgment, such as ensuring safety (Lee, 2018).

Our first key finding about the impact on work performance relates to the positive effect of AR on task accuracy. The analysis of rework frequency showed that both AR formats significantly reduced the number of mistakes compared to traditional drawings. This finding was consistent with a large body of literature demonstrating the performance benefits of AR in complex assembly

tasks (Chaudhari et al., 2025; Qin et al., 2021; Hou et al., 2015). Crucially, this technological benefit was so powerful that it held true regardless of whether participants trusted the source of the design. This supported our hypothesis that a highly usable interface may effectively neutralize potential performance penalties arising from trust issues. A plausible explanation is that AR drastically reduces the user's cognitive load; by presenting information directly in the user's field of view, thereby minimizing the mental effort required to map 2D plans to a 3D space (Wen et al., 2021). This streamlined process leaves less cognitive room for the hesitation and second-guessing that often lead to errors, thus making accuracy more dependent on the quality of the interface than on the user's subjective trust.

In contrast, the analysis of task speed revealed a more complex narrative. While our preliminary analysis suggested that AR also made users faster, this more comprehensive mixed-effects model, which controlled for individual differences, clarified that the primary driver of speed was not the technology itself, but rather the user's innate spatial cognitive ability. This refinement is a critical insight, suggesting that for time-to-completion, a user's inherent skill is a more powerful predictor than the tool they are given. However, the technology was not irrelevant. We observed a marginally significant interaction trend, suggesting that within the most advanced AR environment (LOD 400), users worked slightly faster when they believed a human created the design. This hints that the AR interface, by making the task easier, created an environment sensitive enough to "reveal" a subtle performance effect related to trust that was otherwise invisible.

Finally, the correlation analysis revealed a crucial insight into how individual expertise interacts with trust. While participant age showed no consistent relationship with trust or performance, a user's spatial ability proved to be a significant factor. We found that individuals with higher spatial skills were significantly more skeptical of the AI-generated design from the

outset. A possible explanation for this is "expert skepticism," which suggests that users with a stronger innate grasp of the task are more critical evaluators and are less willing to grant unconditional trust to an opaque, non-human source (Corabi, 2017). This skepticism was notably absent when the design was attributed to a human, highlighting a fundamental challenge for Human-AI collaboration: the very experts whose skills are most valuable may also be the most difficult to convince of an AI's reliability without transparent processes and verifiable results.

The findings of this study have both theoretical and practical implications. Theoretically, they contribute to the field of Human-AI Interaction by demonstrating that "trust in AI" is highly context-dependent. It is influenced not only by technology's performance but also by the nature of the task (accuracy vs safety) and the user's expertise. Our results challenge a simplistic view of trust and performance, showing that a user can be skeptical of a system while still performing accurately with it, provided the interface is compelling enough. Practically, for the construction industry, our findings provide strong evidence for the adoption of AR technologies as a means to significantly reduce costly errors on job sites. They suggest that for tasks where accuracy is the highest priority, investment in high-quality interface technology will yield the greatest returns. The results also suggest that while simply informing workers that a design is from an AI may not harm their accuracy, it may introduce subtle hesitations that affect their speed. This highlights the critical need for robust validation and verification processes for AI-generated designs, especially those with safety implications, to build the necessary user trust for confident and efficient adoption.

4.6 Limitations

As a pioneering study on human factors, AI, and AR technologies, this research also emphasizes key challenges and future research directions. Our methodology aimed to address important gaps in previous AR studies by using a large sample of experienced industry craft

workers, implementing a full-scale experimental setup, and conducting most experiments in a real-world construction manufacturing environment. While these factors enhance the study's ecological validity, some limitations inherent to this emerging research area must be acknowledged.

The primary limitation, we thought, relates to the conceptual conflation of AI and AR by participants. Based on literature and expert opinions, we hypothesized that participants would report significantly less trust in an AI origin than in a human engineer. But during the study, we observed that some participants had difficulty distinguishing between the AI as the source of the design and AR as the medium of its delivery. Given their positive experience with the AR interface, there were instances where this positive sentiment appeared to artificially inflate their trust ratings for the AI, even after they noticed an error in design. We often had to provide clarification to ensure their ratings accurately reflected their trust in the information's origin, rather than the presentation format. This finding is also significant, as it suggests that user perceptions of one technology can be heavily influenced by their experience with another, a critical consideration for any multi-technology system for future research.

Furthermore, the "AI-generated" label was used to manipulate perception. While this is a standard experimental technique, we cannot be certain of the depth to which participants are engaged with the hypothetical origin. Future research is needed to move beyond simple attribution and explore user interaction with true, functioning generative AI systems. Building on our findings, future studies should focus on disentangling user perceptions of AI versus AR, perhaps by first training participants on each technology separately.

4.7 Conclusion

As the construction industry undergoes a digital transformation, the successful integration of technologies such as AI and AR hinges on understanding the human-centric factors that govern

their adoption. This study contributes to this understanding by moving beyond a purely technical evaluation to explore the complex interplay between the perceived origin and formats of design information, user trust, and work performance. Ninety-eight industry participants performed assembly tasks on a full-scale MEP setup. The participants were first divided into two groups based on the origin of design information, where one group was told that the design they would use for the assembly task was created by AI software, while the other group was told that a human engineer created it. Then, further subgroups were created based on the information format they would use for the assembly task, including traditional paper drawings and two AR models created based on the level of detail, i.e., LOD 300 and LOD 400.

The intent was to understand if users trust the content created by AI and humans equally, if they notice an error in the generated information, whether it impacts their initial trust, and finally, if this impact on trust in the origin of the design also affects their work performance in an AR-assisted environment. Our findings demonstrated that the path to effective human-AI collaboration is complex. It revealed that while a powerful interface like AR HMDs can greatly improve task accuracy by overcoming initial user skepticism, it had no effect on users' perception of the origin of design information. Furthermore, this research underscores that "trust" is not a monolithic concept; users differentiate between the risks associated with design accuracy versus those related to safety, showing far greater concern for the latter when information is attributed to an AI.

This is one of the first studies in the construction domain to examine the complex relationships of AI, AR technologies, and human factors. The study's primary contribution to the body of knowledge is the empirical demonstration that the effectiveness of emerging technologies in construction is not merely a function of the tool itself, but of the entire sociotechnical system, the user, the technology, the interface, and the intricate psychology of trust. For industry to move

forward and address its longstanding challenges with productivity and labor, it must not only invest in powerful technologies but also in strategies that build user confidence through transparency, validation, and human-in-the-loop processes. By focusing on this human-centric approach, we can foster a future where AI and AR are not just implemented but are truly and effectively integrated into the framework of the built environment.

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Data Availability Statement

Some or all data that support the findings of this study are available from the corresponding author upon reasonable request.

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CHAPTER 5 – CONCLUSION AND RECOMMENDATIONS FOR FUTURE WORK

5.1 Introduction

The construction industry is experiencing rapid growth and significant technological changes, driven by the need to handle increasingly complex projects and meet rising demands for efficiency, safety, and sustainability. Due to the dynamic nature of construction projects and the diverse demographics of the workforce, it is crucial to evaluate new technologies before their broad adoption carefully. This involves not only assessing their technical capabilities and potential productivity improvements but also understanding their interplay with the human factors.

This research effort, as illustrated in Figure 5.1, specifically focused on exploring and enhancing the understanding of Augmented Reality (AR) and Artificial Intelligence (AI) technologies and their interaction with key human factors in construction, including the ability to detect safety hazards, trust in technology, spatial cognitive skills, and workforce demographics. The objectives were to understand how the delivery of construction design information through AR HMDs affects craftworkers' ability to detect changes and hazards in dynamic environments; evaluating how the level of detail and presentation format of information influence key work performance outcomes, including completion time, error rates, and rework; and how does the perceived origin of design information impact trust in the information and confidence in decisions during construction.

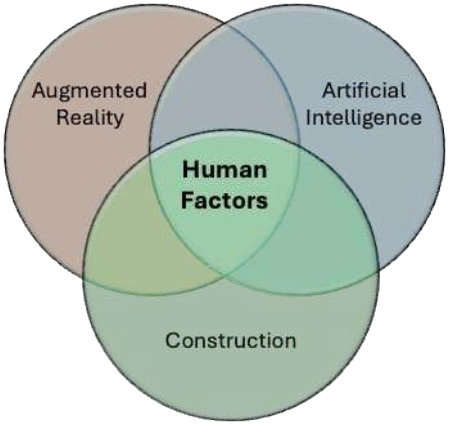


Figure 5.1 Integrative Research on Human-Factors and AR and AI Technologies in Construction

This chapter further summarizes the research findings, discusses the research contribution, addresses the limitations, and offers recommendations for future research.

5.2 Summary of Findings

The progression of this thesis can be likened to peeling an onion, gradually revealing deeper layers of understanding about how AR and AI technologies, as well as human factors, interact in the construction industry. Each study built upon the findings of the previous one, moving from foundational safety concerns to performance optimization and finally to the psychological and perceptual dimensions of technology adoption.

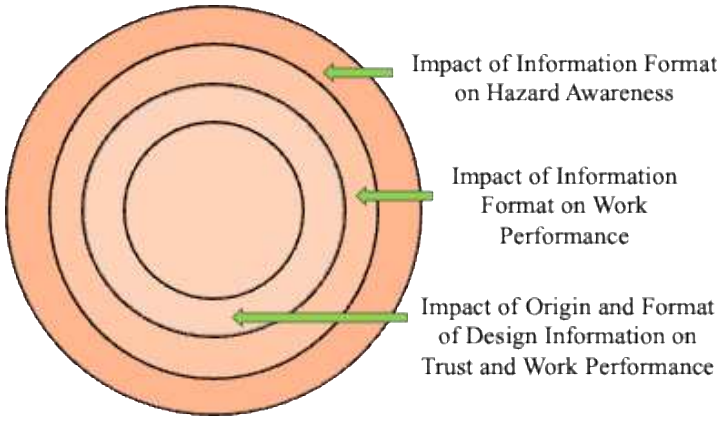


Figure 5.2 Layered Approach to Explore AR and AI in Construction

5.2.1 Chapter 2 (Paper 1- The first layer) How Does Augmented Reality Head-Mounted Display Impact the Ability to Detect Safety Hazards While Performing Piping Assembly?

Based on the literature review, the outermost layer revealed a clear gap, as no prior studies had directly examined how AR head-mounted devices affect the ability of construction workers to detect changes, particularly safety hazards, in real-world environments. This work highlighted the complexities and potential trade-offs of implementing immersive AR technologies in high-risk, dynamic environments.

The study found that using AR HMDs significantly impaired the ability of industry craft workers to detect environmental changes. Participants using AR HMDs were slower to identify safety hazards compared to those who relied on traditional paper-based or non-AR information methods. When the impact of two AR models was compared, it was found that as the density of information increased, so did the time to detect safety hazards. This suggests that the immersive nature of AR interfaces may cause distraction from the surroundings as users focus on the displayed information, thereby reducing their ability to detect changes, a crucial factor in timely hazard detection, which highlights a key safety concern.

Furthermore, based on the correlation analysis, it was expected that participants with higher spatial ability would be more alert to their environment and might notice the hazard more quickly than those with lower spatial ability. Contrary to expectations, spatial cognitive ability did not significantly influence change detection performance among participants using AR HMDs. This suggests that the challenges imposed by the AR interface, such as altered visual processing and distraction, may diminish the advantage typically afforded by higher spatial skills. Thus, even workers with strong inherent spatial cognition can experience impaired hazard detection when interfacing through AR.

However, the analysis revealed a significant negative correlation between participant age and change detection ability. Older workers exhibited significantly slower response times to detect safety hazards compared to their younger counterparts. This age-related performance decline highlights specific vulnerabilities in older workers when using AR HMDs, raising concerns about the inclusivity and safety of AR implementations in aging workforces.

The findings from this study made a significant contribution to the body of knowledge, as it was the first to assess this previously unexplored phenomenon of AR HMDs directly.

5.2.2 Chapter 3 (Paper 2 – The Second Layer) Exploring the Impact of Augmented Reality on Work Performance in a Full-Scale MEP Assembly Task: A Study of Industry and Novice Populations

Peeling back the next layer, the research recognized that while many studies have explored AR's effect on work performance, they are limited by small sample sizes, the use of reduced-scale models, and a focus solely on student participants. Moreover, the influence of different AR LODs on performance had not been systematically investigated. The second study addressed these gaps by involving both novice students and experienced industry craftspeople, and by comparing AR models at different LODs against traditional paper drawings in full-scale assembly tasks. This approach provided a more ecologically valid and nuanced understanding of how AR and information format interact with user expertise and cognitive ability to shape work performance.

The findings demonstrated that AR HMDs significantly enhanced work performance metrics such as task completion time, rework rate, and error rate, particularly when displaying higher levels of design detail (LOD 400). Both industry participants and novices completed assembly tasks faster and with fewer reworks when aided by AR models compared to traditional methods. Surprisingly, novices showed more pronounced benefits, suggesting that AR’s intuitive

visualization supports learning and performance in less experienced workers, enabling them to perform as well as their professional counterparts.

With information format, the spatial cognitive ability of users emerged as a significant predictor of better task performance, especially among novice participants. Individuals with higher spatial skills navigated the AR environment more effectively, resulting in faster completion times and fewer errors. The AR interface appeared to amplify these cognitive advantages by visually supporting spatial understanding. For the experienced workforce, spatial ability was less predictive for rework compared to task completion time, indicating that domain expertise may compensate for cognitive variations. Age did not significantly affect overall work performance measures across delivery methods. This suggests that AR technology may level the playing field, enabling older workers to achieve productivity outcomes comparable to younger workers. This finding is encouraging for supporting an aging workforce during technological transitions.

This study made a significant contribution to the methodological domain of AR-aided construction assembly research by employing full-scale, realistic experimental designs with varied AR models and participant expertise, thereby enhancing ecological validity and providing replicable approaches for future interdisciplinary research.

5.2.3 Chapter 4 (Paper 3- The Third Layer) Human Vs AI: Assessing Trust and Efficiency in Augmented Reality Assembly Tasks Among Construction Industry Professionals

This study was the first in the construction domain to empirically investigate the influence of design origin, AI versus human, alongside information format on trust and work performance in assembly tasks. The research delved deeper by introducing the variable of design origin—human versus AI-generated—and examining its interplay with information format and user trust, and ultimately their impact on work performance factors. The analysis of this complex phenomenon was performed in two stages: 1) Trust analysis – How do participants perceive the trust in the

origin of design information before and after noticing an intentional error? 2) Work Performance Analysis - How the perceived origin of design information and trust in origin impacts the work performance factors.

It was expected that participants would report significantly less trust in AI origin than in human origin, considering the reliability issues with AI models. However, the findings showed that, although participants had higher trust in human origin compared to AI, this difference was not statistically significant. Additionally, we expected that after noticing an intentional error, trust in AI would decrease significantly. But this was not the case when asked about the accuracy of design data; the decline in trust was not statistically significant for either origin. However, when asked about the safety of design data, participants reported a highly significant decrease in trust toward AI origin. This was supported by participants' responses, who noted that when it comes to safety, they would rely more on humans because they doubt AI would consider all safety factors in design, which they believe humans would do. Nonetheless, it revealed that participants' trust in the origin of design information was proportional to their perceived level of risk associated with that information.

To analyze the impact of trust in the design origin and information format on work performance, two primary factors were considered: task completion time and rework. Since error rates were minimal among industry participants, they were excluded from this analysis. The results revealed that AR interfaces consistently enhanced task accuracy across design origins, underscoring AR's critical role in reducing user skepticism regarding the source of design information.

However, the findings related to task speed were particularly insightful. In an earlier study where design origin was not accounted for, improvements in task completion time were mainly

attributed to the use of AR models in conjunction with participants' spatial cognitive abilities. Yet, when design origin was incorporated into the analysis, it became evident that task speed was predominantly driven by participants' cognitive abilities rather than the AR models themselves. This suggests that while AR technology facilitates accuracy and reduces doubt about design sources, the pace of task performance is more closely linked to individual cognitive skills. In contrast to cognitive ability, participant age showed no consistent or significant relationship with either trust or work performance in this context, a finding also observed in the previous study.

5.3 Research Contribution

The construction industry today is navigating a critical transformation driven by the integration of digital technologies such as Augmented Reality (AR) and Artificial Intelligence (AI). These innovations promise to redefine how projects are planned, executed, and managed, potentially alleviating long-standing challenges related to safety, productivity, and labor shortages. However, the path to realizing these benefits is complex and contingent upon a deep understanding of the human dimensions intertwined with technology adoption.

A key takeaway from this research is the necessity to prioritize human-centered design and deployment strategies for AR and AI in construction. The findings underscore that while AR systems enhance visualization and information delivery, their implementation must be sensitive to cognitive limitations and the diverse capabilities of the workforce. For instance, on the one hand, findings suggest that high LOD AR models have been found to negatively impact safety awareness in the construction environment. The increased density and complexity of information presented in these immersive interfaces appeared to distract users, reducing their ability to maintain hazard awareness. On the other hand, these very same high LOD AR models proved to be the most

beneficial format for improving overall task performance, significantly enhancing accuracy and reducing rework during assembly tasks.

This duality underscores a crucial consideration for the adoption of construction technology. While AR interfaces can drive productivity and precision, they must be carefully balanced and optimized to prevent cognitive overload and maintain situational awareness. Achieving this equilibrium between performance enhancement and safety preservation requires adaptive design approaches that tailor the AR experience to the context, task complexity, and individual user capabilities. The research highlights that technology implementation in construction is not a one-size-fits-all solution, but rather demands a thoughtful, human-centered approach to maximize benefits without compromising safety.

Additionally, the research demonstrates that AR technologies can democratize access to expertise and performance gains across the workforce. By making complex design and assembly tasks more intuitive and reducing reliance on prior experience, AR holds the potential to support skill development and overcome workforce shortages. This inclusivity is particularly valuable in an aging industry where maintaining productivity and safety standards requires integrating workers across a broad range of ages and cognitive abilities.

Furthermore, trust in AI-generated design data emerged as a multifaceted and pivotal factor. The research revealed that users' trust varies depending on the perceived level of risk: while participants showed willingness to trust AI outputs in low-risk scenarios, their confidence declined sharply in situations involving safety-critical decisions. This reflects broader societal reservations about embracing AI in high-stakes domains, indicating that trusted adoption of AI will require transparent, explainable systems along with human-in-the-loop oversight mechanisms. Even at this early stage of AI maturity, the nuanced acceptance observed implies a long trajectory ahead before

full confidence in AI can be achieved within the construction industry, particularly in terms of safety and risk management.

However, the findings also suggest that AI skepticism can be lowered by integrating the AI-generated information with enhanced visualization through AR devices. The immersive and intuitive nature of AR helps users better interpret and verify AI outputs, serving as a cognitive bridge that reduces uncertainty and builds confidence. Such synergy between AR and AI holds significant promise for accelerating the safe, effective, and trusted integration of these technologies in complex construction environments.

By examining layered interactions, spanning from safety cognition, through performance metrics, to trust and perception, the study advocates for holistic models of human-technology integration in construction. This comprehensive approach bridges disciplines such as cognitive science, human factors engineering, AI explainability, and construction management. The resultant frameworks support the design of resilient technologies that are not only powerful but also accepted and embraced by those on the frontline of construction projects.

Finally, the methodological rigor embodied in full-scale, multi-population experiments enhanced the reliability and generalizability of the insights. In summary, this dissertation lays the groundwork for a future construction ecosystem where digital technologies and human workers collaborate in synergistic partnerships, enhancing safety, productivity, and sustainability by prioritizing human cognition, trust, and diversity in technological innovation.

5.4 Limitations and Directions for Future Research

Despite the rigorous methodology and significance mentioned above, the research acknowledges limitations that need attention.

5.4.1 Experimental Settings

Although the experiments maintained a high level of control, they did not entirely reflect the complex and ever-changing nature of real-world construction sites. While tasks involving industry craftsmen took place on the industry shop floor, these activities were performed under controlled conditions and not within the context of an active construction project. This distinction is essential, as real sites are subject to unpredictable workflow, environmental hazards, and operational pressures that can influence behavior and outcomes in ways laboratory or simulated settings cannot fully replicate.

The fundamentally non-repeatable nature of construction tasks, which are often unique and shaped by site-specific variables, poses a challenge to conducting standardized experiments in the field. Additionally, strict adherence to industry safety protocols further constrains the range and realism of experimental procedures that can be ethically undertaken with human participants. As a result, while this research provides critical foundational insights, caution should be exercised when generalizing findings to all construction settings. Further, field-based studies are warranted to validate and extend these results.

5.4.2 Technology Familiarization and Crossover Design Effects

Another critical limitation stems from the participants' limited exposure to AR technology prior to the experimental tasks. Without adequate familiarization, participants may not have been able to fully acclimate to the AR interface, which could have potentially impacted their confidence and performance, especially in settings involving novel or complex digital tools. Additionally, this study employed a crossover design in which participants completed multiple consecutive trials with different conditions. Due to time constraints, sufficient cool-down or washout intervals between trials were not feasible. This raises the potential for carryover effects, where experiences

or learning from earlier trials may have influenced subsequent performance, thereby introducing bias or variability into the results. Both of these factors, limited AR familiarization and the lack of appropriate interval periods, should be carefully considered when interpreting the findings. Future studies are encouraged to provide more extensive training periods and better trial spacing to minimize such effects.

5.4.3 Focus on Visual Change Detection

The assessment of change detection in this research was restricted solely to visual signals, as these were directly relevant to the capabilities and constraints of AR head-mounted display devices. Other sensory modalities, such as auditory or tactile cues, that could also influence hazard detection in authentic construction settings were not considered. Focusing exclusively on visual changes may have limited the generalizability of findings, as real-world construction environments often require workers to integrate information from multiple senses to detect and respond to hazards effectively. Future research should incorporate a broader range of sensory inputs to create a more comprehensive understanding of change detection in augmented reality applications.

5.4.4 Perceptions of Origin and Technology Conflation

A central limitation of the study on the origin of design information was the conceptual conflation of AI and AR by participants. Although the hypothesis and experimental design assumed that trust ratings would distinctly reflect beliefs about the AI as the source of design information versus human engineers, in practice, many participants struggled to differentiate between AI as the origin and AR as the medium of delivery. Their positive experiences with the AR interface sometimes led participants to overestimate their trust in AI-generated designs, even after noticing errors, which required repeated clarification to ensure that trust ratings were targeted at the intended source rather than the presentation format.

Furthermore, the use of the "AI-generated" label as a manipulation tool means that participant engagement with the hypothetical origin may not mirror interactions with actual generative AI technologies. This potential overlap in perceptions suggests a need for greater emphasis on training and separation of experiences with AI and AR in future studies, allowing for more precise attribution of trust and fuller exploration of user interactions with genuine, functioning AI systems.

Future research studies must conduct more comprehensive experiments to validate these findings. By conducting long-term experiments at actual construction sites, examining change detection with signals such as sound or text, and providing adequate training on technologies and appropriate cool-down periods, we can further enhance our understanding in this field.

APPENDICES

APPENDIX A – Research Experimental Protocol (Approved IRB 19-0390)

Experimental Protocol for Industry Crafts for Panel 1 and 2

Participants were assigned groups based on the origin of design and the panel side they were working on, as shown in the table below.

Group	**Panel 1**	**Panel 2**
A-1	Side 1, 2D only	Side 2, 2D + AR LOD 400
B-1	Side 1, 2D only	Side 2, 2D + AR LOD 300
C-1	Side 1, 2D + AR LOD 400	Side 2, 2D only
D-1	Side 1, 2D + AR LOD 300	Side 2, 2D only
A-2	Side 1, 2D only	Side 2, 2D + AR LOD 400
B-2	Side 1, 2D only	Side 2, 2D + AR LOD 300
C-2	Side 1, 2D + AR LOD 400	Side 2, 2D only
D-2	Side 1, 2D + AR LOD 300	Side 2, 2D only
Note: AI Design Cover Story – A-1, B-1, C-1 and D-1 Human Design Cover Story – A-2, B-2, C-2 and D-2		

Below is the specific experimental protocol to be followed.

1.Greet the participant. Ask if they have AR experience before. Give the instructions sheet and ask them to read all the instructions carefully.

2.While each participant reads their respective cover story, make sure the test bed is ready by doing the following:

2.1 Ensure all the mechanical piping and electrical conduit to be installed are off the board and in the storage bin.

2.2 Make sure the LED light is functioning and off (The remote-control unit is stored in the electrical panel along with spare AAA batteries).

2.3 Make sure the electrical switch is flipped to ON.

2.4 Make sure the HoloLens units are turned on and fully charged.

3.After each participant has read and acknowledged understanding the instructions, ask them to begin the experiment. Before beginning, they will be equipped with a HoloLens device (If belongs to group C-1, D-1, C-2 and D-2). For participant who belongs to groups A-1, B-1, A-2 and B-2, side 1 is 2D only and hence HoloLens will be equipped when they move to side 2. Make sure to conduct eye calibration on the HoloLens for each participant and make sure the device is recording the participant's eye tracking. Finally, make sure the AR application is activated on the HoloLens and set to the required LOD Level as per the group.

4.Before starting the experiment, ask participants the following trust questions verbally and note down their responses.

Trust questions before (Panel 1) for groups (A-1, B-1, C-1 and D-1):

4.1 On a scale from 1 (no trust) to 7 (full trust), how much do you trust that plans created by an artificial intelligence will be free of errors?

4.2 on a scale from 1 (no trust) to 7 (full trust), how much do you trust that plans created by an artificial intelligence will be free of safety hazards (safe for workers to build)?

4.3 I'm curious, how did you choose your ratings? What considerations did you make?

Trust questions before (Panel 1) for groups (A-2, B-2, C-2 and D-2):

4.1 On a scale from 1 (no trust) to 7 (full trust), how much do you trust that plans created by a senior licensed engineer will be free of errors?

4.2 on a scale from 1 (no trust) to 7 (full trust), how much do you trust that plans created by a senior licensed engineer will be free of safety hazards (safe for workers to build)?

4.3 I'm curious, how did you choose your ratings? What considerations did you make?

5.Once the individual indicates they are ready, record the start time and ask them to begin.

6.While participant perform the task, observe, and look for the number of mistakes or rework.

7.After 90 seconds into the task, turn on the Red Light using remote control.

8.Note if participant notices the flashing light and turns the switch off.

9.Note the time taken to turn off the switch.

10. Whenever the bin is empty, ask the participant if he/she think they have completed the task. If so, note the time.

11. Ask participant to proceed to side 2 to complete the appropriate tasks and make the adjustments as needed to HoloLens per the individual's assigned group. If an individual is not done with a specific side after 15 minutes, acknowledge they have done a great job (this is a complex task) and help them move to the next side.

12. Once the individual indicates they are ready, record the start time and ask them to begin.

13. While participant perform the task, observe, and look for the number of mistakes or rework.

14. After the participant completes the task, ask them to verbally answer the following questions (write down their responses):

Trust questions after Panel 2 for groups (A-1, B-1, C-1 and D-1):

14.1 So, now that you have completed the task, I want to ask you again, on a scale from 1 (no trust) to 7 (full trust), how much do you trust that plans were created by an artificial intelligence will be free of errors?

14.2 On a scale from 1 (no trust) to 7 (full trust), how much do you trust that plans created by an artificial intelligence will be free of safety hazards (safe for workers to build)?

14.3 How was the experience of using the HoloLens with the 2D drawings?

Trust questions after Panel 2 for groups (A-2, B-2, C-2 and D-2):

14.1 So, now that you have completed the task, I want to ask you again, on a scale from 1 (no trust) to 7 (full trust), how much do you trust that plans were created by a senior licensed engineer will be free of errors?

14.2 On a scale from 1 (no trust) to 7 (full trust), how much do you trust that plans created by a senior licensed engineer will be free of safety hazards (safe for workers to build)?

14.3 How was the experience of using the HoloLens with the 2D drawings?

After the trust questions, ask the following last set of exit questions –

14.4 Do you recommend using AR technology on the construction jobsites?

14.5 Was there anything that confused you or you found confusing related to the pipe model?

14.6 Was there anything confusing while using the AR?

15. Once the task is complete, ask participant to fill the demographic questionnaire.
16. Conduct a timed Card and Cube Rotation Test.
17. Ask the participant if he/she noticed the design error. Please let them know that the error was intentional on our part and not a result of a design error.

Experimental Protocol for Student Participants for Panels 1, 2 and 3

Participants were assigned groups based on the origin of design and the panel side they were working on, as shown in the table below.

Group	**Stage 1**	**Stage 2**	**Stage 3**
A-1	Side 1, 2D only	Side 2, 2D + AR LOD 300	Side 3, 2D + AR LOD 400
B-1	Side 1, 2D+ AR LOD 300	Side 2, 2D + AR LOD 400	Side 3, 2D only
C-1	Side 1, 2D + AR LOD 400	Side 2, 2D only	Side 3, 2D + AR LOD 300
A-2	Side 1, 2D only	Side 2, 2D + AR LOD 300	Side 3, 2D + AR LOD 400
B-2	Side 1, 2D + AR LOD 300	Side 2, 2D + AR LOD 400	Side 3, 2D only
C-2	Side 1, 2D + AR LOD 400	Side 2, 2D only	Side 3, 2D + AR LOD 300
Note: AI Cover Story – A-1, B-1, and C-1; Human Design Cover Story – A-2, B-2, and C-2.			

Below is the specific experimental protocol to be followed.

1.Greet the participant. Ask if they have AR experience before. Give the instructions sheet and ask them to read all the instructions carefully.

2.While each participant reads their respective cover story, make sure the test bed is ready by doing the following:

2.1 Ensure all the mechanical piping and electrical conduit to be installed are off the board and in the storage bin.

2.2 Make sure the LED light is functioning and off (The remote-control unit is stored in the electrical panel along with spare AAA batteries).

2.3 Make sure the electrical switch is flipped to ON.

2.4 Make sure the HoloLens units are turned on and fully charged.

3.After each participant has read and acknowledged understanding the instructions, ask them to begin the experiment. Before beginning, they will be equipped with a HoloLens device (If they

belong to group B-1, C-1, B-2 and C-2). For participant who belongs to groups A-1 and A-2, side 1 is 2D only, and hence HoloLens will be equipped when they move to side 2 and so on. Ensure that you conduct eye calibration on the HoloLens for each participant and verify that the device is recording the participant's eye tracking. Finally, ensure the AR application is activated on the HoloLens and set to the required LOD Level as specified by the group.

4.Before starting the experiment, ask participants the following trust questions verbally and note down their responses.

Trust questions before (Panel 1) for groups (A-1, B-1, and C-1):

4.1 On a scale from 1 (no trust) to 7 (full trust), how much do you trust that plans created by an artificial intelligence will be free of errors?

4.2 on a scale from 1 (no trust) to 7 (full trust), how much do you trust that plans created by an artificial intelligence will be free of safety hazards (safe for workers to build)?

4.3 I'm curious, how did you choose your ratings? What considerations did you make?

Trust questions before (Panel 1) for groups (A-2, B-2, and C-2):

4.1 On a scale from 1 (no trust) to 7 (full trust), how much do you trust that plans created by a senior licensed engineer will be free of errors?

4.2 on a scale from 1 (no trust) to 7 (full trust), how much do you trust that plans created by a senior licensed engineer will be free of safety hazards (safe for workers to build)?

4.3 I'm curious, how did you choose your ratings? What considerations did you make?

5.Once the individual indicates they are ready, record the start time and ask them to begin.

6.While participant perform the task, observe, and look for the number of mistakes or rework.

7.Whenever the bin is empty, ask the participant if he/she think they have completed the task. If so, note the time.

8.Ask participant to proceed to side 2 to complete the appropriate tasks and make the adjustments as needed to HoloLens per the individual's assigned group. If an individual is not done with a specific side after 15 minutes, acknowledge they have done a great job (this is a complex task) and help them move to the next side.

9.Once the individual indicates they are ready, record the start time and ask them to begin.

10. While participant perform the task, observe, and look for the number of mistakes or rework.

11. After 90 seconds into the task, turn on the Red Light using remote control.

12. Note if participant notices the flashing light and turns the switch off.

13. Note the time taken to turn off the switch.

14. After the participant completes the task, ask them to proceed to side 3 to complete the appropriate tasks and make any necessary adjustments to the HoloLens according to their assigned group. If an individual is not done with a specific side after 15 minutes, acknowledge they have done a great job (this is a complex task) and help them move to the next side.

15. Once the individual indicates they are ready, record the start time and ask them to begin.

16. While participants perform the task, observe, and look for the number of mistakes or rework.

17. Whenever the bin is empty, ask the participant if he/she think they have completed the task. If so, note the time.

18. After completing the task on panel 3, ask them to verbally answer the following questions (write down their responses):

Trust questions after Panel 3 for groups (A-1, B-1, and C-1):

14.1 So, now that you have completed the task, I want to ask you again, on a scale from 1 (no trust) to 7 (full trust), how much do you trust that plans were created by an artificial intelligence will be free of errors?

14.2 On a scale from 1 (no trust) to 7 (full trust), how much do you trust that plans created by an artificial intelligence will be free of safety hazards (safe for workers to build)?

14.3 How was the experience of using the HoloLens with the 2D drawings?

Trust questions after Panel 3 for groups (A-2, B-2, and C-2):

14.1 So, now that you have completed the task, I want to ask you again, on a scale from 1 (no trust) to 7 (full trust), how much do you trust that plans were created by a senior licensed engineer will be free of errors?

14.2 On a scale from 1 (no trust) to 7 (full trust), how much do you trust that plans created by a senior licensed engineer will be free of safety hazards (safe for workers to build)?

14.3 How was the experience of using the HoloLens with the 2D drawings?

After the trust questions, ask the following last set of exit questions –

14.4 Do you recommend using AR technology on the construction jobsites?

14.5 Was there anything that confused you or you found confusing related to the pipe model?

14.6 Was there anything confusing while using the AR?

19. Once the task is complete, ask participant to fill the demographic questionnaire.
20. Conduct a timed Card and Cube Rotation Test.
21. Ask the participant if he/she noticed the design error. Please let them know that the error was intentional on our part and not a result of a design error.

APPENDIX B – Cover Stories for Industry and Student Participants

Cover Stories – AI and Human for Industry Crafts

Groups A-1, B-1, C-1 and D-1

A. As a mechanical and electrical craft worker, you have been tasked with finishing the mechanical piping (white pipes and valves) and electrical conduit (grey pipes) for an installation of an ethylene cracker unit.

B. This specific unit will take natural gas and convert it to polypropylene to be used to manufacture medical supplies such as syringes, medical vials, and specimen bottles.

C. Today, you are responsible for completing the remaining mechanical piping and electrical conduit installation on two of the sides of the unit. Since not all the mechanical piping and electrical conduit were available to a previous craft worker, the installation could not be completed. However, you now have all the necessary components.

You are being asked to do the following:

D. First complete the task on the two given sides per design specifications in as little time as possible. Let me know when you complete the first side, I will help you transition to the next panel.

E. The drawings and design specifications of the unit were created using an artificial intelligence application developed by AutoCAD. This AI application takes in high-level specifications from the user and automatically generates specific design plans.

F. You will be using design information from a combination of 2D plan sheets and Augmented Reality applications to complete the overall assembly. The AR application will be displayed on the HoloLens system you're wearing and will give you the different specifications for the assembly. The 2D plans will be given to you on paper.

G. All the necessary mechanical piping and electrical conduit necessary to complete the tasks are in the storage bin. None of the pieces need to be cut or modified any way. Each piece is connected simply by pushing and twisting the new piece into an existing piece. Cement or glue is not necessary to connect the pieces. Make sure that the installation is completed accurately per the provided design information.

H. Finally, since the unit does use natural gas if a gas leak is detected a red warning light will be activated. If this occurs, you will need to immediately turn off the gas pump by flipping the switch below the red warning light from on to off. Once the light is off, you can continue with the installation.

Do you have any questions before we begin?

Groups A-2, B-2, C-2 and D-2

A. As a mechanical and electrical craft worker, you have been tasked with finishing the mechanical piping (white pipes and valves) and electrical conduit (grey pipes) for an installation of an ethylene cracker unit.

B. This specific unit will take natural gas and convert it to polypropylene to be used to manufacture medical supplies such as syringes, medical vials, and specimen bottles.

C. Today, you are responsible for completing the remaining mechanical piping and electrical conduit installation on two sides of the unit. Since not all the mechanical piping and electrical conduit were available to a previous craft worker, the installation could not be completed. However, you now have all the necessary components.

You are being asked to do the following:

D. First complete the task on the two given sides per design specifications in as little time as possible. Let me know when you complete the first side, I will help you transition to the next panel.

E. The drawings and design specifications of the unit were created by a senior licensed engineer using AutoCAD software.

F. You will be using design information from a combination of 2D plan sheets and Augmented Reality applications to complete the overall assembly. The AR application will be displayed on the HoloLens system you're wearing and will give you the different specifications for the assembly. The 2D plans will be given to you on paper.

G. All the necessary mechanical piping and electrical conduit necessary to complete the task are in the storage bin. None of the pieces need to be cut or modified any way. Each piece is connected simply by pushing and twisting the new piece into an existing piece. Cement or glue is not necessary to connect the pieces. Make sure that the installation is completed accurately per the provided design information.

H. Finally, since the unit does use natural gas if a gas leak is detected a red warning light will be activated. If this occurs, you will need to immediately turn off the gas pump by flipping the switch below the red warning light from on to off. Once the light is off, you can continue with the installation.

Do you have any questions before we begin?

Cover Stories – AI and Human for Student Participants

Groups A-1, B-1 and C-1

A. As a mechanical and electrical craft worker, you have been tasked with finishing the mechanical piping (white pipes and valves) and electrical conduit (grey pipes) for an installation of an ethylene cracker unit.
B. This specific unit will take natural gas and convert it to polypropylene to be used to manufacture medical supplies such as syringes, medical vials, and specimen bottles.
C. Today, you are responsible for completing the remaining mechanical piping and electrical conduit installation on all three sides of the unit. Since not all the mechanical piping and electrical conduit were available to a previous craft worker, the installation could not be completed. However, you now have all the necessary components.

You are being asked to do the following:

D. First complete the task on the two given sides per design specifications in as little time as possible. Let me know when you complete the first side, I will help you transition to the next panel.
E. The drawings and design specifications of the unit were created using an artificial intelligence application developed by AutoCAD. This AI application takes in high-level specifications from the user and automatically generates specific design plans.
F. You will be using design information from a combination of 2D plan sheets and Augmented Reality applications to complete the overall assembly. The AR application will be displayed on the HoloLens system you're wearing and will give you the different specifications for three sides of the assembly. The 2D plans will be given to you on paper.

G. All the necessary mechanical piping and electrical conduit necessary to complete the tasks are in the respective storage bins of that side. None of the pieces need to be cut or modified any way. Each piece is connected simply by pushing and twisting the new piece into an existing piece. Cement or glue is not necessary to connect the pieces. Make sure that the installation is completed accurately per the provided design information.

H. Finally, since the unit does use natural gas if a gas leak is detected a red warning light will be activated. If this occurs, you will need to immediately turn off the gas pump by flipping the switch below the red warning light from on to off. Once the light is off, you can continue with the installation.

Do you have any questions before we begin?

Groups A-2, B-2 and C-2

A. As a mechanical and electrical craft worker, you have been tasked with finishing the mechanical piping (white pipes and valves) and electrical conduit (grey pipes) for an installation of an ethylene cracker unit.

B. This specific unit will take natural gas and convert it to polypropylene to be used to manufacture medical supplies such as syringes, medical vials, and specimen bottles.

C. Today, you are responsible for completing the remaining mechanical piping and electrical conduit installation on two sides of the unit. Since not all the mechanical piping and electrical conduit were available to a previous craft worker, the installation could not be completed. However, you now have all the necessary components.

You are being asked to do the following:

D. First complete the task on the two given sides per design specifications in as little time as possible. Let me know when you complete the first side, I will help you transition to the next panel.

E. The drawings and design specifications of the unit were created by a senior licensed engineer using AutoCAD software.

F. You will be using design information from a combination of 2D plan sheets and Augmented Reality applications to complete the overall assembly. The AR application will be displayed on the HoloLens system you're wearing and will give you the different specifications for three sides of the assembly. The 2D plans will be given to you on paper.

G. All the necessary mechanical piping and electrical conduit necessary to complete the task are in the storage bin. None of the pieces need to be cut or modified any way. Each piece is connected simply by pushing and twisting the new piece into an existing piece. Cement or glue is not necessary to connect the pieces. Make sure that the installation is completed accurately per the provided design information.

H. Finally, since the unit does use natural gas if a gas leak is detected a red warning light will be activated. If this occurs, you will need to immediately turn off the gas pump by flipping the switch below the red warning light from on to off. Once the light is off, you can continue with the installation.

Do you have any questions before we begin?

APPENDIX C – Data Collection Sheets, Card Rotation and Cube Comparison Tests

Data Collection Sheets

Industry Crafts

Industry Craft Data Collection Sheet										
Participant PIN							**Date**			
Group										
Trust Questions Before The Task Begins										
1										
2										
3										
Panel 1										
Time				To						
Errors										
Rework										
Red Light Noticed				Time to turn off the switch						
Notes										
Panel 2										
Time				To						
Errors										
Rework										
Trust Questions After The Task										
1										
2										
3										
Exit Questions										
1										
2										
3										
Notes										
Card Rotation Test Score					Test completed in time (Y/N)					
Cube Comparisons Test Score					Test completed in time (Y/N)					

Student Participants

Students Data Collection Sheet										
Participant PIN							**Date**			
Group										
Trust Questions Before The Task Begins										
1										
2										
3										
Panel 1										
Time			To							
Errors										
Rework										
Notes										
Panel 2										
Time			To							
Errors										
Rework										
Red Light Noticed			Time to turn off the switch							
Trust Questions After Panel 2										
1										
2										
3										
Panel 3										
Time			To							
Errors										
Rework										
	Noticed an error									
Trust Questions After Panel 3										
1										
2										
3										
Exit Questions										
1										
2										
3										
Notes										

Card Rotation Test Score		Test completed in time (Y/N)	
Cube Comparisons Test Score		Test completed in time (Y/N)	

Demographic Questionnaire

Personal Identification Number (PIN): _____

Demographic Information

Age: _____

Gender:

_____Man

_____Woman

_____Non-Binary

_____Other

Educational Background

Total years of education (e.g. grade school through high school = 12 years): _____

Please select your highest level of education:

- Less than a high school diploma
- High school diploma
- Some college, no degree
- Associate's degree
- Bachelor's degree
- Master's degree
- Professional degree
- Doctoral degree

Have you had any formal training in engineering drawings/blueprint reading?

_____ Yes _____ No _____How much experience/training (Years)

Work Experience

Current Occupation: _____

Years of Experience in Current Occupation: _____

Years of Industry Work Experience: _____

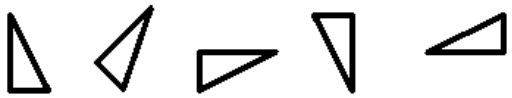
Type of Industry Work Experience (design, construction, co-op, project engineer, etc.):

Department:

Card Rotation and Cube Comparison Tests

Card Rotation Test

This is a test of your ability to see differences in figures. Look at the 5 triangle-shaped cards drawn



below.

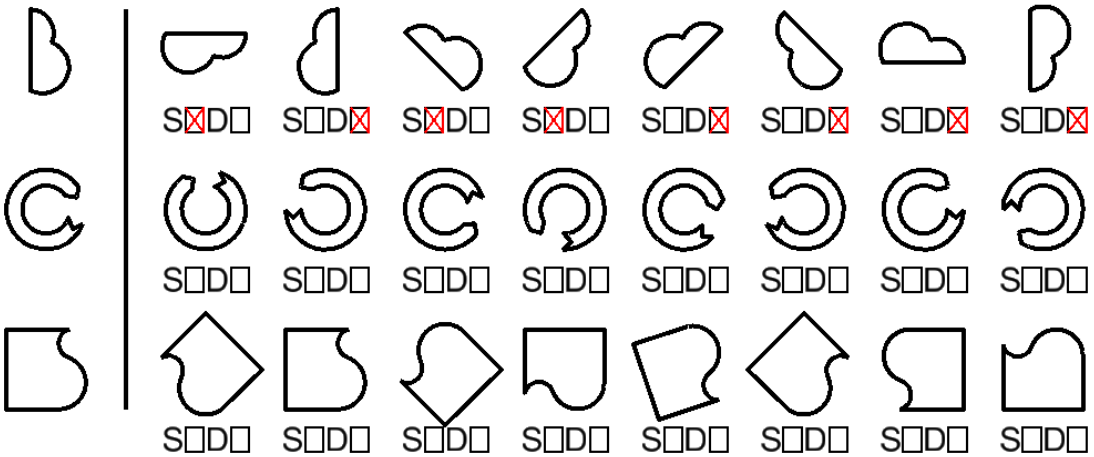
All of these drawings are of the **same** card, which has been slid around into different positions on the page.

Now look at the 2 cards below:

These two cards are **not alike**. The first cannot be made to look like the second by sliding it around on the page. It would have to be **flipped over** or **made differently**.

Each problem in this test consists of one card on the left of a vertical line and eight cards on the right. You are to decide wether each of the eight cards on the right is the **same as** or **different from** the card at the left. Mark the box besides the S if it the **same as** the one at the beginning of the row. Mark the box beside the D if it is **different from** the one at the beginning of the row.

Practice on the following rows. The first row has been correctly marked for you.



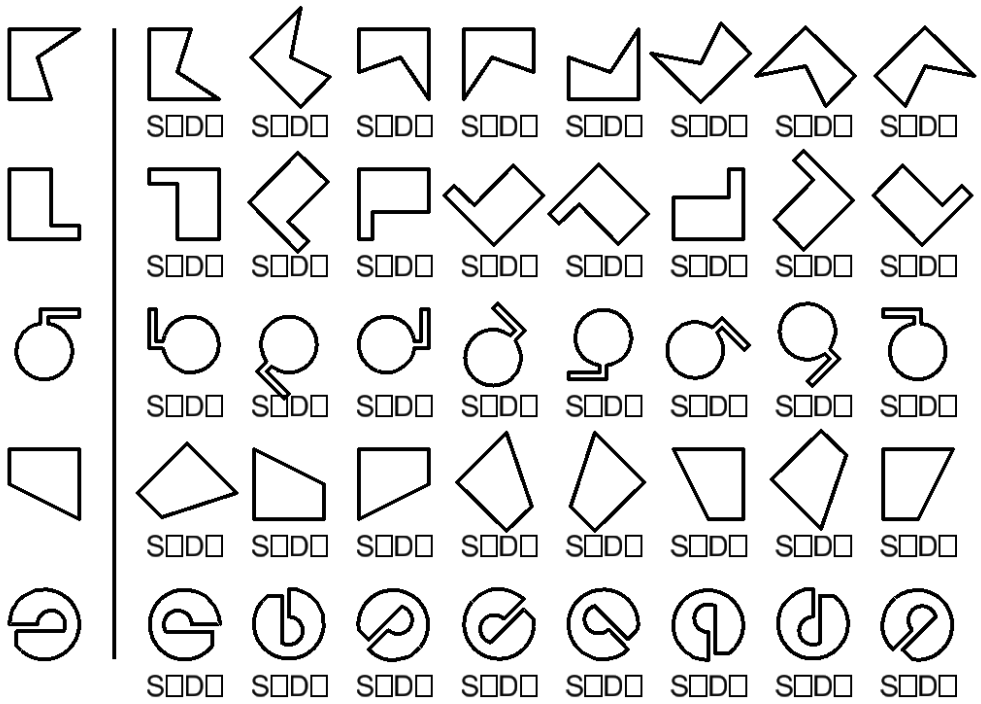
Your score on this test will be the number of items answered correctly minus the number answered incorrectly. Therefore, it will **not** be to your advantage to guess, unless you have some idea whether the card is the same of different. Work as quickly as you can without sacrificing accuracy.

You will have **1.5 minutes** for this test. When you have finished this test, STOP.

Card Rotation Test (1.5 minutes)

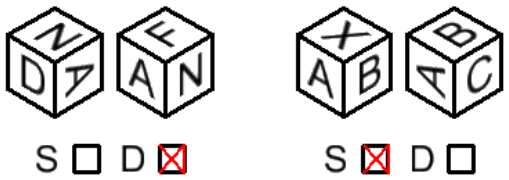
S = same (only rotated)

D = different (flipped and/or rotated)



Cube Comparisons Test

Wooden blocks such as children play with are often cubical with a different letter, number, or symbol on each of the six faces (top, bottom, four sides). Each problem in this test consists of a drawing of pairs of cubes or blocks of this kind. Remember, there is a different design, number, or letter on each face of a given cube or block. Compare the two cubes in each pair below.



The first pair is maked D because they must be drawings of **different** cubes. If the left cube is turned so that the A is upright and facing you, the N would be to the left of the A and hidden, not to the right of the A as is shown on the right hand member of the pair. Thus, the drawings must be of different cubes.

The second pair is marked S because they could be drawings of the **same** cube. That is, if the A is turned on its side the X becomes hidden, the B is now on top, and the C (which was hidden) now appears. Thus the two drawings could be of the same cube.

Note: No letters appear on more than one face of a given cube. Except for that, any letter can be on the hidden faces of a cube.

Work the three examples below.

The first pair immediately above should be marked D because the X cannot be at the top of the A on the left hand drawing and at the base of the A on the right hand drawing. The second pair is "different" because P has its side next to G on the left hand cube but its top next to G on the right hand cube. The blocks in the third pair are the same, the J and K are just turned on their side, moving the O to the top.

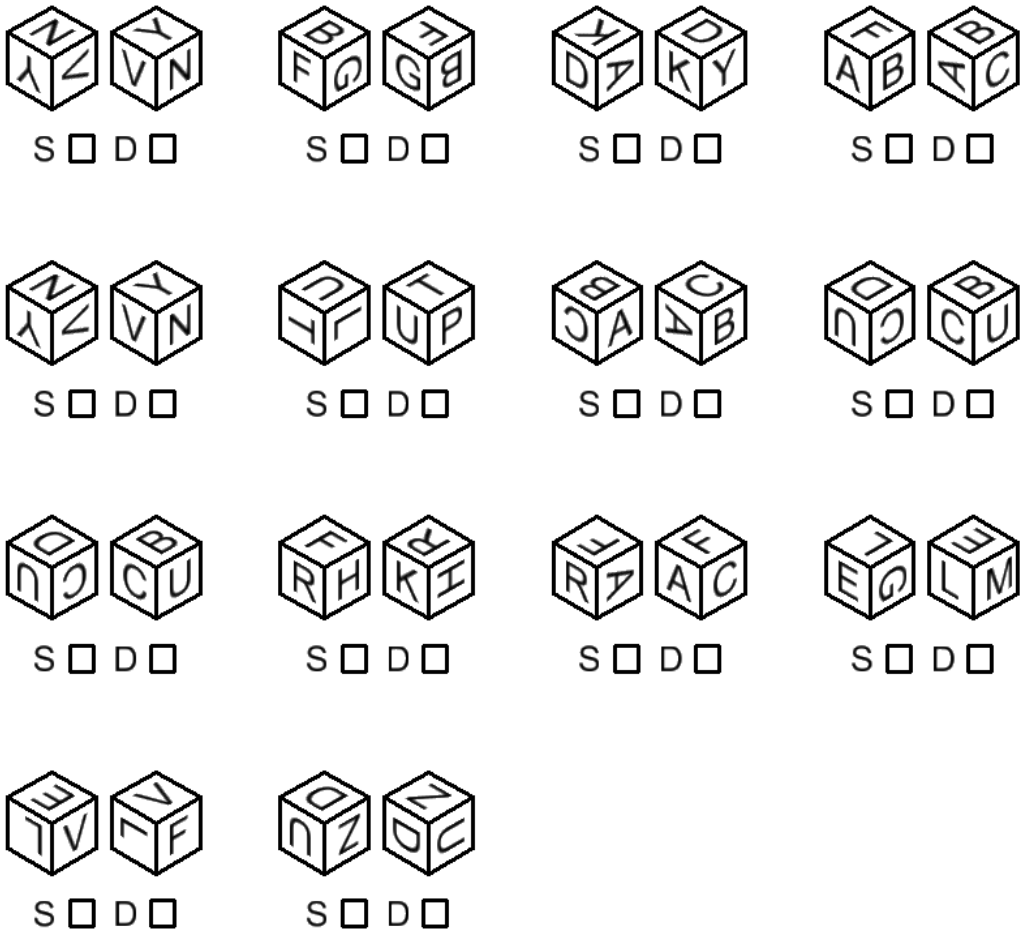
Your score on this test will be the number marked correctly minus the number marked incorrectly. Therefore, it will **not** be to your advantage to guess unless you have some idea which choice is correct. Work as quickly as you can without sacrificing accuracy.

You will have **2 minutes** for this test. When you have finished this test, STOP.

Cube Comparison Test (2 minutes)

S = same (same cube)

D = different (different cubes)



APPENDIX D – Raw Outputs from "R"

This appendix contains the raw outputs for major data analysis items for Chapters 2, 3, and 4.

Chapter 2 – Paper 1

1. Results of Shapiro-Wilk test for normality

Group <fctr>	p_value <dbl>	statistic <dbl>
Paper2D	1.844111e-06	0.7288957
ARLOD300	4.443261e-02	0.8888961
ARLOD400	9.683080e-03	0.8792622

2. Pairwise Comparison for Different Groups

```
Kruskal-Wallis rank sum test
data:  Time_sw by Group
Kruskal-Wallis chi-squared = 13.354, df = 2, p-value = 0.00126
  Kruskal-Wallis rank sum test
data: x and group
Kruskal-Wallis chi-squared = 13.3539, df = 2, p-value = 0

                   Comparison of x by group
                       (Bonferroni)
Col Mean-|
Row Mean |   ARLOD300   ARLOD400
---------+----------------------
ARLOD400 |  -0.459556
       |     0.9688
       |
 Paper2D |   2.572602   3.368640
       |    0.0151*    0.0011*

alpha = 0.05
Reject Ho if p <= alpha/2
$chi2
[1] 13.35391

$Z
[1] -0.4595561  2.5726028  3.3686405

$P
[1] 0.3229174434 0.0050468481 0.0003776994

$P.adjusted
[1] 0.968752330 0.015140544 0.001133098

$comparisons
[1] "ARLOD300 - ARLOD400" "ARLOD300 - Paper2D"  "ARLOD400 - Paper2D"
```

3. Results of Spearman's rank correlation tests

```
        Spearman's rank correlation rho
```

```
data:  Ind73_data$Time_sw and Ind73_data$Age
S = 45858, p-value = 0.01201
alternative hypothesis: true rho is not equal to 0
sample estimates:
    rho
0.2925708
                Spearman's rank correlation rho
data:  Ind73_data$Time_sw and Ind73_data$Card_R
S = 66969, p-value = 0.781
alternative hypothesis: true rho is not equal to 0
sample estimates:
      rho
-0.03309476
                Spearman's rank correlation rho
data:  Ind73_data$Time_sw and Ind73_data$Cube_C
S = 67846, p-value = 0.6953
alternative hypothesis: true rho is not equal to 0
sample estimates:
      rho
-0.04661742
```

Chapter 3 – Paper 2

1. Industry - Task_Time Mixed Effects Model

```
Formula:        Task_Time ~ Inf_For + Age + Card_R + (1 | ID) + (1 | Panel)
Data: Ind98_data
   AIC     BIC   logLik deviance df.resid
 1847.7  1872.5   -915.8   1831.7      156
Random effects:
Conditional model:
 Groups Name        Variance  Std.Dev.
 ID     (Intercept) 9.469e-10 3.077e-05
 Panel  (Intercept) 3.485e-02 1.867e-01
Number of obs: 164, groups:  ID, 98; Panel, 2
Dispersion parameter for nbinom2 family (): 10.6
Conditional model:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)   5.482359   0.173759  31.552  < 2e-16 ***
Inf_ForAR_300 -0.038007   0.063612  -0.597  0.55018
Inf_ForAR_400 -0.113639   0.057429  -1.979  0.04784 *
Age          0.002589   0.002052   1.262  0.20695
Card_R       -0.008132   0.002636  -3.085  0.00204 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

2. Industry - Rework Mixed Effects Model

```
Formula:        Rework ~ Inf_For + Age + Card_R + (1 | ID) + (1 | Panel)
```

```
Data: Ind98_data
    AIC     BIC   logLik deviance df.resid
  563.2   584.9  -274.6    549.2      157
Random effects:
Conditional model:
 Groups Name        Variance  Std.Dev.
 ID     (Intercept) 7.762e-01 8.810e-01
 Panel  (Intercept) 3.773e-09 6.143e-05
Number of obs: 164, groups:  ID, 98; Panel, 2
Conditional model:
             Estimate Std. Error z value Pr(>|z|)
(Intercept)    1.53129    0.52635   2.909  0.00362 **
Inf_ForAR_300 -1.12054    0.22797  -4.915 8.87e-07 ***
Inf_ForAR_400 -0.83115    0.17984  -4.622 3.81e-06 ***
Age           -0.01876    0.01023  -1.834  0.06668 .
Card_R        -0.01405    0.01277  -1.101  0.27108
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

3. Industry - Error Mixed Effects Model

```
Formula:          Error ~ Inf_For + Age + Cube_C + (1 | ID) + (1 | Panel)
Data: Ind98_data
    AIC     BIC   logLik deviance df.resid
  227.8   249.4  -106.9    213.8      156
Random effects:
Conditional model:
 Groups Name        Variance  Std.Dev.
 ID     (Intercept) 4.170e+00 2.042e+00
 Panel  (Intercept) 4.181e-10 2.045e-05
Number of obs: 163, groups:  ID, 98; Panel, 2
Conditional model:
             Estimate Std. Error z value Pr(>|z|)
(Intercept)  -2.835224   1.443639  -1.964   0.0495 *
Inf_ForAR_300  0.552118   0.423875   1.302   0.2034
Inf_ForAR_400  0.093107   0.386503   0.241   0.7230
Age          -0.008316   0.025120  -0.331   0.6034
Cube_C        0.024984   0.097543   0.256   0.7928
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

4. Students – Task Time Mixed Effects Model

```
Formula: log_Task_Time ~ Inf_For + Card_R + (1 | ID) + (1 | Panel)
   Data: Students219_data
REML criterion at convergence: 636.6
Scaled residuals:
    Min      1Q  Median      3Q     Max
-3.9192 -0.5534  0.0324  0.5673  3.2934
```

```
Random effects:
 Groups   Name        Variance Std.Dev.
 ID       (Intercept) 0.06197  0.2489
 Panel    (Intercept) 0.01963  0.1401
 Residual             0.10764  0.3281
Number of obs: 643, groups:  ID, 216; Panel, 3
Fixed effects:
              Estimate Std. Error        df t value Pr(>|t|)
(Intercept)    5.967458   0.115303   7.780998  51.755 3.70e-11 ***
Inf_ForAR_300 -0.035690   0.031761 424.244511  -1.124    0.255
Inf_ForAR_400 -0.168283   0.031714 423.856951  -5.306 1.81e-07 ***
Card_R        -0.011935   0.002784 214.145900  -4.286 2.74e-05 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Correlation of Fixed Effects:
            (Intr) I_FAR_3 I_FAR_4
Inf_FAR_300 -0.136
Inf_FAR_400 -0.139  0.501
Card_R      -0.670 -0.003   0.001
```

5. Students - Rework Mixed Effects Model

```
Formula:          Rework ~ Inf_For + Card_R + (1 | ID) + (1 | Panel)
Data: Students219_data

    AIC      BIC   logLik deviance df.resid
 2198.7   2225.5  -1093.3   2186.7      640
Random effects:
Conditional model:
 Groups Name        Variance Std.Dev.
 ID     (Intercept) 0.36956  0.6079
 Panel  (Intercept) 0.02499  0.1581
Number of obs: 646, groups:  ID, 216; Panel, 3
Conditional model:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)    0.951062   0.222805   4.269 1.97e-05 ***
Inf_ForAR_300 -0.237722   0.076572  -3.105 0.001906 **
Inf_ForAR_400 -0.262272   0.077166  -3.399 0.000677 ***
Card_R        -0.020508   0.007032  -2.916 0.003542 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

6. Students - Error Mixed Effects Model

```
Formula:          Error ~ Inf_For + Cube_C + (1 | ID) + (1 | Panel)
Data: Students219_data

    AIC      BIC   logLik deviance df.resid
 1183.8   1210.6   -585.9   1171.8      639
```

```
Random effects:
Conditional model:
 Groups Name        Variance Std.Dev.
 ID     (Intercept) 0.7050   0.8396
 Panel  (Intercept) 0.1541   0.3925
Number of obs: 645, groups:  ID, 216; Panel, 3
Conditional model:
             Estimate Std. Error z value Pr(>|z|)
(Intercept)   -0.46949    0.35803  -1.311 0.189746
Inf_ForAR_300  0.08335    0.13338   0.625 0.531999
Inf_ForAR_400 -0.53847    0.15731  -3.423 0.000619 ***
Cube_C        -0.07134    0.02991  -2.386 0.017054 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Chapter 4 – Paper 3

1. Paired t-Test Results for Trust Questions (Regardless of the Design Origin)

```
Paired t-test

data:  panel1$Q1_Bef and panel1$Q1_Af
t = 0.31693, df = 97, p-value = 0.752
alternative hypothesis: true mean difference is not equal to 0
95 percent confidence interval:
 -0.2416358  0.3334725
sample estimates:
mean difference
     0.04591837

                Paired t-test

data:  panel1$Q2_Bef and panel1$Q2_Af
t = 3.5334, df = 97, p-value = 0.0006301
alternative hypothesis: true mean difference is not equal to 0
95 percent confidence interval:
 0.2034972 0.7250742
sample estimates:
mean difference
      0.4642857
```

2. Paired t-Test Results for Trust Questions by Design Origin

```
                Paired t-test

data:  panel1_AI$Q1_Bef and panel1_AI$Q1_Af
t = 0.14474, df = 48, p-value = 0.8455
alternative hypothesis: true mean difference is not equal to 0
95 percent confidence interval:
```

-0.3946245 0.4558490
sample estimates:
mean difference
0.03061224

Paired t-test

data: panel1_AI$Q2_Bef and panel1_AI$Q2_Af
t = 3.5374, df = 48, p-value = 0.0009078
alternative hypothesis: true mean difference is not equal to 0
95 percent confidence interval:
0.2554424 0.9282311
sample estimates:
mean difference
0.5918367

Paired t-test

data: panel1_Human$Q1_Bef and panel1_Human$Q1_Af
t = 0.30574, df = 48, p-value = 0.6651
alternative hypothesis: true mean difference is not equal to 0
95 percent confidence interval:
-0.3414072 0.4638562
sample estimates:
mean difference
0.06122449

Paired t-test

data: panel1_Human$Q2_Bef and panel1_Human$Q2_Af
t = 1.6608, df = 48, p-value = 0.1033
alternative hypothesis: true mean difference is not equal to 0
95 percent confidence interval:
-0.07094025 0.74440963
sample estimates:
mean difference
0.3367347

3. Task_Time Mixed-Effects Model

Formula: Task_Time ~ Inf_form * D_origin + Age + Card_R + (1 | ID) + (1 | Panel)
Data: Ind98_data
AIC BIC logLik deviance df.resid
1850.2 1884.3 -914.1 1828.2 153
Random effects:
Conditional model:
Groups Name Variance Std.Dev.
ID (Intercept) 5.176e-10 2.275e-05

```
 Panel  (Intercept) 3.433e-02 1.853e-01
Number of obs: 164, groups:  ID, 98; Panel, 2
Dispersion parameter for nbinom2 family (): 10.8
Conditional model:
                      Estimate Std. Error z value Pr(>|z|)
(Intercept)              5.449433   0.176583  30.860  < 2e-16 ***
Inf_formAR_300           -0.022649   0.087201  -0.260  0.79507
Inf_formAR_400           -0.008875   0.078761  -0.113  0.91028
D_originHuman             0.047100   0.073996   0.637  0.52444
Age                    0.002500   0.002080   1.202  0.22941
Card_R                  -0.007677   0.002665  -2.881  0.00397 **
Inf_formAR_300:D_originHuman -0.064616   0.127195  -0.508  0.61145
Inf_formAR_400:D_originHuman -0.199474   0.113128  -1.763  0.07786 .
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

4. Rework Mixed-Effects Model

```
Formula:         Rework ~ Inf_form * D_origin + Age + Card_R + (1 | ID) + (1 |      Panel)
Data: Ind98_data

    AIC      BIC   logLik deviance df.resid
  580.4    611.4   -280.2    560.4      154
Random effects:
Conditional model:
 Groups Name        Variance  Std.Dev.
 ID     (Intercept) 7.794e-01 8.829e-01
 Panel  (Intercept) 3.272e-10 1.809e-05
Number of obs: 164, groups:  ID, 98; Panel, 2
Conditional model:
                      Estimate Std. Error z value Pr(>|z|)
(Intercept)              1.34558    0.54759   2.457   0.0140 *
Inf_formAR_300           -0.54351    0.26954  -2.016   0.0438 *
Inf_formAR_400           -0.49808    0.23481  -2.121   0.0339 *
D_originHuman             0.09753    0.27065   0.360   0.7186
Age                    -0.01590    0.01017  -1.564   0.1178
Card_R                  -0.01419    0.01309  -1.084   0.2784
Inf_formAR_300:D_originHuman -0.62182    0.42444  -1.465   0.1429
Inf_formAR_400:D_originHuman -0.61084    0.37281  -1.639   0.1013
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

LIST OF ABBREVIATIONS

AR	=	Augmented Reality
VR	=	Virtual Reality
MR	=	Mixed Reality
AI	=	Artificial Intelligence
BIM	=	Building Information Modelling
LOD	=	Level of Detail/Development
HMDDs	=	Head Mounted Display Devices
HMD	=	Head Mounted Display
GD	=	Generative Design
SA	=	Situational Awareness
CD	=	Change Detection
IB	=	Inattentional Blindness
CB	=	Change Blindness
CL	=	Cognitive Load
CLT	=	Cognitive Load Theory
ML	=	Machine Learning
ANN	=	Artificial Neural Network
DL	=	Deep Learning
GAI	=	Generative Artificial Intelligence
GANs	=	Generative Adversarial Networks
VAEs	=	Variational Autoencoders
ACS	=	American Community Survey
NABH	=	National Association of Home Builders
SMEs	=	Subject Matter Experts
MEP	=	Mechanical, Electrical, and Plumbing
AEC	=	Architecture, Engineering, and Construction