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Implementing Virtual Reality-based Design Review in the Construction Industry

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Abstract

Implementing Virtual Reality-based Design Review in the Construction Industry

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Building Information Modeling (BIM)-enabled digitalization has been innovating the entire workflow and information management in the Architecture, Engineering, and Construction (AEC) industry. Emerging visualization technologies such as Virtual Reality (VR) have extended BIM-based 3D visualization to an immersive and intuitive virtual prototyping experience. VR applications have shown their potential for making construction design review tasks more effective and collaborative, thus attracting growing research attention and efforts. However, despite the increasing technological capabilities, the adoption of VR applications has still been lagging in the AEC industry, leaving the theoretical potential unrealized.

One major reason for the gap between the state-of-the-art and state-of-practice is the lack of validation on VR performance. Therefore, the first research question in this dissertation addressed this issue by measuring user performance when undertaking four design review tasks using VR-based or desktop-based devices. The experiment controlled more testbed-related variables, such as functions and navigation methods, than existing VR performance validation research to reveal the contribution exclusively from VR

technology. Results show that VR users can detect significantly more design errors and commit significantly fewer mistakes in scheduling installation sequence when using VR as compared to desktop-based interactions. Experiments in the first research question revealed the lack of approaches to visualize occluded objects in 3D models. In order to facilitate a comprehensive design review, the second research question proposed a semi-automatic occlusion detection framework for building information models. It converts objects in a 3D model to point clouds and overlaps them with a virtual scan of the model to identify occlusion. A ready-to-implement VR application does not guarantee industry adoption because the development cost for VR can be demanding. The last part of this dissertation proposed a Generic Extended Reality (GenXR) model that supports all XR development in the AEC industry. The author compared BIM-to-XR durations in two case studies and six XR prototype development. The result shows that the GenXR model could save over 65% of model transfer time for XR development.

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Chapter 1: Introduction

Effective construction design review and coordination play an indispensable role in financial success in the Architecture, Engineering, and Construction (AEC) industry projects (Mehrbod et al. 2019a). However, the review and coordination processes are challenged by scattered industry organizations and the growing complexity of building systems, such as Mechanical, Electrical, and Plumbing (MEP) systems (Wang and Leite 2016). Consequently, issues such as design errors and inadequate constructability continue causing cost overruns and schedule delays in the AEC industry.

Visualizations supported by Building Information Modeling (BIM) have mitigated some of these issues (Kumar and Cheng 2015, Moon et al. 2015, Kim, Cho, and Zhang 2016, Guo, Yu, and Skitmore 2017, Martinez-Aires, Lopez-Alonso, and Martinez-Rojas 2018). The growing industry acceptance of BIM applications (Hartmann, Gao, and Fischer 2008, Mostafa and Leite 2018) and their beneficial results (Ghaffarianhoseini et al. 2017, Kim et al. 2017) indicate that visualization is a promising solution for these design review tasks. However, BIM has not mitigated design review-related issues as prototyping did in the manufacturing industry (Mujber, Szecsi, and Hashmi 2004, Huang et al. 2007). Currently, BIM software programs were deliberately designed for information integration and processing (Ding, Zhou, and Akinci 2014, Li et al. 2017), and visualization functions were developed to an extent merely sufficient for presenting the information (Ivson et al. 2018b). Enhancing the performance of model-based design and constructability review demands integrating BIM with other advanced visualization and interaction solutions (Seth, Vance, and Oliver 2011, Leite et al. 2016).

Virtual Reality (VR) has been applied in a variety of industries to improve the consistency between product design and its manufacturing process (National Academy of

Engineering 2017). Research in the construction domain also implied that VR can potentially enhance the performance of professionals in construction design review tasks (Wolfartsberger 2019). Theoretically, VR technology empowers industry practitioners to intuitively review and interact with virtual representations of construction projects (Whyte et al. 2000). As a result, they can effectively detect design errors and constructability issues (Johnston et al. 2016). However, the slow progress of VR implementation in the construction industry conflicts with its theoretical advantages. A gap between state-of-the-art and state-of-practice was identified in 2005 and has remained valid since then (Bouchlaghem et al. 2005, Leite et al. 2016). In spite of the increasing amount of VR research conducted after 2011 (Li et al. 2018, Wang et al. 2018), industry generally maintains a conservative attitude towards integrating VR applications into their workflows.

This dissertation aims to facilitate the industrial implementation of VR-based design review applications. Three engineering challenges that impeded VR implementation were identified from the standpoint of performance measurement, field-specific techniques, and collaborative development with other Extended Reality (XR) applications. This dissertation proposed three Research Questions (RQs) that revealed fundamental knowledge gaps in correspondence to identified engineering challenges, which will be discussed in section 1.2. In RQ 1, the dissertation compared user performance between VR users and desktop users in the same design review tasks and used statistical analysis to reveal the variance caused by VR. Next, a point cloud-based algorithm that automatically detects occluded objects in 3D models was developed in RQ 2 to expand the scope of VR-based design review from visible objects to all objects in 3D construction models. Finally, a generic XR model will be developed with a BIM-to-XR framework in RQ 3 to avoid repetitive development efforts when multiple XR applications are used in the same AEC project and consequently, decreasing implementation cost for VR-based design review applications.

1.1 ENGINEERING CHALLENGES

1.1.1 Performance Measurement

Researchers have acknowledged the Head-Mounted Display (HMD) as a defining characteristic of VR in the AEC industry (Kasireddy et al. 2016, Institute 2019). Therefore, clarifying the contribution, or interference, of the HMD to user performance is essential to prove the necessity of VR (Huang, Rauch, and Liaw 2010). Unfortunately, research dedicated to performance comparison between HMD-based VR and best practice of its desktop-based counterpart is still lacking in the construction research domain. Paes, Arantes, and Irizarry (2017) compared user performance in a desktop-based VR environment to a projector-based semi-immersive VR environment. Although this comparison was conducted in a scientific manner, it did not provide direct support to the HMD-based, fully immersive VR experience. Other researchers compared VR performance versus guidebooks (Chittaro and Buttussi 2015), images (Perlman, Sacks, and Barak 2014), presentations (Leder et al. 2019), and 2D drawings (Sampaio and Martins 2014). Although VR applications outperformed these dated methods, their results did not support replacing the current 3D model-based design review with VR applications.

Cross-project comparison of user performance is also challenging due to variances in experimental design. Han and Leite (2020) observed significant variance in user performance due to different VR environment settings. Meanwhile, the quality and quantity of samples can impact the reliability of experimental results (Button et al. 2013). For example, Niu, Pan, and Zhao (2016) observed enhanced user performance in occupancy information integrity in HMD-based VR programs. However, they only validate the results on groups with a maximum of three participants. Their results may include false positives due to limited sample size (Simon and Greitemeyer 2019). To the best of the authors' knowledge, to date, scholars have yet to draw a comparison between HMD-based VR and its desktop equivalent unaffected by extraneous variables in the construction research community.

1.1.2 Visualizing Occluded Objects

The objective of a design review or virtual walkthrough is to comprehensively inspect all relevant objects instead of only inherently visible ones (Neuville, Pouliot, and Billen 2019). However, occluded objects are common in construction models (Liu et al. 2016, Han, Cline, and Golparvar-Fard 2015, Yu, Zhou, et al. 2020). For example, designers can intentionally occlude mechanical, electrical, plumbing, and fire protection (MEPF) systems for aesthetics purposes, and heat insulation occludes pipe spools when processing heated materials in industry facilities. Visualizing such occluded objects in 3D models is a challenge in VR-based design review applications (Johansson, Roupe, and Bosch-Sijtsema 2015, Son, Bosche, and Kim 2015).

Occluded 3D objects can be revealed manually in BIM-based design review applications, although it is an error-prone and time-consuming process (Yu, Liang, et al. 2020, Elmqvist and Tsigas 2007). Mehrbod et al. (2019b) found that navigational interactions constituted over 60% of all participants' interactions in building design coordination meetings, and two out of the 13 recognized navigational interactions aimed to reveal occluded objects. Ivson et al. (2018b) adjusted object transparency to visualize occluded objects in their Building Information Modeling (BIM)-based 4D virtual construction planning application. Neuville, Pouliot, and Billen (2019) found that the lack of visualization tools for occluded objects is a major limitation for BIM-enabled visual tasks. These findings demonstrate that visualizing occluded objects is an indispensable function for design review applications.

Occluded 3D objects also require a revealing function in VR-based design review applications. Researchers in the domain of VR technology developed real-time see-through or highlighting functions for all objects in a 3D model (Feiner and Seligmann 1992, Elmqvist and Tsigas 2007). These functions can automatically identify and reveal occluded objects, but the computational cost increases with the number of objects in the VR model. Currently, a building information model with a level of development (LOD) of 300 or higher can contain thousands or tens of thousands of objects (Meza, Turk, and Dolenc 2014), and many research projects proved the required computational power exceeded what commercially available desktop computers can provide. For example, Yu, Liang, et al. (2020) designed the 3DWedge+ visualization technique that facilitated users' awareness of off-screen and occluded objects in VR. However, their experiments did not show if the technique can support 3D models with thousands of objects. Lin et al. (2018) experienced a similar challenge when attaching an interactive function to all objects in one floor of a hospital model. The real-time computational cost impaired the frame rate and thereby, the performance of their VR-based communication application. These research projects shed light on how occluded objects can be visualized in real-time in VR, but they are neither practical nor efficient for complex models in the construction industry.

1.1.3 Complex and Repetitive Development Process

Despite theoretical benefits, implementing multiple XR applications in different stages of a construction project can be financially challenging for companies in the AEC industry (Lin et al. 2018). The Construction Industry Institute (CII) reported that developers' salary constituted 62% of overall VR investment in pilot projects (Institute 2019). Unfortunately, the developing effort for XR applications is unaffected by whether they leveraged the same BIM or shared similar BIM-to-XR process. Current XR applications were developed in an ad-hoc approach (Li et al. 2018, Zhang, Liu, et al. 2020), and developers lacked knowledge and techniques to avoid the repetitive and time-consuming BIM-to-XR process. Moreover, facilities – and, consequently, their digital twins – commonly experience updates through a construction project's lifecycle (Leite et al. 2016). The lack of seamless information retrieval approaches for XR applications from BIM leads to additional BIM-to-XR iterations.

1.2 Research Vision and Research Questions

This research aims to facilitate VR implementation in design review tasks in the construction industry. The author depicted the following vision when design review or coordination is needed. First, 3D models of different building systems are collected from stakeholders and federated in BIM. BIM-based clash detection is performed to solve hard clashes before moving onto any VR applications.

Then, stakeholders, particularly the general contractor, evaluate if a VR-based design review or coordination meeting is needed based on quantified VR benefits (generated by RQ 1) and the characteristics of the project, such as system complexity and site constraints. The decision may be to implement VR due to the number of remaining issues after a traditional BIM-based design review.

Next, a federated BIM is converted into a generic XR model composed of 3D geometry, relevant information, and links to align BIM objects in VR. The generic XR model supports the development of all XR applications throughout the project lifecycle.

It contains all BIM-supported information required by existing XR applications in an interoperable data format for XR development software systems. In addition, the generic XR model can automatically update itself with an evolving BIM to keep geometry and attached information up-to-date. Thereby, repetitive BIM-to-XR activities can be avoided when the model used in the VR application needs update or when other XR applications are implemented in the same project.

Eventually, a point cloud representation of each 3D object is overlapped with the virtual scan of the federated BIM. The visibility of points determines the visibility of objects, and the generic XR model is separated into one "Occluded model" and one "Visible model" before importing into VR development software systems. The occlusion identification process is automated so that end-users, such as VR developers in construction companies, can simply execute the algorithm as a "black box". Subsequently, highlight effects are implemented to the "Occluded model" during VR development to reveal occluded objects when needed. Both implementing highlight effects and following VR development for design review applications have been well-developed. The three key knowledge gaps in the research vision were explored with the following research questions.

Research Question #1: What is the impact of the Head-Mounted Display (HMD) on user performance in construction design review tasks when compared to desktop-based Virtual Reality (VR)?

- What are the influential factors for user performance in design review? How can factors that are independent of an HMD in experiment design be controlled?
- How can both VR-based and desktop-based user testing environments be developed to their best available practices?

Research Question 2: How can occluded building elements be automatically identified in 3D Models for VR-based construction design review applications?

- What are the appropriate approaches and procedures for occlusion detection in complex construction models which are normally composed of more than 1,000 objects?
- How can the occlusion identification process be automated?

Research Question 3: How can a generic 3D model for BIM-based XR applications throughout the lifecycle of a construction project be developed?

- What are the model and information requirements from existing XR applications in the AEC industry?
- How can information from BIM be retrieved while keeping a comprehensible geometry-information link for VR development software?
- How can model changes be automatically identified so as to update the generic XR model?

1.3 Reader's Guide to the Dissertation

This Ph.D. dissertation is divided into five chapters. Chapter 1 introduced state-of-the-art VR research for construction design review and coordination and discussed engineering challenges associated with VR implementation. The following three chapters answered each research question of this dissertation. Specifically, chapter 2 presents performance measurements for HMD-based VR in design review tasks. Chapter 3 introduces a semi-automatic occlusion detection algorithm for 3D construction models, while Chapter 4 proposes a generic XR model that standardized BIM-to-XR workflow. Notably, Chapters 2, 3, and 4 are each written as stand-alone documents that contain independent introduction, literature review, research method, results, and conclusions sections. Chapter 5 summarizes the dissertation’s findings, contributions, and limitations, and finally, Chapter 6 proposes future research directions.

Chapter 2: Virtual Reality Performance Measurement in Construction Design Review Applications

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As the first and corresponding author of the journal article, Bing Han designed and performed the experiment described in this chapter, performed data analysis, and wrote the manuscript. The co-authors of the journal article, Fernanda Leite and Daniel Oliveira, provided guidance and feedback on the study and manuscript, and revised the manuscript.

2.1 INTRODUCTION

The low efficiency and effectiveness of the construction design review process is a long-lasting challenge for the construction industry (Mehrbod et al. 2019b). With wide industry implementation of Building Information Modeling (BIM), a multi-dimensional representation of the construction project becomes more accessible (Leite 2019). Emerging information technologies, such as Virtual Reality (VR), can leverage the model and support industry professionals in visualization and decision making for construction design review tasks.

VR has been applied in a variety of industries to improve the consistency between product design and its manufacturing process (National Academy of Engineering 2017). Research in the construction domain also implied that VR can potentially enhance the performance of professionals in construction design review tasks (Wolfartsberger 2019). Theoretically, VR technology empowers industry practitioners to intuitively review and interact with virtual representations of construction projects (Whyte et al. 2000). As a result, they can effectively detect design errors and constructability issues (Johnston et al.

2016). However, the slow progress of VR implementation in the construction industry conflicts with its theoretical advantages.

The gap between state-of-the-art VR research and state-of-practice VR implementation was identified in 2005 and has remained valid since then (Leite et al. 2016, Bouchlaghem et al. 2005). Implementing VR in an actual construction project requires investments in workforce, infrastructure, and changes in the existing workflow (Institute 2019). Construction companies need direct and quantitative evidence for the benefits of VR to justify the investment. Unfortunately, in spite of the increasing amount of VR research conducted after 2011 (Li et al. 2018, Wang et al. 2018), the actual contribution from VR technology to specific construction scenarios is still ambiguous. Therefore, the construction industry has maintained a conservative attitude towards integrating VR applications into its workflows, leaving the potential benefits unrealized.

This research aims to identify measurable benefits of VR in construction design review scenarios and facilitate VR implementation in the construction industry. In 2019, The Construction Industry Institute (CII) (2019) defined that Immersive Virtual Reality (IVR) “is a computer-generated virtual simulation that is experienced through Head-Mounted Displays (HMD) and other input–output devices”. HMD closely matches industry requirements in terms of portability and cost (Spanlang et al. 2014). Therefore, this paper derived CII’s definition and developed research and experiments using HMD-based VR in order to keep consistency with industry practice.

This paper bridges the gap between academia and industry by quantitatively measuring the contribution of HMD to construction design review tasks. The authors created four realistic design review tasks and performed between-subject user tests with both construction engineering novices (i.e., graduate students) and industry experts. Researchers measured and compared user performance in an HMD-based VR environment to its desktop-based counterpart. Both testbeds leveraged a game engine and provided equivalent information to users; thereby, the results can shed light on the benefits and limitations of HMD in these applications.

The paper is structured as follows: The first section briefly introduces the motivation of this research. The second section identifies the knowledge gap and presents the theoretical point of departure. The following section establishes the methodology for the user test design and data analysis. The fourth section demonstrates the user performance data and discusses its implications. Finally, the last section draws key conclusions and discusses the limitations of this research.

2.2 Literature Review

2.2.1 Visualization in Construction

Visualizations supported by BIM have already proven their value in communication and collaboration in construction projects (Kumar and Cheng 2015, Moon et al. 2015, Kim, Cho, and Zhang 2016, Guo, Yu, and Skitmore 2017, Rock et al. 2018). Researchers identified a growing industry acceptance of BIM applications (Hartmann, Gao, and Fischer 2008, Mostafa and Leite 2018) and observed beneficial results from these projects (Ghaffarianhoseini et al. 2017, Kim et al. 2017). However, BIM has not yet fully connected design and construction as prototyping has in the manufacturing industry (Mujber, Szecsi, and Hashmi 2004, Huang et al. 2007). BIM-enabled visualizations have been developed to an extent merely sufficient for presenting particular information (Ivson et al. 2018b, Ding, Zhou, and Akinci 2014, Li et al. 2017). Realizing major prototyping functionalities, such as in-depth defect detection and constructability review, requires integrating BIM with other advanced visualization and interaction solutions (Seth, Vance, and Oliver 2011).

Advances in human-model interaction can be an opportunity to complement remaining visualization functions, and HMD-based VR is arguably one of the most practical approaches to reap full benefits through a virtual prototyping process (Huang et al. 2007, Kadir, Xu, and Hammerle 2011, Li et al. 2012). Alsafouri and Ayer (2018) reviewed currently available Information and Communication Technologies (ICTs) and concluded that HMD-based VR transcended many other competitors for information flow between virtual and realistic environments. In addition, Heydarian et al. (2015) and Maffei et al. (2016) both found that HMD-based VR can push the envelope of virtual experiences to their corresponding real-world situations. Therefore, HMD-based VR can be a promising technology for construction design review tasks.

2.2.2 Established VR Applications

Established VR research experiments and industrial applications in the construction industry include design review or optimization (Motamedi et al. 2017), preconstruction planning (Waly and Thabet 2003), skill or safety training (Manca, Brambilla, and Colombo 2013, Garcia et al. 2016, Perlman, Sacks, and Barak 2014), and remote communication and collaboration (Le, Pedro, and Park 2015, Zaker and Coloma 2018). Unfortunately, when narrowing the scope down to HMD-based VR, qualified projects become scarce and recognized ones were developed in an ad hoc approach (Li et al. 2018). Du et al. (2018) developed a cloud-based platform that promoted collaborations among remote stakeholders by HMD-based VR. Boton (2018) proposed a comparable HMD-based VR environment for collaborative constructability analysis meetings. Shi et al. (2019) applied HMD-based VR to evaluate the effectiveness of training approaches for construction workers. Teizer et al. (2013) combined location-tracking data with an HMD-based VR-enabled training program to enhance ironworkers' safety awareness and productivity. These projects developed HMD-based VR applications and demonstrated their potential for various use cases. However, they failed to provide scientific data on user performance to support industry implementation of these applications.

2.2.3 Performance Measurement Issues

Clarifying the contribution (or interferences) of an HMD to the aforementioned applications is essential to prove its necessity (Huang, Rauch, and Liaw 2010). Unfortunately, research dedicated to the performance comparison between HMD-based VR and its desktop-based counterpart is lacking in the construction research domain. Paes et al. (2017) compared user performance in a desktop-based VR environment to a projector-based semi-immersive VR environment. Although this comparison was conducted in a scientific manner, it did not provide direct support to the HMD-based, fully immersive VR experience.

Cross-project comparison of user performance is also challenging due to variances in experimental design. Researchers compared user performance in HMD-based VR with different traditional competitors in different projects, such as 2D images, drawings, and texts (Sampaio and Martins 2014, Perlman, Sacks, and Barak 2014, Leder et al. 2019). Even with the same competitor, Han and Leite (2020) observed significant variance in users' performance due to differences in the VR environment setting. Meanwhile, the quality and quantity of samples can impact the reliability of experimental results (Button et al. 2013). For example, Niu et al. (2016) observed enhanced user performance in occupancy information integrity in HMD-based VR programs. However, they only validate the results on groups with a maximum of three participants. Their results may include false positives due to the limited sample size (Simon and Greitemeyer 2019). To the best of the authors' knowledge, to date, scholars have yet to draw a comparison between HMD-based VR and its desktop equivalent unaffected by extraneous variables in the construction research community.

User performance in VR applications has been extensively researched in the field of human-computer interaction (HCI). Proxies for the effectiveness of HCI can be automatically measured and documented via different sensing technologies. Zou et al. (2019) designed an electroencephalograph (EEG)-based sensing system for measuring human responses during the VR experience. Ergan et al. (2019) combined the system with galvanic skin response (GSR) data and utilized the system to quantify occupants' stress and anxiety in different architectural designs. Similarly, Wang et al. (2019) connected the thermal condition of an indoor environment with occupants' mental workload and task performance using EEG. Researchers also utilized EEG and electrocardiogram (ECG) signals for emotion recognition (Katsigiannis and Ramzan 2018), eye-tracking data for facial expression recognition (Hickson et al. 2019), and business development (Meissner et al. 2019). These research projects demonstrate objective descriptions of participants' biological status. However, mapping these conceptual data sets with user performance on specific tasks in the construction workflow is still challenging considering the myriad influential factors, such as users' emotional responses and resting conditions (Piumsomboon et al. 2017). Although these projects shed light on the mechanism of HCI in VR, these proxies cannot be directly interpreted as user performance in the construction industry.

2.2.4 Knowledge Gap

This paper recognized the lack of HMD-based VR performance measurement that exclusively focused on the contribution of HMD as a major knowledge gap. Contemporary HMD-based VR experiences are typically composed of 3D models, game engine-enabled functions, and one or more HMDs. Considering that most HMD-based VR contents can be displayed on a computer monitor while still maintaining fundamental functionalities, this paper posed the following research question, asking 'What is the impact of the HMD on user performance in construction design review tasks when compared to desktop-based VR?' In this paper, 'desktop-based VR' refers to the VR-ready contents experienced via a computer monitor, keyboard, and mouse. Filling this gap in knowledge can strengthen the theoretical foundation of HMD-based VR capability in the construction research domain. In the meantime, it provides guidance to the industrial implementation of HMD-based VR applications.

2.3 METHODOLOGY

This research compared user performance between HMD-based VR and desktop-based VR in a series of construction design review tasks. Figure 2-1 demonstrates the research approach of the comparison with three color-coded key components. Researchers developed four design review tasks as well as performance metrics. Related activities are shown in green in Figure 2-1. Then, two testbeds were created for HMD-based VR and desktop-based VR experiments, see activities represented in blue in Figure 2-1. The two testbeds satisfied all the required functions from the four tasks and maintained the equivalence of model and functionalities from a software standpoint. Finally, forty-eight participants performed the user test with one researcher observing and measuring their performance. Researchers conducted statistical analyses to identify correlations between user performance and the equipment they used or their industry experience, see activities represented in yellow in Figure 2-1. The following subsections introduce these steps in detail.

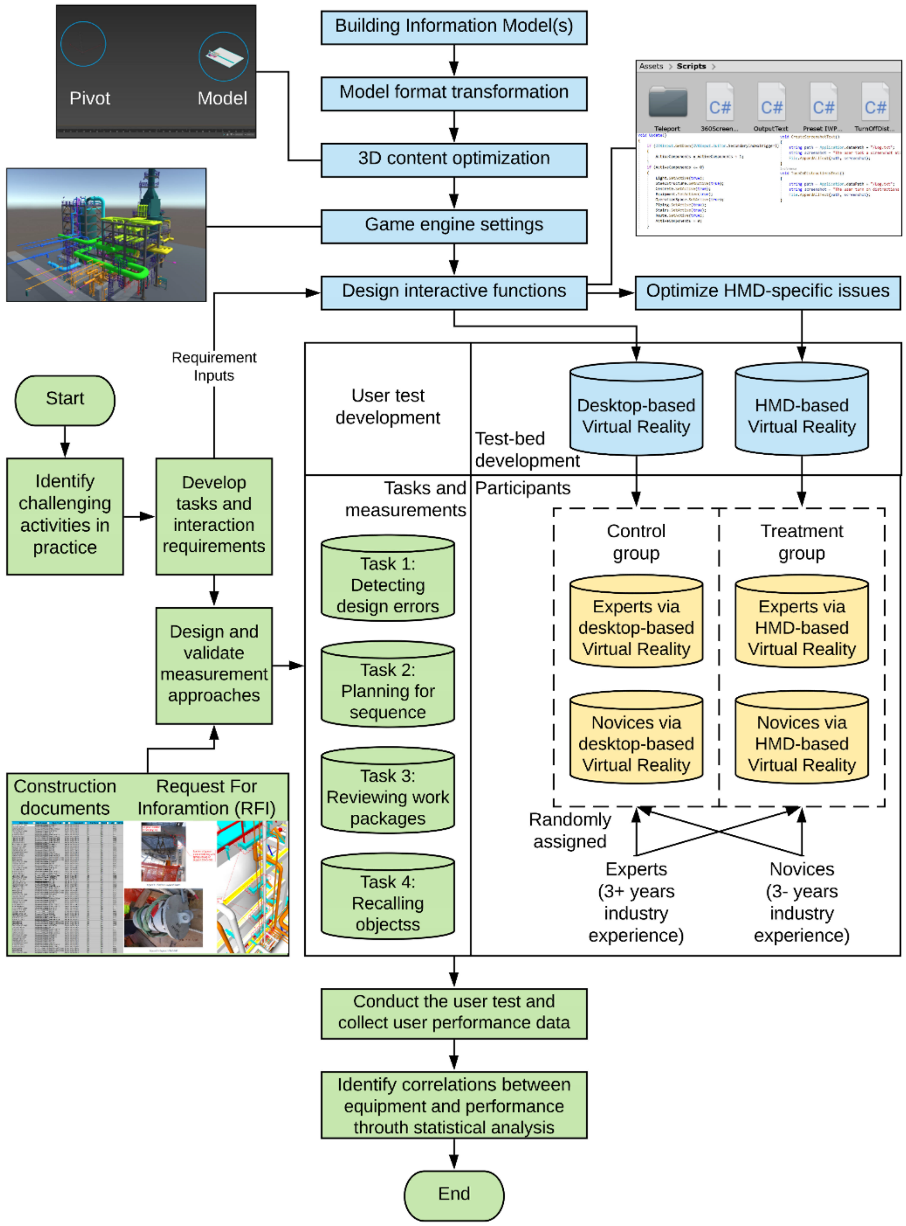
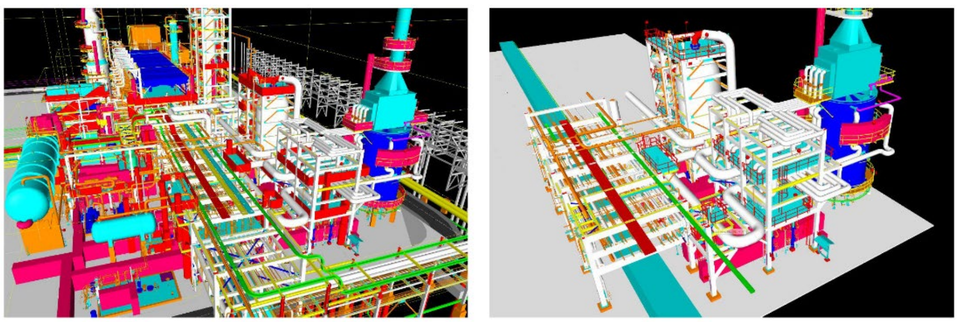


Figure 2-1: Research approach for user tests between HMD-based VR and desktop-based VR

2.3.1 Background Project of the User Test

User tests were conducted using a model for an existing gasoline refinery facility. The testbed is composed of a crucial section of a processing unit, where the feed gasoline is heated to a high temperature to initiate the process of reducing chemical pollutants. Figure 2-2 shows the overall facility and the testbed model in a BIM environment. The facility mainly consists of concrete and steel structure, a large heat reactor, piping systems for gasoline circuits, and supporting equipment.



(a) **(b)**

Figure 2-2: The BIMs of (a) the whole facility and (b) the testbed area

The actual construction team of the facility proposed four challenging activities in their workflow, namely detecting design errors, construction sequence planning, reviewing work package completeness, and recalling the scope of work packages. All tasks focused on the piping system in the testbed area because of its geometric complexity.

Each challenging activity was converted into one task in the user test. User performance in all tasks was quantitatively measured by end results in order to maintain consistency between experiments and real-world industry practices. Researchers acquired project planning and executing files from the construction team, including:

- A federated model that contains all permanent objects in the facility;
- Work packaging files of piping systems with construction sequence; and
- Requests for Information (RFI) submitted by workers during construction.

With this available data, the research team developed tasks that could replicate user behavior and performance in real-world scenarios.

2.3.2 Experimental Design and Data Collection Methods

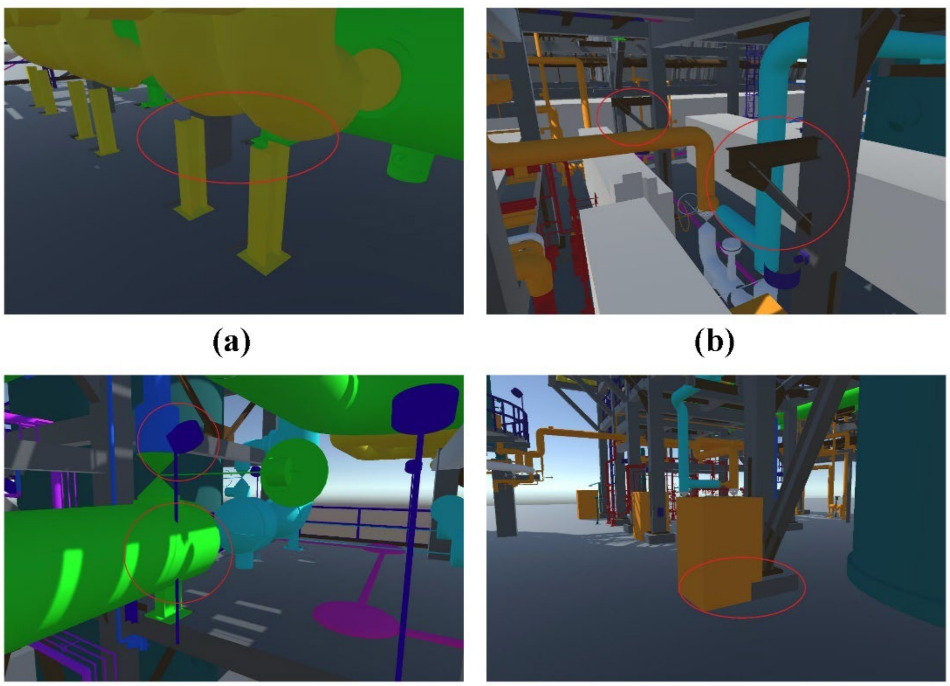
2.3.2.1 Task 1: Detecting Design Errors

In Task 1, participants were instructed to review the piping system via a virtual walkthrough and try to detect all remaining design errors in the model. In a federated BIM, most hard clashes can be detected by a geometry-based clash detection process. However, design errors that do not lead to physical clashes can elude the detection algorithm, and this situation poses a challenge to construction professionals.

The authenticity of preset design errors determines the credibility of user performance data. Targets in this task were common design errors that cannot be detected by BIM-based clash detection. To this end, design or constructability issues discussed in RFIs were directly used as target errors. Moreover, researchers collected error samples with six Subject-Matter Experts (SMEs) from different construction companies in the oil and gas industry and replicated these errors in the user test model. These SMEs committed 10 hours per month for one year to the development of this research. They have 21.33 years of industry experience, on average, with a Standard Deviation (SD) of 4.89. Eventually, three categories of errors were used for this task.

- Design errors that do not cause physical clashes, such as the lack or redundancy of pipe support, see Figure 2-3 (a) and (b);

- Clashes caused by items that were not included in clash detection, such as a temporary lighting system, see Figure 2-3 (c);
- Clashes caused by modifications performed after clash detection, for example, vendors may change equipment size after the design is complete, see Figure 2-3 (d).



(a) **(b)**

(c) **(d)**

Figure 2-3: Examples of target design errors in Task 1 - detecting design errors

Researchers embedded eleven design errors that fall in these three categories in both VR testbeds. One investigator monitored the entire virtual walkthrough process for each participant and documented every participant-detected error in a checklist. Each hit counted as one point in the result.

2.3.2.2 Task 2: Installation Sequence Planning

The second task required participants to plan for the installation sequence of the piping system. In practice, the construction team developed work packages for the piping system in order to streamline the planning and execution process. Each work package contains approximately 1,000 work hours so that one crew of workers can install the work package in one week. In Task 2, researchers retained the original work package settings and color-coded the nine work packages that participants should focus on, as shown in Figure 2-4. During the user test, researchers introduced how work packages can be used in the sequence planning process and answered all related questions from participants. Then, participants were required to identify relationships among the nine work packages and create (1) a general installation sequence when one crew of workers is available, and (2) a fast-track installation sequence if two crews of workers are available.

This task measured user performance by the cumulative errors committed in participants' replies because multiple sequences would function well in practice. Researchers explored the key decision-making principles for setting sequences with the same group of SMEs and the construction team of this project. The major considerations for the viability of a sequence included the object dimension, its connections with other work packages, and the elevation where the installation would occur. A thorough list of 29 possible mistakes in the installation sequence was then compiled and validated. User performance in this task was measured by comparing users' installation sequences with these mistakes. Each hit counted as one point in the result.

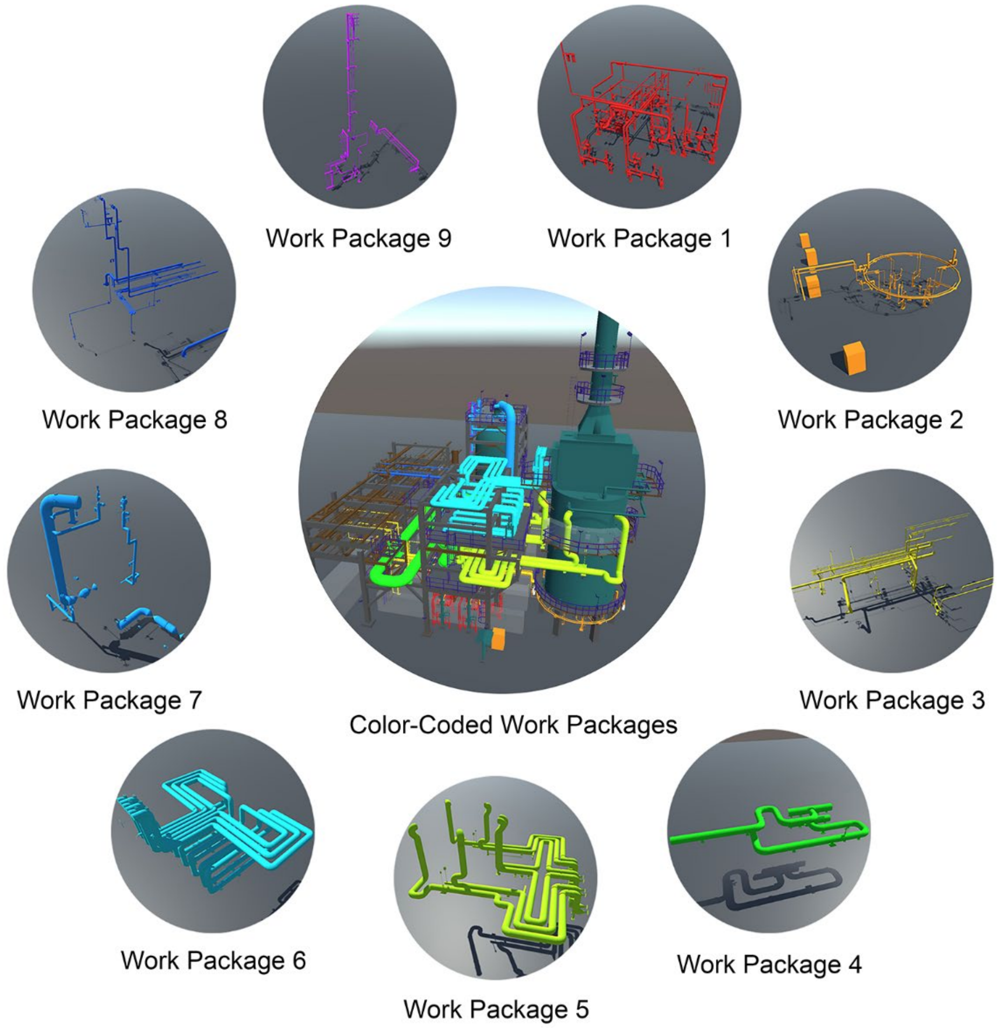


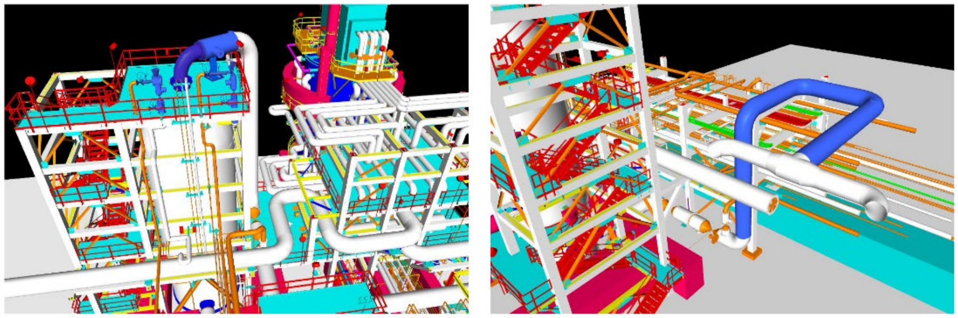
Figure 2-4: Work packages of piping system in the testbed model

2.3.2.3 Task 3: Reviewing the Completeness of Work Packages

The next work package-related task focused on identifying objects that were located in the testbed area but did not belong to any work packages. This task is critical since engineers and workers would plan and install the piping system based on work packages and therefore, overlook those objects. Unlike Task 1, this task measures users' ability to review the information attached to objects as opposed to the geometric characteristics of objects. The real-world project files contained two leftover objects, and each error was replicated once in similar situations. Participants were instructed to identify these objects. Each hit on the target objects counted as one point in the result.

2.3.2.4 Task 4: Recalling Objects

The last task measures the impact of HMD on users' memory. Researchers selected ten objects located in the interface areas between the nine work packages and other systems (see Figure 2-5). Five of the selected objects were part of the nine work packages. All Task 4 test-takers received a follow-up questionnaire with screenshots of these objects ten days after their original user test. Only questionnaires that were replied to within two days were presented in this paper. Participants could answer "inside" or "outside" the scope of the nine work packages for recognized objects, or reply "not sure" for objects they found difficult to recall. According to the potential impact of their memory and confidence, correct, not sure, and incorrect answers earned participants three, one, and zero points, respectively. This paper assumed that the three answers reflected the user's reaction when they receive an RFI. Answers with certainty should lead the user to a memory-based decision-making process. In cases where a "not sure" answer was provided, the user would review the model again for more information before making a decision. SMEs suggested this scoring system because it graded the potential impact of user's memory on the project.



(a) (b)

Figure 2-5: Memory test objects (a) inside and (b) outside the scope of work packages

2.3.3 Testbeds Development

The concept of a "fair" comparison for technology performance was the most innovative characteristic in the experimental design. Besides commonly discussed factors, such as demographics, this paper promoted the fairness of the comparison by two essential elements. First, all technologies should provide users with equivalent content and functionalities to the greatest extent possible. In this experiment, desktop-based VR users and HMD-based VR users reviewed identical models and interacted with the virtual environment with the same functions. Second, each involved technology should be implemented to the best of its current functionality (Joseph J. LaViola 2000). Therefore, the interaction equipment became the only testbed-related variable in the user tests.

Building information models required various modifications before they could be experienced through the HMD-based VR. Han and Leite (2020) developed a model transformation framework and achieved a 47% enhancement of user performance in a best-case scenario. This paper derived their framework for developing both HMD-based VR and desktop-based VR testbeds, see Figure 2-6. Generally, a VR testbed development begins with one or several building information models. Developers applied Autodesk® Navisworks® to convert the 3D model of the target area from an NWD file to an FBX file, which connected 3D models with the VR environment. Then, Autodesk® 3ds Max® and Blender® were used for performing essential optimizations on 3D contents. Finally, both the HMD-based VR and the desktop-based VR testbeds were developed in Unity3D®. Appendix B presents more details in software settings.

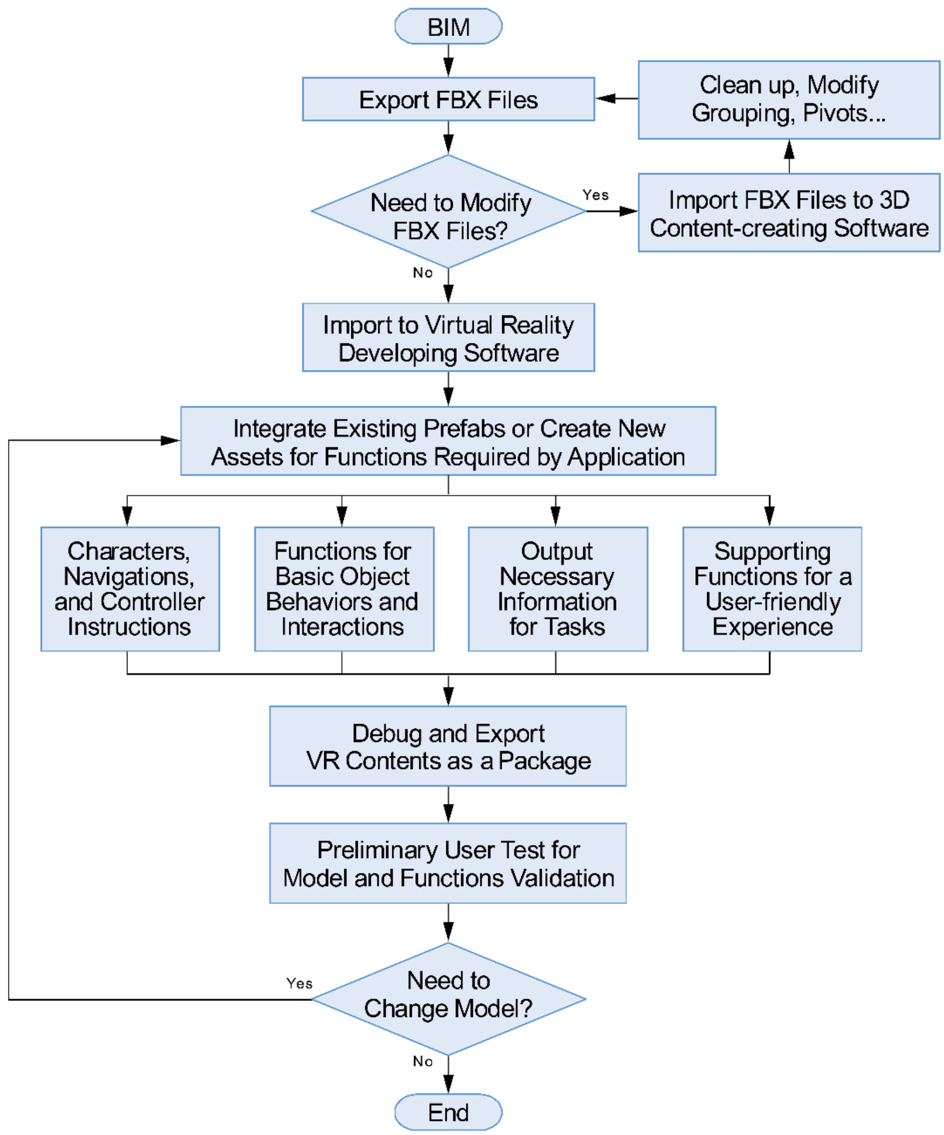
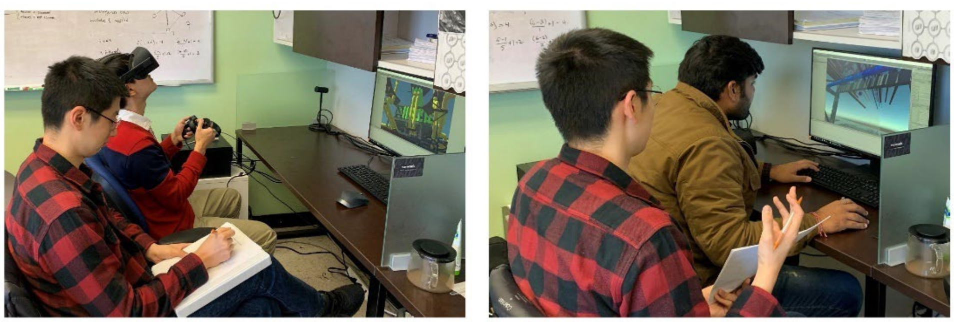


Figure 2-6: Model transformation procedures from BIM to VR

2.3.4 User Test Procedures

Researchers performed a between-subject experiment considering that users' memory on experiment content can impact their performance (Niu, Pan, and Zhao 2016, Garcia et al. 2016, Sacks, Perlman, and Barak 2013, Du, Shi, et al. 2018). The human-involved experiment presented in this paper was reviewed and approved by the University of Texas at Austin's Institutional Review Board (IRB).

Before the user test, qualified participants were randomly divided into two groups: those using HMD-based VR in the user test and the others using desktop-based VR (see Figure 2-7). In this paper, the HMD-based VR group was also referred to as "the treatment group", while the desktop-based VR group was referred to as "the control group".



(a) **(b)**

Figure 2-7: User tests in (a) HMD-based VR group and (b) desktop-based VR group

Earlier research revealed that users' field experience or established habits can significantly influence users' performance in HMD-based VR applications (Aggarwal et al. 2006, Thomsen et al. 2017). Therefore, participants were further labeled as "expert" or "novice" based on their full-time working experience in the construction industry. SMEs proposed that three years of industry experience can be a reasonable threshold for adequate amount of knowledge on construction projects and workflows.

The user tests started with a brief introduction to the research background, procedure, tasks, and safety precautions. Participants would then perform all tasks via the hardware assigned to their group, one at a time with the order from one to four. One investigator monitored the entire test and answered any questions that were not related to what was being measured. All participants were instructed to cease the experiment whenever they experienced physical or emotional discomfort. Researchers did not encounter such cases in this experiment. Since the research mainly focused on effectiveness, the user tests did not have a limitation on the test duration. Participants performed all tasks in, on average, 20 minutes and 6 seconds with an SD of 5 minutes and 18 seconds. Table 2-1 shows the number of data samples collected in each task. Researchers ceased collecting data from Task 3 after acquiring correct answers from all 24 participants. The noticeably lower number of data samples in task 4 was caused by the limited response rate to the follow-up questionnaire. The questionnaires used in this experiment are attached in Appendix C.

Group	Error detection	Sequencing planning	Completeness review	Recalling objects
Experts - HMD-based VR	12	12	6	4
Experts - desktop-based VR	12	12	6	4
Novices - HMD-based VR	12	12	7	6
Novices - desktop-based VR	12	12	5	6
Total	48	48	24	20

Table 2-1: Data samples collected in each task

2.3.5 Participants

Participants included 24 construction engineering graduate students and 24 construction industry professionals. All participants were assumed to possess sufficient background knowledge on all tasks. The research team recruited graduate students via email. CII helped recruit engineers and project managers in the oil and gas industry, via their Board of Advisors. All users volunteered their time to participate in this research.

This paper collected the demographics of participants that may impact experimental results, see Table 2-2. The potential influence of participants' former experience with VR was mitigated by a training program. Before performing any task, researchers demonstrated device operations to HMD-based VR users and provided an opportunity for these users to practice inside the HMD-based VR environment. Researchers did not limit the duration of the training program, and participants would perform the user tests only after they felt confident about the operations. On average, users practiced for five minutes. The age and gender of participants are not in the scope of this research, and they did not show a statistically significant impact on user performance in existing research. Therefore, this paper made the assumption that potential differences in users' age and gender in each group had no significant impact on user performance and accepted the fluctuations without creating more groups. This setting helped this paper focus its resources on the two major independent variables.

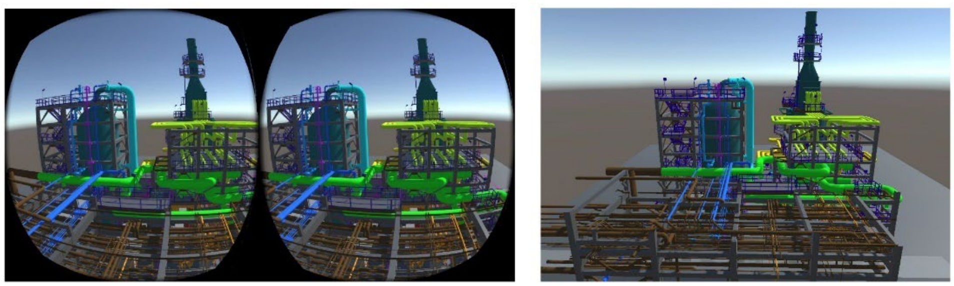
Characteristics	Number (%)
Average age ± SD, years	35.23 ± 10.94
Gender	
Male	32 (66.67%)
Female	16 (33.33%)
HMD-based VR Experience	
Never used HMD	43 (89.58%)
Used HMD before	5 (10.42%)

Table 2-2: The demographics of the experiment participants

2.3.6 Equipment for Testing

The HMD-based VR group conducted the user tests via an Oculus® Rift Commercial Version 1 (CV1) VR system, which comprises one HMD, two touch controllers, and two motion trackers. The tethered HMD was selected to take advantage of the computing power from the dedicated workstation for processing and rendering complex, real-world models. In this experiment, the HMD displayed contents in 1080×1200 resolution per eye at a 90 Hz refresh rate and a 110° Field of View (FoV).

Participants in the desktop-based VR group reviewed the model through one 27-inch 4K display and interacted with the virtual environment through one keyboard and one mouse. Figure 2-8 demonstrates the model visualization effects for the HMD-based VR group and the desktop-based VR group.



(a) (b)

Figure 2-8: Model visualization via (a) Oculus® Rift CV 1 HMD and (b) 4K monitor

A Dell® Precision 3630 Tower Workstation was used to process and render tasks for both visualization media. The configuration of the workstation included one 6-core Intel® Core™ 8700K @ 3.70GHz, one Nvidia® GeForce® GTX 1080 graphics card, 32GB DDR4 2666 MHz memory, and 1 TB PCIe solid-state drive. All hardware functioned as intended during the user tests.

2.3.7 Statistical Analysis

Our general hypothesis in this user test is that HMD-based VR users achieve higher scores in each design review task, compared to desktop-based VR users. Industry experience and visualization devices were the two categorical independent variables, while the score in each task was considered as the discrete dependent variable. Considering the intrinsic different requirements on the four tasks, the performance scores in each task were analyzed separately. Therefore, four individual hypotheses were developed for testing, including:

1. HMD-based VR users detect more design errors than desktop-based VR users in Task 1;
2. HMD-based VR users commit less errors in their schedules than desktop-based VR users in Task 2;
3. HMD-based VR users detect more unassigned objects for Work Packages than desktop-based VR users in Task 3; and
4. HMD-based VR users get a higher score for their object recall performance than desktop-based VR users in Task 4.

The hypotheses were tested using user performance data collected from Task 1 to Task 4. Researchers applied Analysis of Variance (ANOVA) to identify correlations between variables from collected user performance data. An independent t-test was performed to explore the correlations between scores and each independent factor, respectively. Then, a logistic regression-based ANOVA was conducted to determine whether there was statistical significance when considering the two independent variables at the same time. The significance level of the t-value and p-value was set to 0.05.

2.4 Results and Discussion

This section presents the major findings from the user tests. The performance data in each task is exhibited by the mean values and SDs on a group basis. The following statistical analyses on Task 1 and Task 2 revealed the relationship between user performance and visualization equipment or industry experience. At the end of this section, researchers discussed the benefits and limitations of HMD-based VR, its feasibility in construction, and appropriate use cases.

2.4.1 Mean Scores and Standard Deviations

Figure 2-9 depicts the participants' scores of each group in Task 1 - detecting design errors. Among these groups, the experts in the HMD-based VR group earned the highest mean score of 6.42 with an SD of 2.31, followed by the novices in the HMD-based VR group with a mean score of 4.50 and an SD of 2.47. Experts in the desktop-based VR group performed similarly to the novice-HMD group, scoring 4.33 on average with a 1.16 SD, while novices in the desktop-based VR group received the lowest score of 2.83 with a 1.12 SD. On average, experts in the treatment group detected 48.27% more design errors than those in the control group, while novices in the treatment group detected 59.01% more errors than the control group.

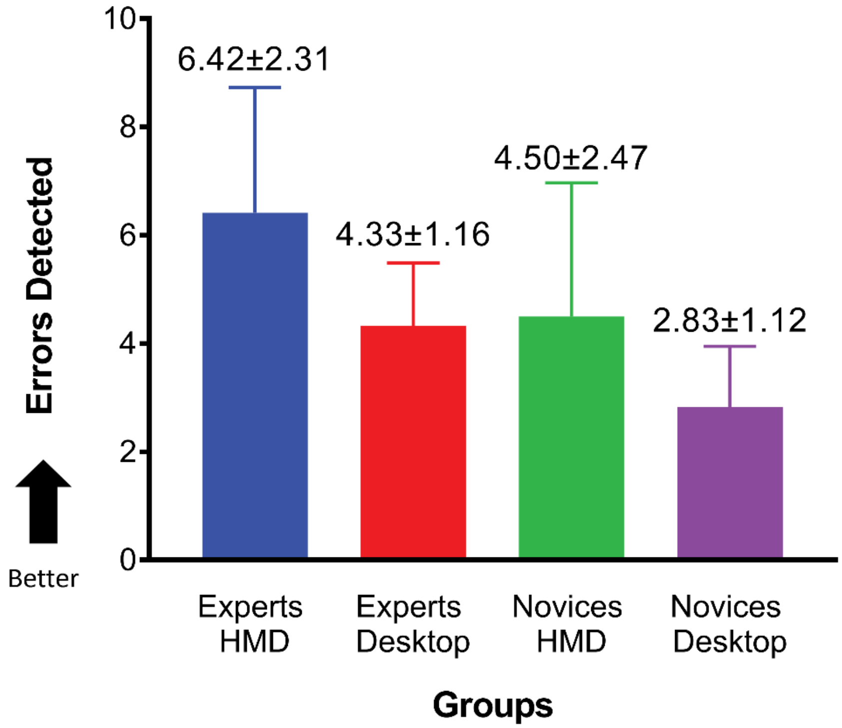


Figure 2-9: Scores from different groups in Task 1 - detecting design errors

User performance in Task 2 - installation sequence-planning is shown in Figure 2-10. In this task, researchers tallied the number of committed errors to quantify user performance. Therefore, the lower the number, the better the measured performance. The means and SDs of user performance in each group are 3.88±2.23 for experts in the HMD-based VR group, 5.25±1.16 for novices in the HMD-based VR group, 5.83 ±1.88 for experts in the desktop-based VR group, and 6.42±1.41 for novices in the desktop-based VR group. In this task, experts in the HMD-based VR group decreased errors committed in their installation sequence by 33.45%, comparing to experts in the desktop-based VR group. Novices in the HMD-based VR group also committed 18.22 % fewer mistakes in their sequences than novices in the desktop-based VR group.

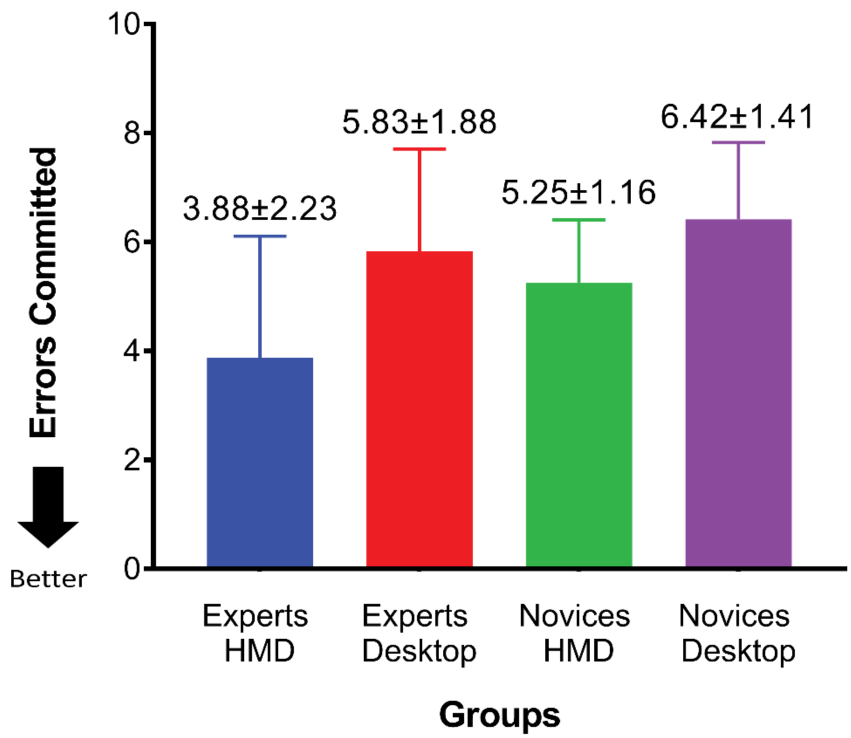


Figure 2-10: Scores from different groups in Task 2 - installation sequence planning

In Task 3 - reviewing the completeness of work packages, all participants, despite their differences in experience and visualization equipment, pinpointed every leftover object in the model. As a result, researchers did not perform any analysis on the third task result and only discussed the implications of this result in the next section.

Figure 2-11 presents user performance in Task 4 - recalling objects. The means and SDs of the scores that participants earned for this task were 18.83±4.36 in the novices-desktop group, 17.00±3.16 in the experts-desktop group, 16.50±5.24 in the novices-HMD group, and 13.50±3.78 in the experts-HMD group. Unlike task 1 and task 2, experts in the HMD-based VR group scored 20.59% lower in the memory test.

Novices in the HMD-based VR group also received 12.37% lower scores than the novices in the desktop-based VR group.

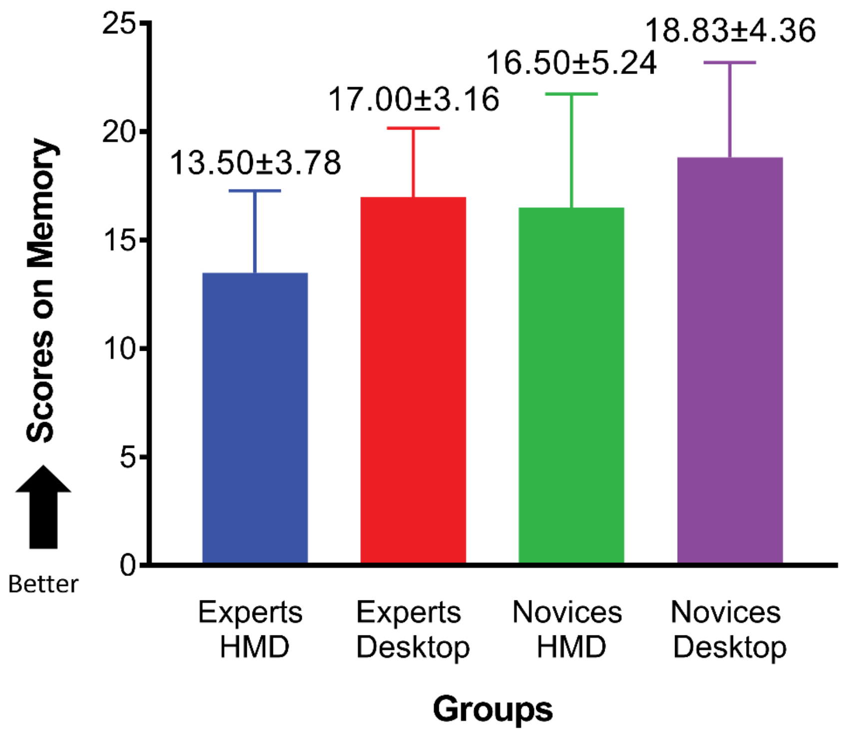


Figure 2-11: Scores from different groups in Task 4 - recalling objects

2.4.2 Analysis of Variance

Researchers first applied independent sample t-tests to analyze the causality between scores and equipment deployed, see Table 2-3. The HMD-based VR users detected significantly more design errors than that of the desktop-based VR users. The HMD-based VR users also made fewer mistakes than desktop-based VR users ($p=0.004$) in the sequencing task due to the difference in equipment. User performance in Task 3 and Task 4 was not included in the statistical analysis considering the limited data samples.

Factors and statistics	Error detection - HMD	Error detection - Desktop	Sequence planning - HMD	Sequence planning - Desktop
Sample size	24	24	24	24
Mean scores	5.46	3.58	4.56	6.13
Standard deviations	2.54	1.35	1.87	1.65
Significance (p-value)	0.003*		0.004*	

Note: Results that showed statistical significance are marked with an asterisk

Table 2-3: Results from independent sample t-tests between use case and visualization equipment

Researchers conducted the same independent sample t-test to analyze the impact of industry experiences on user performance. Table 2-4 shows industry experience had significant influences on users' scores in Task 1 (p=0.006) but not in Task 2 (p=0.076).

Factors and statistics	Error detection - Novices	Error detection - Experts	Sequence planning - Novices	Sequence planning - Experts
Sample size	24	24	24	24
Mean scores	3.67	5.38	5.83	4.85
Standard deviations	2.06	2.08	1.40	2.25
Significance (p-value)	0.006*		0.076	

Table 2-4: Results from independent sample t-tests between use cases and users' industry experience

Subsequently, researchers applied a linear regression analysis to reveal the connections between users' scores in each task and the two independent variables. The analysis demonstrated similar results to the t-test, see Table 2-5. The number of mistakes committed in the scheduling task was associated with visualization devices (p=0.003) but not with users' industry experience (p=0.054). In the error detection task, the number of detected errors were significantly impacted by both users' industry experience (p=0.003) and visualization devices (p=0.001).

Factors and statistics	Error detection - Devices	Error detection - Experience	Sequence planning - Devices	Sequence planning - Experience
Nominalized Coefficient β	-0.426	0.389	0.412	-0.258
t-statistic	-3.502	3.191	3.163	-1.982
p-value	0.001*	0.003*	0.003*	0.054

Table 2-5: Linear regression of scores considering both variables

2.4.3 Discussion

2.4.3.1 Task 1: Detecting Design Errors

The experimental results from the error detection task indicate that the HMD can reinforce participants' perceptions of details in the 3D model. The intuitive navigation approach and stereopsis are likely to be game changers. Researchers observed that participants were generally not capable of pinpointing design errors immediately when they appeared in users' scenes. Instead, the trivial nature and overlapping layout of design errors require reviewers to observe conspicuous targets from various desirable perspectives before making a judgment. The vast majority of participants in all groups endeavored to gain preferable perspectives during the user test. Acquiring these perspectives can be challenging and time-consuming (Mehrbod et al. 2019b), and the intuitive navigation method reproduced by an HMD assisted users in acquiring these perspectives.

User performance in Task 1 was also significantly influenced by participants' industry experiences. On the one hand, this result reflects the knowledge disparity between novices and experts. Although the task was designed to avoid knowledge-based judgments, experts typically review more efficiently with target objects in mind. On the other hand, established reviewing patterns or habits may impair experts' performance in this task. Design review in contemporary construction industry workflow is generally accomplished by collaborations among experts from different fields (Shen et al. 2010, Merschbrock and Munkvold 2015). Therefore, experts spontaneously paid more attention to their routine responsibilities rather than following instructions and reviewing the model comprehensively. As a result, better expert performance can be expected in real-world scenarios, where individuals with disciplinary-specific expertise collaborate in the review process.

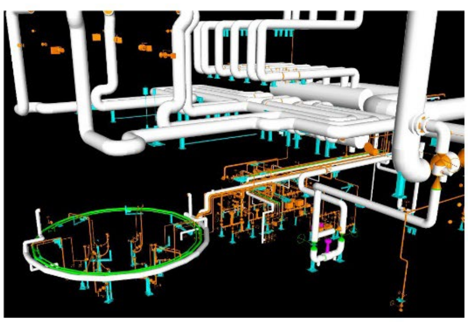
2.4.3.2 Task 2: Installation Sequence Planning

The HMD significantly enhanced users' performance in the installation sequence planning task. Task 2 examines participants' perceptions of the spatial layout and interconnections among work packages. One explanation for the performance improvement is that the HMD provided users with a wider FoV so that they can access additional information in surrounding areas (Ragan et al. 2015). Moreover, the HMD displayed objects in a more realistic scale, which can facilitate mapping the virtual model with realistic project elements. This effect explained the fact that five experts and two novices in the HMD-based VR group prioritized the work package with the largest pipe spool, compared to one expert and no novice in the desktop-based VR group.

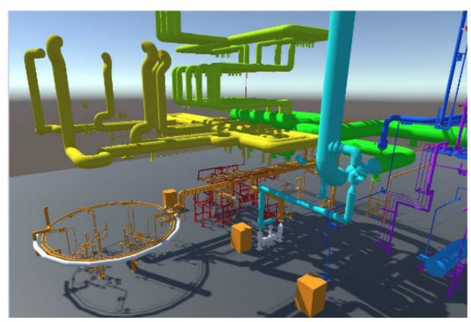
Experts have similar opportunities to perform better in a real-world scenario. The user test adopted predetermined work packages so that performance could be measured objectively. However, in practice, work packaging strategies vary according to company conventions, and it is closely related to the installation sequence. Constrains on work packages were likely to compromise the creativity and thoroughness of experts' answers. During the user test, nearly half of the experts mentioned that they would propose better solutions if they can tweak the work packages. Therefore, although the ANOVA result stated that industry experience did not have a significant impact, more promising results can be expected from experts.

2.4.3.3 Task 3: Reviewing the Completeness of Work Packages

Tasks 3 and Task 4 demonstrated limitations of HMD-based VR. Although checking the completeness of work packages was recognized as a challenging task by the construction team, overlooked objects became apparent once researchers color-coded all work packages (see Figure 2-12). All participants identified every missing object, regardless of the equipment applied or industry experience. In this case, the color-coding effect should be acknowledged rather than the technologies per se. This result shows that hardware is not the bottleneck for Task 3. Creating appropriate visualization effects on desktop-based software systems can be a more reasonable approach to facilitate this task. Additionally, this is a typical case where comparison at an application level can overestimate the actual capability of HMD-based VR, as discussed in section 2.3. Task 3 demonstrates how these effects can be mitigated by the experimental design.



(a)



(b)

Figure 2-12: Visualizations of work packages in (a) a conventional BIM environment and (b) a color-coded VR environment

2.4.3.4 Task 4: Recalling Objects

In Task 4, the average scores of treatment groups were slightly lower than their corresponding control groups. This result seems to contradict earlier experimental findings, where Krokos et al. (2019) found HMD-based VR users had a superior recall rate of images compared to desktop-based VR users. It is reasonable to argue that the intrinsic difference in experimental design caused the divergent results. The user tests in this paper primarily concentrated on the review workflow which mimicked construction industry routines, while the research conducted by Krokos et al.(2019) focused on creating a virtual environment that maximizes HMD-based learning and memory development. For most industrial applications, manipulating influential factors, such as visual complexity (Ragan et al. 2015) for technology is impractical and unreasonable. Therefore, although HMD has the potential to strengthen users' memory, the actual effect needs to be substantiated by field-specific or scenario-specific research.

2.4.3.5 HMD-based VR Implementation

The experimental results indicate that HMD-based VR is a robust tool for specific applications. The construction industry should implement HMD-based VR intentionally in suitable scenarios so that full benefits can be reaped from the technology. This paper demonstrated that construction design review is an appropriate use case for HMD-based VR. It is reasonable to assume other visualization-intensive tasks can potentially share similar benefits, but validations for other applications are still needed before implementation.

The noticeably larger performance fluctuation in the treatment groups implied opportunities for better results once these users became skilled in operating HMD and controllers. Researchers compared the four pairs of SDs between the treatment and the control groups in Task 1 and Task 2. The average SD of the treatment group was 2.04 with a range from 1.16 to 2.47, while the average SD of the control group was 1.39 with a range from 1.12 to 1.88. Moreover, the highest and lowest scores in each task came from the treatment group. Three out of four SDs from treatment groups were higher than the corresponding control groups. The higher SDs can be explained by the diverse proficiency in operating given equipment. Therefore, this paper recommends that HMD users undergo training in equipment operations before deploying VR applications in practice.

2.5 Conclusions and Limitations

This paper measured the impact of an HMD on user performance in four construction design review tasks. Twenty-four novices and twenty-four experts participated in the user test. They were randomly assigned to treatment or control groups, performing a user test with HMD-based VR or desktop-based VR, respectively. In the design error detection task, experts and novices in the HMD-based VR group detected significantly more design errors (48.27% and 59.01%, respectively). Similarly, they committed 33.45% and 18.22% fewer errors than the desktop-based VR group in the installation sequence planning task. Statistical analysis also found that the HMD had a significant impact on user performance. All participants provided the correct answer in the task where they reviewed the completeness of work packages, and HMD-based VR users scored slightly lower than desktop-based VR users in the recalling objects task.

Experimental results indicate that the construction industry can substantially benefit from HMD-based VR in specific use cases. Therefore, HMD-based VR should be intentionally applied for appropriate scenarios and tasks. This paper also validated that HMD-based VR applications can significantly enhance the effectiveness of design error detection and installation sequence planning. This paper contributes to the body of knowledge by measuring the impact of HMD in VR applications in construction design review tasks. Moreover, the methodology developed in this paper enhanced contemporary methods of validating the practical impact of technologies by excluding extraneous variables.

Besides the intellectual contributions, the limitations of this paper were also imposed by the experimental design. First, some human factors that were not fully controlled in this paper can pose a threat to the results. For example, the fluctuation of participants' earlier experience with both VR and industry projects cannot be perfectly controlled, especially when industry experts were involved in the user test. Then, user test participants were not responsible for any possible outcome of their result. Therefore, the motivation and level of engagement of HMD-based VR groups and desktop-based VR groups can be different. Differences in these factors can cause variance in user performance. Next, the error detection task was established on the hypothesis of all design errors being visually accessible. However, design errors may exist in invisible places, such as missing supports for a pipe spool inside the insulation material. User performance on detecting those design errors was not measured in this paper. Last but not the least, all tasks in this experiment were designed to be general so that they did not require detailed background knowledge. The discrepancy between experts' and novices' performance was expected to be higher in a more complex, real-world scenario.

This paper recommends two directions for future research in this field. First, the limitation of design error visibility can be addressed with further development of the model visualization methods. These methods can help users get a comprehensive review of all objects included in the project model. Second, the model transformation procedure from BIM to VR can potentially be fully- or semi-automated, as well as key design review functions. This automation can streamline the process of creating an HMD-based VR environment and, thereby, facilitate its industry-wide implementation.

Chapter 3: Semi-automatic Occlusion Detection

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As the first and corresponding author of the journal article, Bing Han designed, programmed, and tested the algorithm proposed in the journal article. Bing Han also drafted the journal article.

As a co-author of the journal article, Jong Won Ma assisted Bing Han in algorithm development and reviewed the journal article manuscript. The co-authors of the journal article, Fernanda Leite and Daniel Oliveira, provided guidance and feedback on the study and manuscript, and revised the manuscript.

3.1 Introduction

Virtual Reality (VR) has shown its potential in facilitating communication and coordination at an early stage of a project in many industries (National Academy of Engineering 2017). It creates a unique environment where stakeholders can intuitively visualize and interact with 3D representations of a product before it is manufactured. These features and objectives align with the design review and coordination process in the construction industry. Consequently, the construction research domain has also expressed interest in VR applications, particularly for design review and coordination tasks (Davila Delgado et al. 2020, Mehrbod, Staub-French, and Tory 2019, Institute 2019, Han and Leite 2020). Researchers developed VR-based design review applications and observed that VR can enhance user performance in many use cases, such as identifying design errors and constructability issues (Boton 2018, Alizadehsalehi, Hadavi, and Huang 2020, Du, Shi, et al. 2018, Han and Leite 2021b). However, some design intent can lead to occluded objects in 3D models (Liu et al. 2016, Han, Cline, and

Golparvar-Fard 2015, Yu, Zhou, et al. 2020). For example, mechanical, electrical, plumbing, and fire protection (MEPF) systems are commonly occluded by ceiling tiles for aesthetics purposes, and heat insulation can occlude pipe spools and their connections in industry facilities. Visualizing such occluded objects in 3D models is a challenge in VR-based design review applications (Johansson, Roupe, and Bosch-Sijtsema 2015, Son, Bosche, and Kim 2015).

The objective of a design review or virtual walkthrough is to comprehensively inspect all relevant objects instead of just the inherently visible ones (Neuville, Pouliot, and Billen 2019). However, occluded 3D objects remain hidden in current VR-based design review applications unless revealed manually by those conducting the review, which is an error-prone and time-consuming process (Yu, Liang, et al. 2020, Elmqvist and Tsigas 2007). Occluded objects are often represented as dashed lines or on different drawings in 2D, but these approaches do not pertain to 3D models or VR. Therefore, developing an automatic occlusion detection and visualization method is critical to realize greater benefits from VR-facilitated construction design review.

This paper aims to establish a framework that semi-automatically identifies occluded objects in 3D construction models and processes them so that VR developers can easily implement visualization effects, such as highlighting. The framework classifies each object as “visible” or “occluded” by converting model objects into point clouds and comparing them to a virtual laser scanning result of the model. Most of the processing and scanning activities were automated via Python scripts. The authors validated the framework with building information models of two construction projects: an industrial facility and an academic building. Recall and precision rates and overall computation time were measured and discussed as key performance metrics of the framework and algorithms. This paper contributes to the body of knowledge by enabling the occlusion detection process in 3D models and automating a large proportion of the process for VR applications in the construction industry. It enhances the comprehensiveness of current VR-based design review applications and strengthens their feasibility to current industry practices. Furthermore, other VR applications that recognized occluded objects as a limitation can potentially extend their scope of work by implementing the framework.

3.2 Literature Review

3.2.1 Fully Occluded Objects in Construction

Fully occluded objects in a construction site limited the scope of many existing research projects in the construction research domain. For example, capturing and modeling occluded objects in an existing building when reconstructing as-built models is an extensively researched topic (Barazzetti 2018). Dai et al. (2018) developed a convolutional neural network to automatically complete partial input from laser scanning. Son, Kim, and Kim (2015) developed a rule-based 3D model reconstruction algorithm for incomplete laser scanning data using prior knowledge. Han and Golparvar-Fard (2015) discussed that one limitation of their research on construction site photo-logging was that it did not apply to occluded objects. Researchers also tried to capture occluded objects via real-time data collection approaches (Franz, Irmler, and Rüppel 2018, Chen et al. 2020). Although these use cases were not directly related to model-based design review, they demonstrated the importance of involving occluded objects in decision-making processes in construction projects (Livingston et al. 2003).

Occluded virtual objects in 3D models challenged the design review and coordination process in a similar way. Mehrbod et al. (2019b) found that navigational interactions constituted over 60% of all participants' interactions in building design coordination meetings, and two out of the 13 recognized navigational interactions aimed to reveal occluded objects. Ivson et al. (2018a) adjusted object transparency to visualize occluded objects in their Building Information Modeling (BIM)-based 4D virtual construction planning application. Neuville, Pouliot, and Billen (2019) found that the lack of visualization tools for occluded objects is a major limitation for BIM-enabled visual tasks. These findings demonstrate that visualizing occluded objects is an indispensable function for design review applications.

3.2.2 Occluded Objects in VR

Researchers have leveraged available building information models and developed VR applications as an extension for specific use cases in the construction industry (Leite 2019). Some of these applications replicated a real-world scenario where only visible objects matter to the users in that particular task. Lin et al. (2018) developed a VR-based design review application where medical staff and patients can experience the design and provide feedback prior to the construction of a healthcare facility. Motamedi et al. (2017) used VR to optimize the location of signage in a building. Other visual-only applications include behavioral simulation (Feng, González, Amor, et al. 2020, Lin et al. 2020, Ozcelik and Becerik-Gerber 2018), training (Feng, González, Mutch, et al. 2020, Goulding et al. 2012), and engineering education (Bashabsheh, Alzoubi, and Ali 2019). In these cases, the VR environment should only simulate and represent visible objects to provide users with an experience that resembles the real world.

Many other VR applications, especially those developed for construction design review, are meant to help users visualize all objects in a model. However, researchers limited their scope to visible objects in these applications because they lacked a practical approach to identify and reveal fully occluded objects. For example, researchers conducted experiments to measure the effectiveness of VR-based design review and observed that VR could enhance user performance in various design review tasks (Du, Shi, et al. 2018, Wolfartsberger 2019, Han and Leite 2021b). However, all experiments in these projects were performed using visible objects, and excluding fully occluded objects was discussed as a limitation of these experiments. Khalili (2021) developed an extensible markup language (XML)-based data exchange approach from BIM to VR and reached a 99.1% visibility rate. However, commonly occluded objects, such as MEPF systems, were not included in their case study model. Du, Zou, et al. (2018) developed a similar real-time BIM to VR synchronization system. It facilitated a simultaneous feedback loop for design, but only works for intrinsically visible objects. Zhang, Hou, et al. (2020) ignored all occluded objects on their BIM/GIS integration platform (BGIP). The scope and benefits of these research projects can potentially be broadened by leveraging an automatic occlusion detection algorithm.

3.2.3 State-of-the-art Solutions

VR developers can create real-time revealing or highlighting functions for all objects in a 3D model (Feiner and Seligmann 1992, Elmqvist and Tsigas 2007). These functions can automatically identify and reveal occluded objects, but the computational cost increases with the number of objects in the VR model. Currently, a building information model with a level of development (LOD) of 300 or higher can contain thousands or tens of thousands of objects (Meza, Turk, and Dolenc 2014), and many research projects proved the required computational power exceeded what commercially available desktop computers can provide. Yu, Liang, et al. (2020) designed the 3DWedge+ visualization technique that facilitated users' awareness of off-screen and occluded objects in VR. However, their experiments did not show if the technique can support 3D models with thousands of objects. Lin et al. (2018) experienced a similar challenge when attaching an interactive function to all objects in one floor of a hospital model. The real-time computational cost impaired the frame rate and thereby, the performance of their VR-based communication application. These research projects shed light on how occluded objects can be visualized in real-time in VR, but they are neither practical nor efficient for complex models in the construction industry.

The visibility of an object in a construction model is not likely to change during construction design review. Therefore, researchers can pre-classify occluded objects instead of analyzing the visibility status of all objects per frame (Yu, Liang, et al. 2020). Although a classification algorithm specifically for occluded objects has not been developed, this paper takes several related works as a point of departure. Hu, Castro-Lacouture, and Eastman (2019) programmed a projection-based algorithm to filter relevant clashes by overlapping projections of objects with clashes. Their algorithm cannot be directly used for occlusion detection, but the idea of using geometric information to determine spatial relationship aligns with the logic of this paper. Abualdenien and Borrmann (2019) developed a meta-model approach to classify the vagueness of information associated with 3D objects in building information models. Based on the classification, they then adjusted the color and transparency of these objects to visualize the level of vagueness (Abualdenien and Borrmann 2020). Their work demonstrates that applying visualization effects to a predefined set of objects in VR is a viable solution for complex construction models. Therefore, classifying occluded objects and putting them into a compatible format with VR is key to visualizing occluded objects in VR-based construction design review.

It is worth mentioning that the occlusion challenges discussed in Augmented Reality (AR) research are fundamentally different from the topic of this paper. Concerns for occlusion in AR research focuses more on the overlapping relationship between virtual objects (Du et al. 2016, Hamasaki and Itoh 2019, Frikha, Ejbali, and Zaied 2016, Dong, Feng, and Kamat 2013) instead of visualizing fully occluded objects. Therefore, this paper did not leverage existing methods on handling occlusion from past AR research.

3.2.4 Knowledge Gap

The literature review reveals a knowledge gap in visualizing occluded objects in VR-based construction design reviews. Adding a highlight effect to occluded objects in VR development is a mature process already. However, identifying fully occluded objects remains an unsolved challenge. Therefore, this paper proposes a point cloud-based semi-automatic occlusion detection framework that identifies occluded objects and outputs the results in a format that is compatible with VR development software. Filling this knowledge gap can extend the scope of many existing construction VR research projects and applications from only visible objects to all objects. It also enhances the comprehensiveness of current VR-based design review and coordination meetings for the construction industry.

3.3 METHODOLOGY

The objective of this paper is to develop a framework that semi-automatically identifies fully occluded objects in 3D construction models for VR applications. Based on findings from the literature, this paper proposed four requirements for the framework. First, identifying occluded objects is the fundamental function of the framework. To measure this objective, the authors prioritized reaching a high recall rate in the algorithm. However, because this is the first classification algorithm for occlusion that the authors are aware of, this paper did not draw comparative conclusions on recall performance.

Secondly, the majority of the occlusion identification process should be automated in order to save development time for VR applications and mitigate human errors. Thirdly, the inputs and outputs of the framework should be consistent and compatible with current industry practices, including data formatting, reasonable computing time, and adaptability to model iterations. Finally, the output from this framework should streamline the process of applying visualization effects for occluded objects in VR development software.

3.3.1 General Workflow

The framework is introduced using a pipe spool covered by heat insulation as an example, shown in Figure 3-1. The workflow started with a building information model of a construction project. The model was converted to a Filmbox (FBX) file and pre-processed to exclude irrelevant information. In step 3 (a), every object in the pre-processed model was converted into a point cloud file. In a parallel process, the authors used virtual laser scanners to scan the pre-processed model. The scanning results were then combined into a scanned point cloud file, see Step 3 (b). As a result, the converted point cloud files contained location information for all objects in the pre-processed model, while the scanned point cloud file only contained visible objects. Step 4 compared the coordinates of all points in each converted point cloud to the scanned point cloud. Converted points were tagged as "visible" or "occluded" based on the comparison, and the visibility status of converted points determined their corresponding model object. Finally, all objects in the pre-processed model were transformed into two models based on their visibility tag: either the "visible" model or the "occluded" model. Every step is expanded in the following subsections in detail.

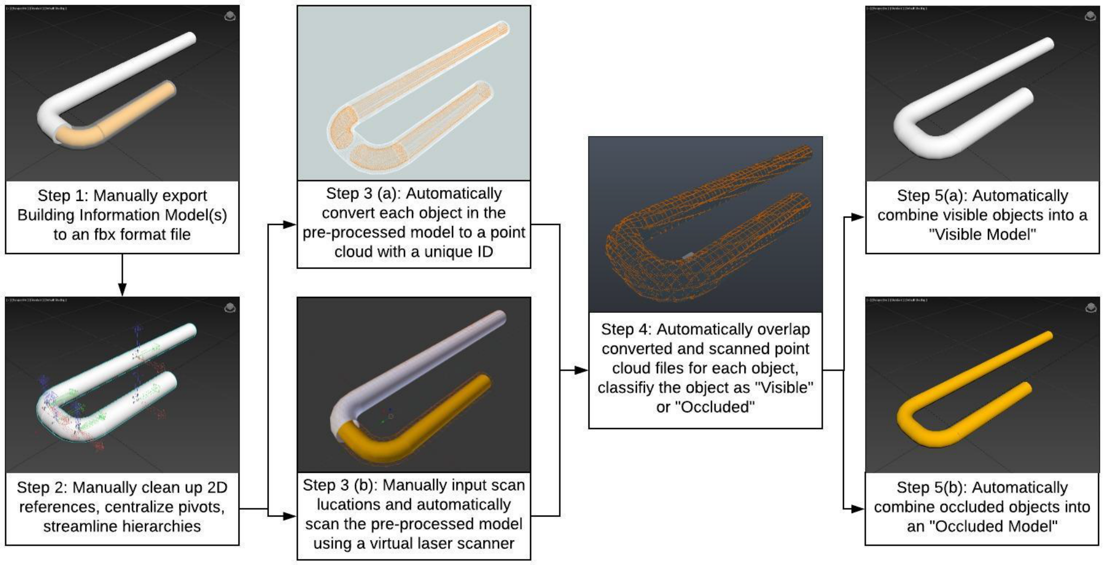


Figure 3-1: The general workflow of the semi-automatic occlusion identification framework

3.3.1.1 Step 1 & 2: Model Pre-processing

The raw contents of a building information model can be overwhelming and uninterpretable for the point cloud generation algorithm. In this framework, 3D objects were exported in FBX format from building information models using Autodesk® Navisworks® Manage 2020 . The authors then applied three essential modifications to the exported model using Autodesk® 3ds Max® 2020 . First, all 2D references were deleted, including 2D engineering drawings, reference points for 3D objects, and empty objects. Then, the authors moved the pivot of each object from the center of the original building information model to the center of each object. This helped the authors better navigate the model and select the locations for virtual laser scanners in the following steps. Finally, the hierarchy of objects was streamlined by deleting empty and unnecessary levels. The output model remained as one file in the FBX format and is referred to as the “pre-processing model” throughout this paper.

3.3.1.2 Step 3 (a): Converted Point Clouds

Each 3D object in the pre-processed model was converted to a point cloud file and an FBX file in this step. The authors automated the conversion using Feature Manipulation Engine (FME)® Desktop and processed the output data using Python. Figure 3-2 demonstrates the detailed workflow in FME®. After loading the model with a built-in FBX file reader, the UUIDGenerator function assigned a Universally Unique IDentifier (UUID) to each object. Then, the PointCloudCombiner function converted every object to a point cloud file to record the geometry and location of the object. Theoretically, finer granularity in converted point clouds can facilitate accurate occlusion classification with the cost of additional computational power. The authors conducted several preliminary tests on case study models and found that the classification results remained the same with a point interval set at 10 millimeters (mm) or lower. Therefore, the point interval was set to 10 mm to achieve the best classification performance while reducing the overall computation time. Under this setting, the least represented object in the two case study models was converted to 14 points. An XYZ file writer exported the converted point cloud files to XYZ files with a matching UUID. Similarly, the AttributeManager function and the following FBX writer separated objects in the pre-processed model and created an FBX file for each object. Thereby, each object in the pre-processed model possessed a point cloud file and an FBX file with a matching UUID, and both files were accessible in Python.

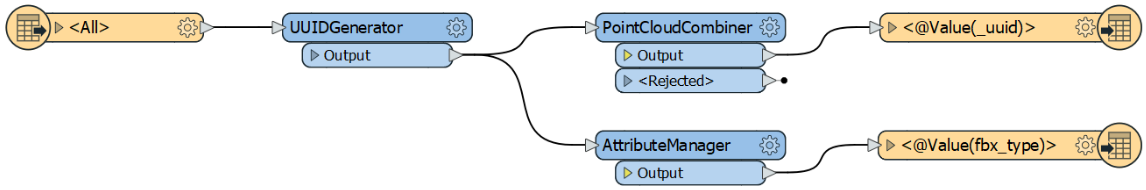


Figure 3-2: The workflow of converting objects into point cloud files in FME®

The converted point cloud data was then processed before comparison. In some commonly used modeling software systems in the construction industry, 3D objects can be represented by one or a combination of 3D surfaces instead of a solid entity, such as the pipe spool shown in Figure 3-1. The PointCloudCombiner function in FME® scanned both sides of these surfaces and thus, created recurring points in the converted point cloud file. The authors programmed a Python-based repeat point detector that ran automatically after all converted point clouds were created. The algorithm removed repetitive points for all converted point clouds and saved the remaining points in a comma separated values (CSV) file with the same UUID.

In addition, the authors noticed that the size of objects in construction models varied significantly, especially for industrial projects. Converting all objects to low-density point clouds left some small objects underrepresented or unrepresented, but large objects with high point density significantly increased the computation time. The authors designed a sampling algorithm and appended it after the repeat point detector to mitigate this problem. The sampling algorithm randomly selected 5,000 sample points to substitute for the original point cloud file, if it still included more points after deleting repeated points. Thereby, FME® can convert all objects to point cloud files with high point density. Small objects were represented in detail, and large objects did not significantly extend the computation time.

This paper used a Python script to automate the point cloud converting process. After the model was prepared, the script called a batch file that automatically ran the point cloud conversion and file creation workflows in FME®. The repeat point detector was then called to clean up the converted point clouds, followed by the sampling algorithm. With these processing steps completed, the script saved all output files to target folders in preselected file formats. As a result, the output data became accessible for subsequent algorithms, and the process was fully automated. For the purpose of this paper, the output point cloud files are referred to as the "converted point cloud" files.

3.3.1.3 Step 3(b): Scanned Point Cloud

The pre-processed model was also virtually scanned to a point cloud file that was exclusively composed of visible objects. This paper used BlenSor (Marion et al. 2012) in this step for model interoperability and automation. BlenSor simulates the functions of real-world laser scanners and generates virtual scanning results for digital models (Gschwandtner et al. 2011). The simulated Velodyne HDL-64E2 laser scanner was used to scan the model because it was easy to manipulate for rotation. Other virtual equipment, such as a Time-of-flight (TOF) camera, can also work for this task but requires more specific coding for its rotation. Table 3-1 shows the settings of major parameters for virtual scanning using BlenSor. Users can also manually set different parameters for specific scans in unique situations. Theoretically, an object is fully occluded when it cannot be seen from all accessible locations in a VR-based virtual walkthrough experience. In this paper, if an object can be seen from a given location was determined by if part of the object can be scanned by virtual laser scanners from that location. However, qualified scanning locations were unlimited for a construction model, and adding scanning locations can increase overall computational requirements. Therefore, the authors manually selected scanning locations, aiming to incorporate all visible objects with minimum scanning locations. The coordinates of these locations were saved in a CSV file for the following automatic scanning operations.

Key parameters	Values
Scanner type and model	Velodyne HDL-64E2
Scan resolution	5 mm
Noise	0
Coordinates	World coordinates
Start and end angles	0 and 360

Table 3-1: Key parameters for virtual laser scanners

The virtual scanning process was automated by a batch file that ran BlenSor and a Python script that controlled virtual scanners and outputs. The Python script read scanning locations and parameters as a list, ran BlenSor by a batch file, and automatically scanned the model at each user-specified location with corresponding parameters. Every virtual scan generated a Numpy file, and the Python script combined all these files into a point cloud file. This file is referred to as the "Scanned Point Cloud" in this paper.

3.3.1.4 Step 4 & 5: Classification and Output

The visibility status of an object is determined by the visibility of its converted points. Objects with one or more visible points were classified as visible objects, and objects without visible points were classified as occluded objects. This paper determined the visibility of converted points by comparing their coordinates to all the scanned points. This paper used a Python script to automate the comparison, classification, and output processes. To begin with, the algorithm calculated the maximum and minimum value of x, y, and z coordinates in the converted point cloud for a given object. Then, a potential point cloud composed of scanned points that all x, y, and z coordinates fell within the coordinates range of the converted point cloud was created for that object. Subsequently, all converted points were paired and compared with all potential points, as shown in Figure 3-3. A converted point was classified as visible if there was a potential point located within 5 mm. Otherwise, the converted point was classified as occluded. The classification process repeated itself automatically for all objects in the pre-processed model. Finally, the individual FBX files generated in step 3 (a) were merged into the "Visible" model or the "Occluded" model in FME® based on their classification results.

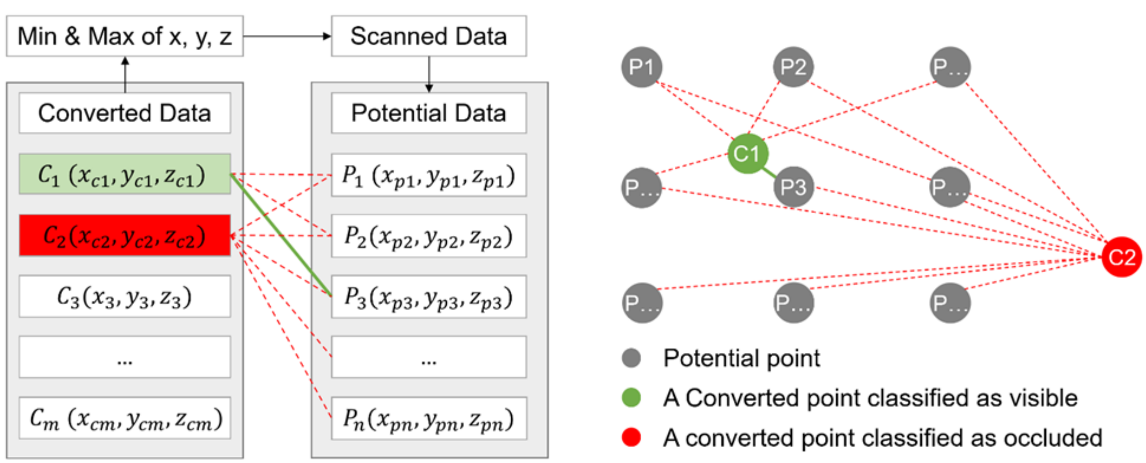


Figure 3-3: Determining the visibility of converted points for a given object (a) the algorithm logic and (b) an illustration of the classification process

3.3.1.5 Update for Iterations

Design coordination is an iterative process during construction (Abualdenien and Borrmann 2020). It is a common practice that contractors from different disciplines detail their systems separately and append their various models for design coordination. Thus, federated building information models also experience constant changes. To keep pace with this rapidly iterative process, the authors designed an automatic update function that can revise the classification results without running the workflow from scratch. The update function works under the assumption that updated objects neither change the visibility status of existing objects nor require changes in the locations or specifications of virtual scanners. The assumption matches many design coordination scenarios during the construction stage. However, the automatic update function does not support drastic design changes and early-stage design development of a project.

The update function was also automated by a Python script and shared similar steps to the original occlusion detection process, except that it only analyzes updated objects. After pre-processing, each object in the model was converted into a point cloud. Then, the algorithm calculated and compared the maximum and minimum coordinates of the updated converted point clouds to the original ones. Object pairs with the same extreme values of coordinates and more than 1% matching points were classified as unchanged objects. The visibility of the unchanged object was determined by the original object. For those objects without a pair, objects in the updated model were classified as new objects, and objects in the original model were classified as deleted objects. The algorithm ran the virtual scanning in the updated model again and performed the comparison and classification process described in section 3.3.1.4 only for the updated objects. Eventually, the visible and occluded models were automatically revised. Deleted objects were removed from both models, and new objects were merged into the "visible" model or the "occluded" model, based on classification results.

3.3.2 Validation Cases

The occlusion detection framework was validated with two case studies: a gasoline refinery facility project and an academic building project. The construction teams of the two projects provided the building information models used for construction design review. The authors ran the framework and algorithms on the two models. Both projects used Autodesk® Navisworks® for model integration and design coordination. Therefore, the two models were exported to FBX files from Autodesk® Navisworks® Manage 2020 and optimized in Autodesk® 3ds Max® 2020. The authors manually selected scanning locations in each model. Thereafter, all other activities in the framework ran automatically, including converting point clouds, scanning models, comparing point cloud files, classifying objects, and generating final output models.

3.3.3 Performance Measurements

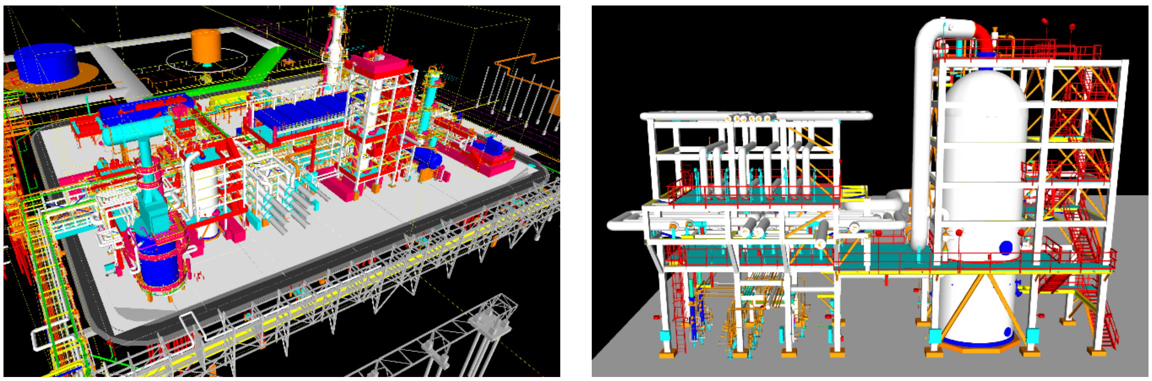
Recall and precision rates are two crucial metrics for the classification tasks. In order to calculate these metrics, the authors manually labeled all objects in the two models as “Occluded” or “Visible” based on their actual visibility in a virtual walkthrough. The manual labeling process took around twelve to sixteen hours for a Ph.D. student to complete, although the duration can significantly vary with different modeling experiences and industry knowledge of labelers. With these labels attached, four groups of results are expected: true positive, false positive, true negative, and false negative. An object detected as “occluded” is a positive result, and a “visible” classification is a negative result. If the classification result is consistent with the actual visibility status of the object, it is a “true” classification; otherwise, it is a “false” classification. Precision is the fraction of true positives among all positive results, and recall is the fraction of true positives among all actually occluded objects. In this study, the objective is to maximize recall rate, in order to detect all possible occluded objects. On the other hand, a high precision rate avoids applying inaccurate highlight effects for visible objects. Although desirable for the final result, high precision is not as critical as a high recall rate.

Another critical factor for the performance is the overall computation time (Han and Golparvar-Fard 2015). The framework was designed to support construction design and coordination in the field. Therefore, a commercially available desktop computer should be able to run every step, and a short computation time facilitates the process of integrating the algorithm into the existing design coordination workflow. This paper recorded the computation time for each major step in both projects using a desktop computer with an AMD® Ryzen® 3900x 12-core central processing unit (CPU), an NVIDIA® GeForce® RTX 2060 graphics processing unit (GPU), and 32 GB RAM. Therefore, the result not only confirmed feasibility of the framework, but also revealed potential for optimization and directions for framework improvement.

3.4 Case Studies

3.4.1 Project Backgrounds

This paper conducted two case studies to measure the performance of the proposed framework and algorithms. The proposed framework was first implemented on the building information model of a gasoline refinery facility. The model was developed to the LOD of 350 and used during design coordination meetings. The construction team recommended using a section of the facility for this case study because it matches the scope of their routine design review. The complete model and the selected unit model are shown in Figure 3-4. The selected section contains a processing unit that heats gasoline to a certain temperature so that chemical pollutants can be extracted in the following units. This section is comprised of foundation, upper structure, piping systems, heating equipment, fire protection systems, and other supporting systems. The model contains 5,387 objects in total, and 1,196 of them are fully occluded.



(a) (b)

Figure 3-4: The building information models for (a) the gasoline refinery facility and (b) the selected section

The second case study was conducted on the building information model of an academic building. This paper intentionally selected a different type of project to validate the comprehensiveness and flexibility of the framework. Similarly, the model was developed to LOD 350, and the authors selected a section comprised of three laboratories and the corridor that connects them. The case study model covers all systems related to the selected section, including architectural and structural elements, as well as MEPF systems, as shown in Figure 3-5. The model includes 1,571 objects in total, and 1,286 of them are not visible in a virtual walkthrough.

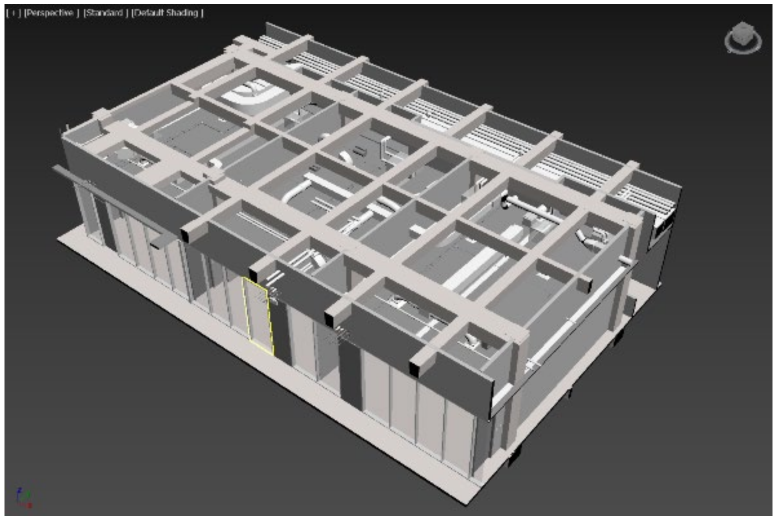


Figure 3-5: The building information models for the selected section in the academic building

3.4.2 Case Study Results

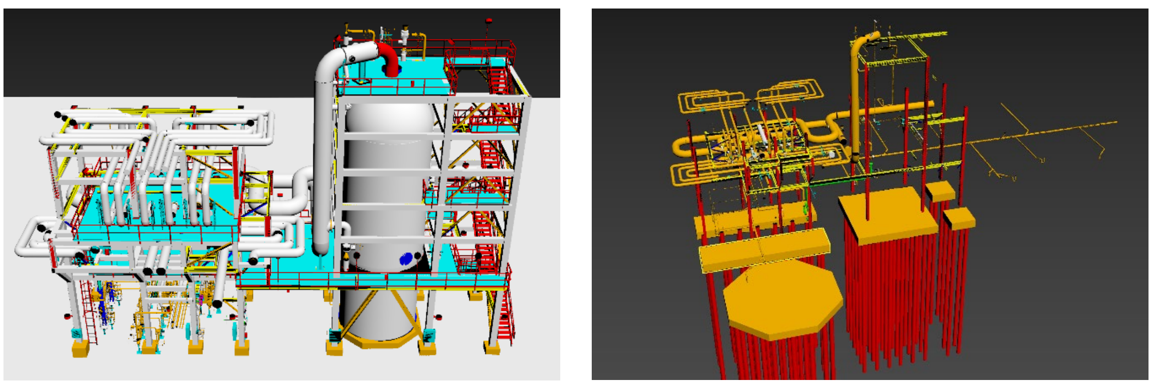
Table 3-2 summarizes the key results from the two case studies. Since the proposed algorithm is the first algorithm that identifies occluded objects in 3D models, the key results were compared with the random guessing algorithm result and the zero rule algorithm result as baselines. The four possible classification results were presented in Table 3-3 as a confusion matrix. Precision is the proportion of true positives in all positive results, and recall is the proportion of true positives in all actually occluded objects. The algorithm achieved a 90.30% recall rate and a 75.05% precision rate for all objects in the gasoline refinery facility model. It took approximately three hours overall, and 10.7% of the time was spent on manual input. The algorithm automatically generated models consisting of objects classified as "visible" and composed of objects classified as "occluded" as shown in Figure 3-6. In the academic building model, the algorithms reached a higher recall rate of 98.06% and a 97.53% precision rate in approximately one hour of processing. Additionally, 23.8% of the overall duration was spent on manual input. Figure 3-7 demonstrates the two output models for the academic building after classification. It is worth mentioning that the authors only virtually scanned three laboratories and the corridor that connects them from the accessible perspectives of a virtual walkthrough. Therefore, the algorithm classified the MEPF system above the ceiling and the light switches on the opposite side of the corridor wall as “Occluded”.

Parameters	Gasoline refinery facility	Academic building
Recall rate (proposed algorithm / random guessing / zero rule)	90.30% / 48.88% / 0%	98.06% / 51.28% / 100%
Precision rate (proposed algorithm / random guessing / zero rule)	75.05% / 27.00% / 0%	97.53% / 83.19% / 82.30%
Pre-processing time	About 10 mins	About 10 mins
Converting point cloud time	10 mins	3 mins
Selecting scanning location time	About 10 mins	About 5 mins
Virtual scanning time	15 mins	12 mins
Classifying time	141 mins	33 mins
Output model time	1 min	< 1 min
Manual input time	About 20 mins	About 15 mins
Automatic computing time	187 mins	63 mins
Overall computing time	About 207 mins	About 78 mins

Table 3-2: Key results measured from the two case studies

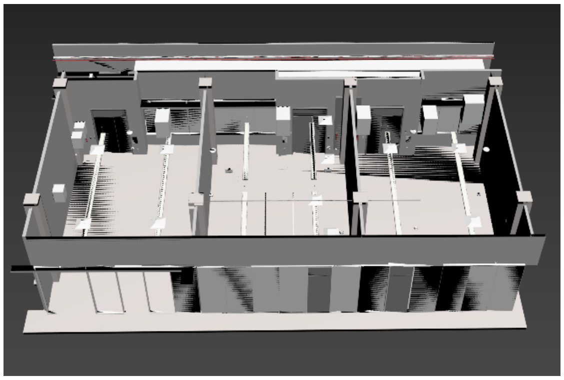
Actual Status	Classification	
	Occluded	Visible
Occluded	Ture Positive: 1080 in case study one and 1261 in case study two	False Negative: 116 in case study one and 25 in case study two
Visible	False Positive: 359 in case study one and 32 in case study two	True Negative: 3832 in case study one and 253 in case study two

Table 3-3: Classification results from the two case studies

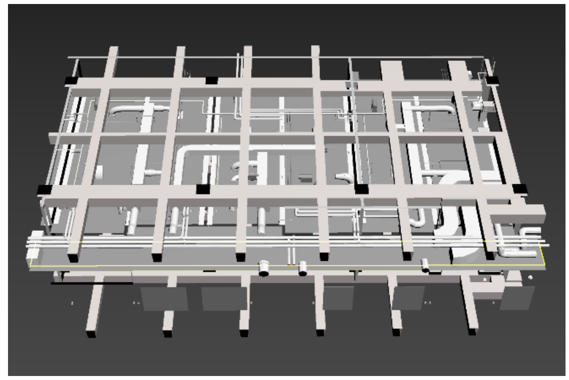


(a) (b)

Figure 3-6: Outputs for the gasoline refinery facility model: (a) the "visible" model and (b) the "occluded" model



(a)



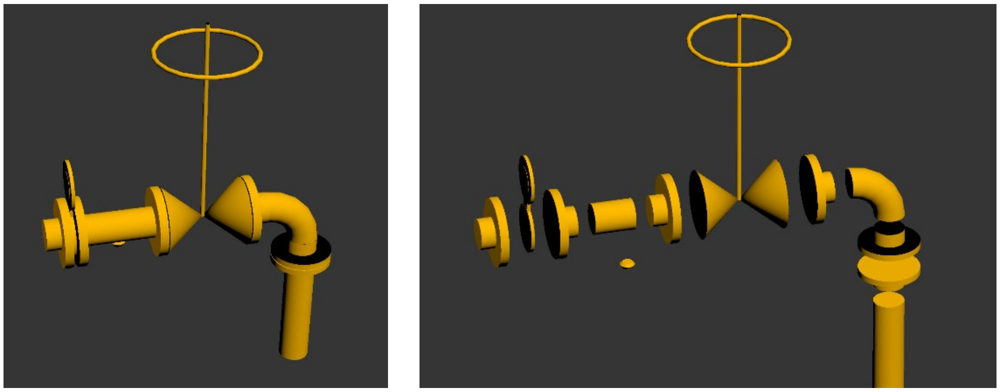
(b)

Figure 3-7: Outputs for the academic building model: (a) the "visible" model and (b) the "occluded" model

3.4.3 False Positive and Negative Classifications

3.4.3.1 False Positive Results

A false positive result refers to an object that is "visible" in the model but classified as "occluded" by the algorithm. Trivial objects in the detailed MEPF systems caused 63.88% and 43.75% false positive results in the gasoline refinery model and the academic building model, respectively. As an example of the type of object causing large false positives is a component of the MEPF system that has complex geometry which was modeled by a large number of regularly shaped objects in the two LOD 350 models, instead of as a single object. Figure 3-8 demonstrates this, graphically, by showing a valve modeled as 12 independent objects in the building information model of the gasoline refinery facility. Scanning all these objects is arguably unpractical due to their sizes.



(a) (b)

Figure 3-8: Modeling (a) a complex geometry using (b) 12 independent objects in a LOD 350 model

The size of the object was not the only reason for false negatives results. Some objects in the model can only be scanned from specific locations with a narrow perspective, such as the short support between beams and pipe spools shown in Figure 3-9. These objects can be invisible from nearly all scanning locations and thus incorrectly classified as "occluded". This issue resulted in 37.12% false positive results from the first case study and 9.38% false positive results from the second case study.

Another problem leading to false positives was that the virtual scanner missed some 3D objects that were undersized in two dimensions. 46.88% of the false positive results in the academic building model were caused by aluminum window frames with significantly smaller magnitudes of width and depth compared to their height. The gasoline refinery model did not have any false positive cases caused by this issue because it does not contain objects with a similar profile.

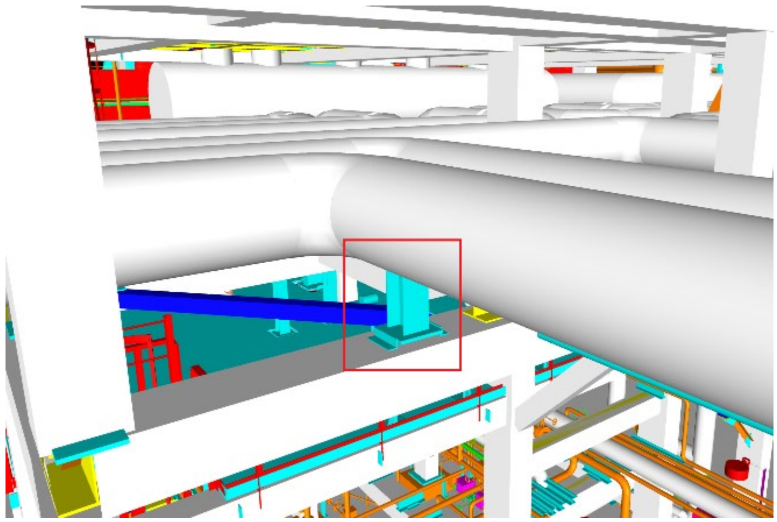


Figure 3-9: An example pipe support that can only be scanned from specific locations

3.4.3.2 False Negative Results

A false negative result means that an object was classified as “visible” while it is actually “occluded” in the model. Overlapping surfaces caused all false negative results in both case studies. This problem occurs where multiple objects’ surfaces are modeled in the same location in space. Figure 3-10 typifies the issue using an air duct from the academic building model as an example. The bottom surface of the air duct was designed at the exact height of the ceiling. The solid ceiling object fully occluded the air duct in the 3D model except for the attaching surface. Unfortunately, the scanning result did not differentiate which object generated these points. It only showed that there were points scanned at the overlapping surface location, and this was then misinterpreted by the algorithm as “all objects that have these scanned points on their surface were scanned” and thus, were classified as “visible”.

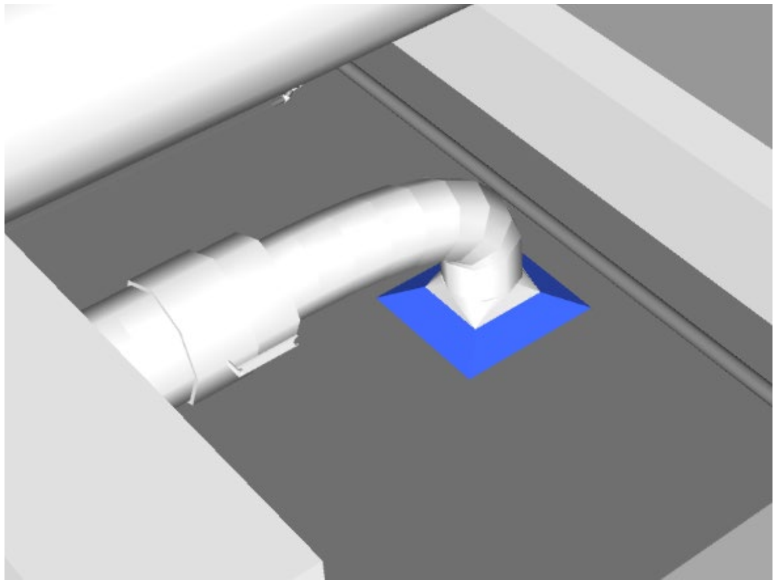


Figure 3-10: An example of false negative result caused by an overlapping surface

3.5 DISCUSSION

3.5.1 Performance of the Framework

Results from the two case studies show that the point cloud-based framework and algorithms achieved the research objectives of this paper. First, the recall rate is a determining criterion for the quality of results, and both case studies reached an over 90% recall rate for occluded objects. The over 75% precision rate for both cases is also acceptable, although comparative conclusions cannot be drawn because research has not been found with similarly functioning algorithms. The framework meets the study's objectives by being highly automated, especially for time intensive activities. Although manual inputs are required at the beginning of the framework, they account for less than one-fourth of the overall computation time. Additionally, the overall process is practical for industry implementation. The framework is applicable for buildings and industrial facility models using a commercially available desktop computer. Furthermore, the framework provides development ready models to VR development software. Although the integration of VR visualization effects is not in the scope of work for this paper, supporting the straightforward employment of these effects is a fundamental requirement for the output models.

3.5.2 Tradeoff and Optimization

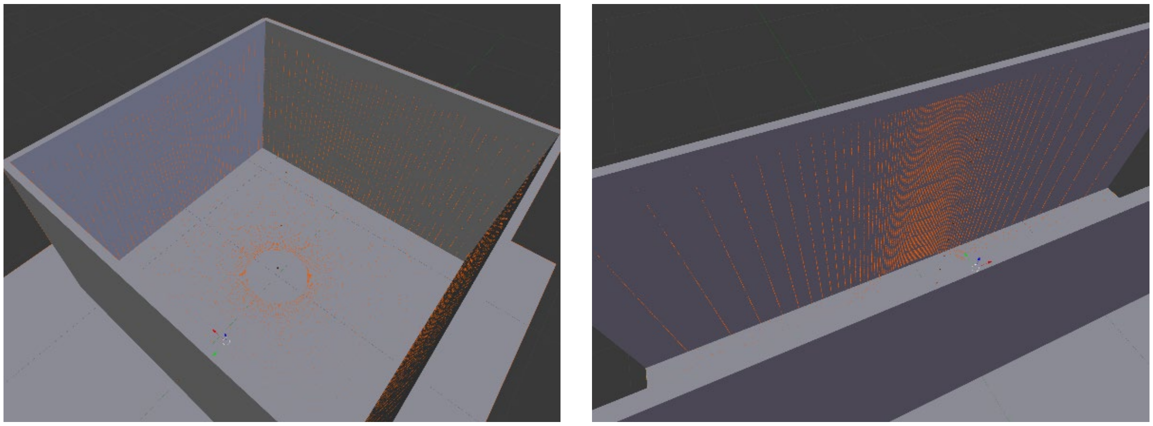
The trade-off between computation time and the precision and recall rates was a major challenge for optimizing the algorithms. For objects in the same location, the probability of being scanned is positively correlated to its visible surface area. Unfortunately, the size of object surface areas varies significantly in the same model. For example, the size of the equipment for heating gasoline is 36.89 times larger than a valve in the same gasoline refinery facility model. This is a specific characteristic for construction models and drives the need for trade-off.

The scanning density was the key parameter to balance the trade-off. Virtual laser scanners can capture more details of the model with denser point distributions. However, this greater density results in a larger number of scanned points and consequently, longer computation time. On the other hand, wider point intervals can shorten the computation time, but can miss small objects and lower the recall rate. The authors performed exploratory experiments for scanning resolution by varying the distance between points. The result showed that a denser scanning setting can increase the number of scanned objects if the interval between points is larger than 5 mm. After the point interval falls below the 5 mm threshold, all visible objects at the scanning location were scanned. The combination of the Velodyne HDL virtual laser scanner and a 5 mm scanning resolution was selected as the balanced option for this paper. The test did not consider the trivial objects caused by the detailed MEPF model, as discussed in Section 3.4.3.1. Therefore, this paper recommends the scanner and resolution combination, but other combinations or modifications may best fit different model environments.

3.5.3 Selecting Scanning Locations

Selecting scanning locations is the only manual input to the framework. Scanning locations play a determining role in acquiring high quality scanned point cloud data. Virtual scanners can reach objects without distance limits, so the major bottleneck for scanning more visible objects is overlapping objects in a certain scanning location. To overcome this limitation, scanning from many different locations is more effective than increasing scanning resolution.

The authors recommended selecting scanning locations based on the geometrical distribution of objects in the model. For example, a single scanner was deployed at the center of each laboratory in the academic building model. However, many scanners were deployed at a shorter distance to cover narrow spaces, such as corridors. Figure 3-11 shows the scanning result for the corridor in the academic building model. Scanned points showed a concentrated distribution near the scanner, but the density decreases rapidly with distance.



(a) (b)

Figure 3-11: A comparison between (a) scan result in open spaces and (b) scan result in narrow spaces

3.5.4 Limitations

One limitation of the framework is that it only detects fully occluded objects. Currently, the proposed algorithm would classify an object as "occluded" only if no converted point from the object was scanned. As a result, any object with a visible proportion was classified as a visible object, no matter how small that proportion was. Figure 3-12 shows a piece of pipe that was classified as a “Visible” object. However, most of the pipe is occluded by the equipment except for the narrow connecting surface. Although not fully occluded, these objects would also benefit from a highlight effect in design review scenarios.

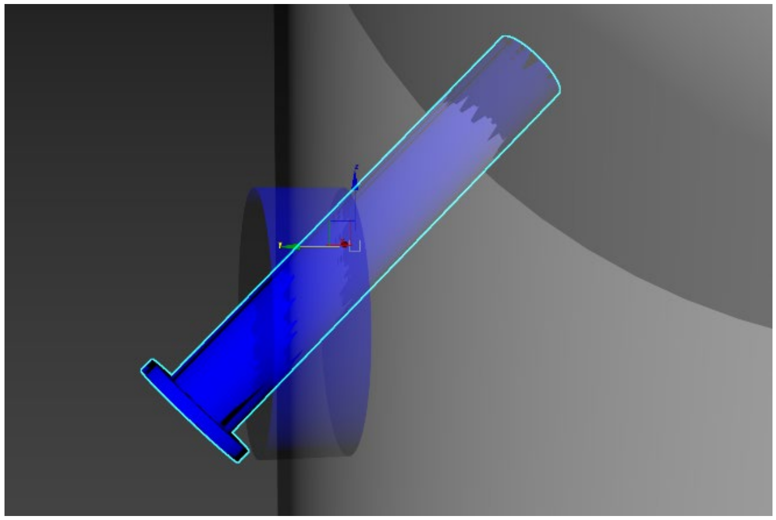


Figure 3-12: An example of a partially occluded object that would benefit from a highlight effect

The biases included in the performance measurement of the framework is another limitation of this paper. As discussed in section 3.4.3.1, the geometry-based representation of the MEPF systems in LOD 350 generated a large number of MEPF objects in both models. As a result, the recall and precision rates for MEPF objects exerted an extended influence on the overall recall and precision rates. Modeling or grouping MEPF objects by function or installation segments can mitigate this bias, and both precision and recall rates of the framework should improve under that circumstance.

Moreover, the converted point clouds can contain a large proportion of redundant points if the object is modeled as solid. The PointCloudCombiner function in Step 2 creates points inside a solid object with the same point density as the surfaces. Therefore, the algorithm would convert a solid cube with a 10 centimeter (cm) x 10 cm x 10 cm dimension into 1 million points. Only the 52,000 points on the six surfaces are meaningful for occlusion detection, but all 1 million points will go through the comparing process. This limitation does not impact the result of the algorithm, but it elongates the overall computation time.

3.6 Conclusions and Future Work

This paper recognized a knowledge gap for visualizing occluded objects in VR-based construction design review and coordination. This paper established a framework that semi-automatically identified fully occluded objects in 3D models and creates interoperable outputs for VR development software. The framework converts each object into a point cloud and compares it with virtual scanning results to classify the visibility status of each object. The authors validated the framework on two case studies, a gasoline refinery facility model and an academic building model. The algorithms achieved over 90% recall rate and 75% precision rate in both case studies, and the manual inputs accounted for less than one quarter of the overall computation time. Results show that the point cloud-based framework can effectively identify occluded objects in 3D models, and a commercially available desktop computer can provide adequate computation power for executing the framework.

This paper contributes to the body of knowledge by creating a framework that semi-automatically identifies fully occluded objects in 3D construction models. Case studies validated that point cloud-based algorithms can achieve higher than 90% recall rates and higher than 75% precision rates. Existing research on VR applications that limited their work to visible objects can expand their research scope by combining this framework to their model processing approaches. Meanwhile, the results set a baseline for occlusion identification algorithms and shed light on future research directions.

The proposed framework can also facilitate the implementation of VR-based design review in the construction industry. It enabled visualization of over 90% of occluded objects in virtual models and therefore, extended the potential benefits of reviewing these elements during design. In addition, the framework is consistent with the current development workflow of VR environments. The output models can be loaded and manipulated directly in VR development platforms. Therefore, VR developers can also easily combine the framework with current applications.

The authors recommend the following topics for future research projects that aim to improve point cloud-based occlusion detection algorithms or workflows. First, this paper did not streamline the scanned point cloud by sampling due to the uneven distribution of scanned points. Manual input for scanner locations was consequently required for scanning and computation efficiency. In this case, an intelligent sampling strategy that accounts for surrounding point density and the parent objects of the point has the potential to fully automate the scanning process and shorten the computation time at the same time. Next, the algorithms developed in this paper only utilized one CPU core. The authors assumed that multi-core optimization for these algorithms could further shorten the overall computation time and allow the framework to handle models with more objects when needed, but this requires further study. Lastly, the current geometry-based definition of an object resulted in large numbers of MEPF objects in building information models with LOD 350. It challenged the algorithm with trivial objects and biased the performance measurement of precision and recall rates. Therefore, the framework and measurement methods can benefit from a function-based definition of an object in building information models. In addition to optimizing the algorithm, surveys or interviews with industry experts are needed to evaluate the results presented in this paper, such as the recall and precision rates. These expert opinions can shed light on the major future algorithm optimization requirements for industry implementation of the occlusion detection framework.

Chapter 4: A Generic Extended Model for AEC Applications

4.1 Introduction

Extended Reality (XR) represents reality technologies that merge the virtual world with reality to provide intuitive, immersive, and interactive user experiences (Diao and Shih 2019). It is primarily composed of Virtual Reality (VR), Augmented Reality (AR), and Mixed Reality (MR) in the Architecture, Engineering, and Construction (AEC) research domain (Alizadehsalehi, Hadavi, and Huang 2020, Osorto Carrasco and Chen 2021). These technologies have contributed to various visualization-related challenges the industry faces throughout the project lifecycle (Guo, Yu, and Skitmore 2017, Davila Delgado et al. 2020). Researchers observed promising results from XR applications in terms of enhanced end-product quality (Boton 2018, Han and Leite 2021b, Heydarian et al. 2015), increased time efficiency (Baek, Ha, and Kim 2019, de Klerk et al. 2019), and improved communication (Du, Shi, et al. 2018, Bouchlaghem et al. 2005, Du, Zou, et al. 2018). The theoretical benefits of XR applications have also received growing recognition in the AEC industry. Although XR implementation is still at an early stage (Zhang, Liu, et al. 2020), implementation guidance that combines XR into the current industry workflow has been developed (Institute 2019), and case studies of promising applications have been performed in construction projects (Getuli et al. 2020).

Implementing multiple XR applications in the same project can be a financially demanding decision for AEC companies, despite the potential benefits (Cheng, Chen, and Chen 2020, Zhang, Liu, et al. 2020). The Construction Industry Institute (CII) reported that developers' salary constituted 62% of overall VR investment in initial implementation projects (Institute 2019). The traditional XR development process needs to transfer a Building Information Modeling (BIM) to an XR-ready model when new XR applications are developed or when the BIM gets updated during the operation period of an application (Davila Delgado et al. 2020). The AEC industry encounters these situations frequently. For example, design coordination meetings are commonly held weekly or bi-weekly during construction, and the BIM used in these meetings experiences constant updating. Transferring the complete, up-to-date BIM to XR is typically a time-consuming process. Repetitive activities and overall model transfer time accumulate with the number of 3D objects in the BIM, resulting in inefficient workflow and high XR development costs.

This paper identified the lack of knowledge on a generic XR model and a standard BIM-to-XR model transfer workflow for AEC applications. Collecting all XR-related BIM information in an interoperable format is indispensable for a generic XR model that supports all XR development. Meanwhile, automatic BIM update detection and XR model merging could decrease the BIM-to-XR transfer duration, considering that BIMs experience gradual but constant updates through a project's lifecycle. Currently, developers lack knowledge and techniques to avoid these repetitive tasks, despite the fact that a large proportion of XR applications retrieved 3D geometry and semantic information from the same BIM (Li et al. 2018, Zhang, Liu, et al. 2020, Leite 2019).

This paper aims to decrease the implementation cost of BIM-enabled XR applications by streamlining the BIM-to-XR model preparation process. The authors reviewed existing AEC XR literature and summarized XR information requirements from BIM. Then, a generic XR (GenXR) model is proposed to support diverse BIM-based XR development in a project lifecycle. The model enables automatic change identification between the GenXR model and an up-to-date BIM. Therefore, only new and updated objects experienced the BIM-to-XR model preparation process, saving development time and revealing new XR use cases. This paper developed VR, AR, and MR prototypes in two case studies for validation purposes. Typical XR functions were developed to test the applicability of the GenXR model, while development durations with and without the GenXR model were measured to investigate its efficiency.

The paper contributes to the body of knowledge by three key results. First, the authors summarized all XR-related model requirements from BIM, including the information type and format, for all existing XR applications in the AEC research domain. Second, by leveraging the summarization, the GenXR model and prototypes demonstrated the applicability of developing all XR applications using a generic XR model for the first time. Next, this paper quantified development time savings using the GenXR model. Practically, the model and workflow can significantly decrease XR development time. Therefore, XR implementation requires less investment, and the technology could be applied to support new challenging tasks in the AEC industry.

4.2 LITERATURE REVIEW

4.2.1 BIM-enabled XR Applications

The AEC industry has experienced an increasing BIM usage with measurable benefits (Troncoso-Pastoriza et al. 2019, Hartmann, Gao, and Fischer 2008, Mostafa and Leite 2018). BIM has enabled project data management to address a variety of engineering challenges, such as design coordination, scheduling, and various simulations (Ding, Zhou, and Akinci 2014, Mehrbod et al. 2019a, Moon et al. 2015, Rock et al. 2018). In addition to BIM's native applications, the comprehensive and well-organized information has aided the implementation of other emerging technologies (Leite 2019).

Many XR applications have leveraged BIM in model generation and realized advanced visualization, communication, and human-model interaction for industry professionals (Li et al. 2017, Yan, Culp, and Graf 2011). Each XR technology has its unique features, which determine appropriate use cases for the technology. CII defined VR by two fundamental characteristics, the computer-generated simulation and the visually immersive experience enabled by a Head-Mounted Display (HMD) (Institute 2019). On the other hand, both AR and MR technologies overlay virtual environments with the real world (Xiang, Wang, and Feng 2021). AR applications perform the overlay without an intellectual understanding of the content, while MR applications comprehend the reality in real-time and allow interactions between the virtual environment and reality (Milgram and Colquhoun 1999, Li et al. 2018, Osorto Carrasco and Chen 2021).

Considering that VR is independent of real-world objects, many VR applications focus on tasks before construction. Motamedi et al. (2017) designed a VR-based signal visibility analysis application for pathfinding and information provision in public spaces. Kang et al. (2010) extended VR applications to the design phase, creating visual design and simulation analysis functions for road design. Similarly, de Klerk et al. (2019) investigated the usability of VR on architectural modeling in an early stage of a project. VR applications were also used for safety training (Shi et al. 2019, Teizer, Cheng, and Fang 2013, Manca, Brambilla, and Colombo 2013), behavioral simulation (Feng, González, Amor, et al. 2020, Lin et al. 2020, Lin et al. 2018), and lighting analysis (Keshavarzi, Caldas, and Santos 2021) in the AEC industry.

The requirement in a real-world environment determined that AR and MR applications were more commonly utilized in the construction and operation stages (Cheng, Chen, and Chen 2020). Hou et al. (2013) found AR guidance improved users' learning, productivity, and cognition, compared to a paper-based manual system. Zhou, Luo, and Yang (2017) implemented AR-based Quality Control (QC) in a tunnel construction project, empowering real-time displacement inspection on tunnel segments. Kwiatek et al. (2019) enhanced workers' spatial cognition and productivity in complex pipe spool installation via a hand-held AR device. Lee and Akin (2011) also observed increasing in fieldwork efficiency when operations and maintenance instructions were delivered to workers by an AR application. Sangiorgio et al. (2021) integrated the Analytic Hierarchy Process in AR to support façade material decision-making.

MR applications take advantage of the intellectual reality recognition function in problem-solving. For example, in a renovation project, Osorto Carrasco and Chen (2021) overlapped architectural design with the original building to perform design review and feedback collection. El Ammari and Hammad (2019) designed an MR application that delivers maintenance information as well as sensor data to workers onsite via a tablet. Chalhoub and Ayer (2018) found that using an MR application to deliver assembly information could enhance worker productivity as compared to using 2D drawings. XR has also been used for construction progress tracking (Kopsida and Brilakis 2020).

The scope of existing XR applications has included various visualization and communication use cases in the lifecycle of a construction project. The review shows that each application has contributed to a specific scenario or engineering challenge. Consequently, reaping the full benefit of XR technology requires multiple XR applications at different stages of the same project.

4.2.2 Functions and Model Requirements

Presenting the correct information to end-users in an interoperable format was a grand challenge identified in visualization and information modeling in the construction industry (Leite et al. 2016). It is especially true for contemporary XR research and development. Alsafouri and Ayer (2018) reviewed 119 journal articles in Information and Communications Technology (ICT) in the AEC industry and found that most of them utilized a unidirectional information flow that works for specific use cases or functions of an application. Li et al. (2018) and Zhang, Liu, et al. (2020) both pointed out that VR and AR applications were developed in an ad-hoc approach in their review articles.

Han and Leite (Accepted) proposed standardizing BIM-related information requirements and workflow to streamline the BIM-to-XR process. This review of literature extended the work by comprehensively reviewing XR applications in the AEC industry, mapping applications with model-related XR functions, and tracking information requirements for each function in terms of content and format. According to the literature review section, common AEC XR functions from an application development perspective include:

1. Visualize a BIM in real-scale.
2. Overlap a BIM with reality.
3. Select an object/object group in a hierarchy.
4. Operate objects based on semantic information and user input.
5. Create realistic texture and lighting effects.
6. Display semantic information of an object.

To support these developments, the following information should be retrieved and processed from BIM before importing to XR development software systems, including Interactable geometry, object coordinates, construction schedule, object material, light location and intensity, model hierarchy, object identifier (ID), and attached notes.

4.2.3 BIM-to-XR Workflows

Various BIM-to-XR workflows were established in existing XR research. Although geometry transfer between BIM and XR development software systems is a mature process already, attaching semantic information to 3D geometry is still challenging. Han and Leite (2021a) extracted geometric data from BIM in the Autodesk®

Filmbox (FBX) format and used Feature Manipulation Engine® to obtain geometric features of BIM objects. Boton (2018) attached XML Timeline files to the FBX model files to integrate construction schedule and 4D simulation information into VR. Khalili (2021) extracted semantic data from BIM in an Extensible Markup Language (XML) file and created an XML parser to encode the XML file in XR development software systems, so as Tavares et al. (2019). El Ammari and Hammad (2019) transferred BIM data to XR in an Industry Foundation Classes Extensible Markup Language (ifcXML) format. Lin et al. (2018) exported object parameters, such as device name and type, with object ID using Autodesk® Revit Application Programming Interface (API). Chen, Lai, and Lin (2020) used the Autodesk® COBie Extension to extract inspection and maintenance for of fire safety equipment in COBie standard format. Although these methods supported the specific XR application, none created an XR model that satisfied development requirements for other AEC XR applications.

Many commercial software systems and plug-in applications tried to automate the BIM-to-XR process for the AEC industry. For example, IrisVR, Enscape, and InsiteVR can automatically acquire 3D models from different BIM software systems and create VR applications. Twinmotion and Unity Reflect, on the other hand, automated the model transferring process from BIM to XR development software systems. These efforts provided the industry with off-the-shelf solutions. However, they also compromised the development flexibility and extendibility of XR applications. Firstly, these workflows lack key model optimization processes. 3D geometry directly exported from BIM contains redundant objects, such as 2D drawings and reference points. To minimize the computing workload of XR applications and allow the application to handle more 3D objects, the aforementioned research projects cleaned up their models in computer graphics software systems. Next, these software systems lack connections to essential model preparation algorithms, such as occlusion detection (Han, Ma, and Leite 2021). Additionally, commercial model transferring software systems commonly enable connections between specific software systems. Their workflows cannot support project stakeholders' use of different modeling software systems. Therefore, existing commercial model transfer software systems are not practical for industry implementation, and their limitations demonstrate the need for a flexible and generic BIM-to-XR workflow.

4.2.4 Knowledge Gap

This paper identified the lack of knowledge on a standard XR model that can leverage existing XR models in future developments. It resulted in repetitive activities in XR development when building a new application or when a BIM got an update. This section summarized existing BIM-related information requirements and information transfer methods from the standpoint of XR developers. The knowledge is meant to help explore a standard XR model with an efficient and collaborative BIM-to-XR model preparation process when multiple XR applications are utilized in the same project. This literature review imparts the opportunity of standardizing the existing XR model development process because information requirements from these applications have considerable overlap. The opportunity could reduce XR development durations in various AEC use cases and enable project engineers to implement more appropriate visualization technologies with less technical and financial constraints.

4.3 METHODOLOGY

Based on the knowledge gap and opportunities identified in the literature, we propose a GenXR model for developing XR applications in the AEC industry. The GenXR model aims to streamline the BIM-to-XR process when multiple XR applications are implemented in the same project. Therefore, the model should satisfy three essential requirements. First, the model should provide geometric and semantic information in a format consistent with current industry practice. Then, considering the dynamic nature of a construction project, synchronizing with an up-to-date BIM becomes a prerequisite for the XR model. In addition to the applicability, the practical contribution of the XR model is primarily determined by productivity enhancement. As a result, the workload of implementing the XR model should be lighter than traditional approaches. It is worth noting that the BIM-to-XR process is a generic workflow. Software systems used in each step are presented with the intent of assisting peers in replicating this work. Other software systems with similar functions should also be able to follow the workflow and achieve similar functions.

4.3.1 Workflow

Many existing BIM-based XR applications in the AEC industry share a linear development workflow, as shown in Figure 4-1. XR developers initiate the workflow with a BIM of a target project. After federating models from different disciplines, model geometry is exported from BIM and modified in computer graphics programs for XR development. Semantic information for the specific XR application can be retrieved from BIM with geometry or as a separate component. Next, geometric and semantic information is imported into XR development software systems. Finally, XR developers leverage a game engine to create effects, functions, and human-computer interactions. This linear BIM-to-XR process only contains the required information of one XR application at the time when the application was built. The lack of extensibility and information adaptability determined that developers needed to repeat the process for new XR applications or when a BIM is updated or modified.

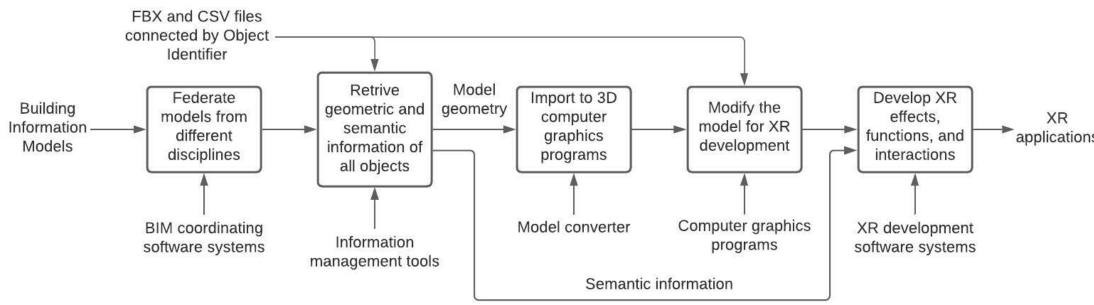


Figure 4-1: The traditional XR development process in the AEC industry

Developers' productivity can be enhanced by decreasing the number of objects that experience the repetitive and time-consuming BIM-to-XR process. Figure 4-2 introduces the GenXR model-facilitated information flow when the BIM-to-XR process is needed multiple times in the same project. In the initial cycle of the BIM-to-XR iteration, the transfer of model geometry from BIM to XR is identical to the linear method. However, all XR-related semantic information is retrieved from BIM and preserved in a compatible format with XR development software systems. In the following BIM-to-XR iterations, model updates are automatically detected by comparing geometric and semantic information between the original XR model and the updated BIM. XR developers only need to perform model transfer and optimization activities to new and updated objects. These objects were imported to XR development software systems as an update package, while deleted and updated objects from the original XR model were deactivated and kept only for version control-related functions.

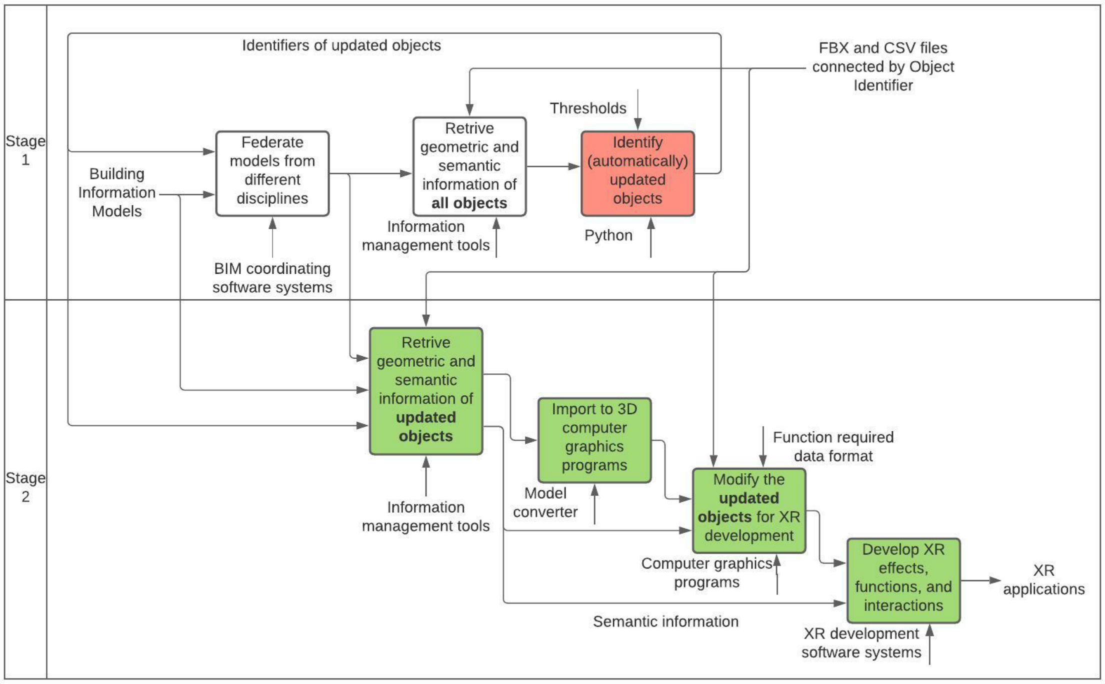


Figure 4-2: The GenXR model-facilitated BIM-to-XR process

4.3.2 Assumptions

The methodology was built on two major assumptions. First, the authors assume that an up-to-date BIM is available in the construction project for which XR applications are to be applied. As indicated in the literature review section, BIM serves as the information source for many existing XR applications, and having a "living BIM" that is maintained up to date throughout the construction project aligns with current research trends. Second, this paper made the assumption that in some construction projects, the BIM-to-XR process would be performed multiple times. This assumption is valid when multiple XR applications are implemented in the same project, such as using VR for design review before construction and using AR for Quality Control (QC) during construction. Another circumstance that justifies the assumption is when model iterations happen during the operation period of an XR application. For example, if VR is used to support design coordination meetings during construction, the VR model is likely to be updated with BIM weekly or bi-weekly.

4.3.3 Model Development

The GenXR model was composed of model geometry and semantic information. The two components were kept separately and connected by the object identifier (Object ID). As shown in Figure 4-2, BIMs (created by Autodesk® Revit®) from different disciplines were federated in Autodesk® Navisworks® Manage when they were separately modeled. The authors exported the geometry of all BIM objects in the FBX format. Then, geometry in the FBX file was imported into Autodesk® 3ds Max® to adjust for XR development (Han and Leite 2020). First, pivots of all objects were moved from the center of the BIM to the center of each 3D object, and thereby, physical movements of these objects can be achieved by editing their transforms in XR development software systems. Then, 2D drawings, reference points, and empty objects were deleted to simplify the model. Meanwhile, empty and redundant hierarchies were also deleted to simplify object selection functions in XR. The detailed model optimization process is described in Han and Leite (2021b). The optimized 3D model was exported as an FBX file and finally imported into Unity3D, an XR development software system commonly used in the AEC industry.

Semantic information was retrieved from Autodesk® Revit® using Dynamo, see Figure 4-3. All XR-related BIM information summarized in the literature review section was exported from BIM into a Comma-Separated Values (CSV) file, including Object Name, Object ID, Categories, Unique ID, Coordinates of Object Transform, Coordinates of Object Bounding Box, and Object Material. The authors wrote a Python script to automatically formalize the exported data into semantic information lists that were comprehensible by Unity3D. Eventually, the pre-processed semantic data was maintained in a CSV file and directly imported into Unity3D with model geometry.

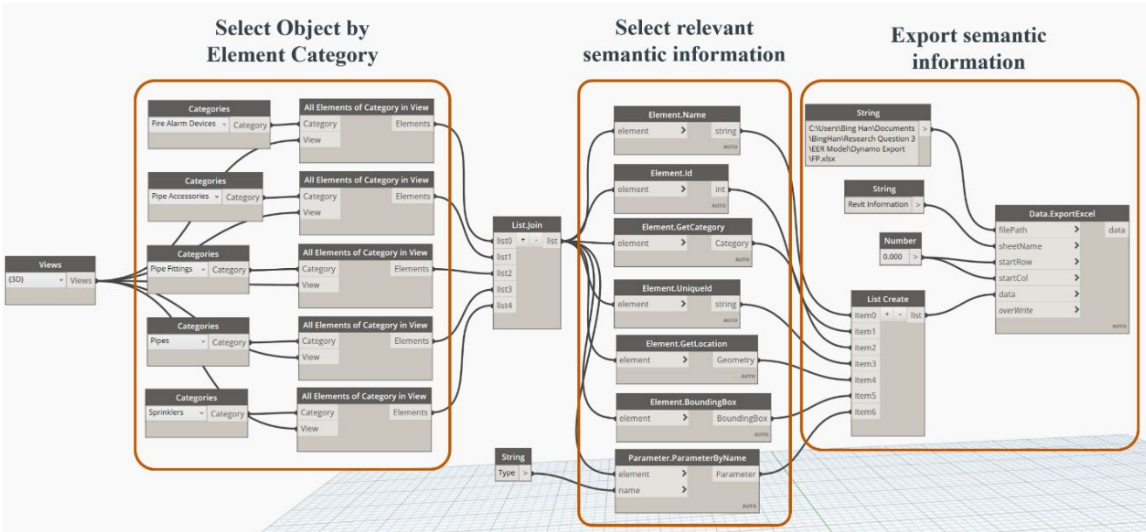


Figure 4-3: Exporting semantic information from BIM using Dynamo

In Unity3D, the authors programmed a function that automatically connected the geometry and semantic information of an object using C#. Figure 4-4 used pseudocode to demonstrate the information integration process. To begin with, BIMObject is created as a new reference type. It specifies the properties and corresponding variable types for each instance. The properties of a BIMObject include semantic data exported from BIM and the name of its corresponding geometry. For example, a BIMObject has an "Object ID" property in the integer type and a "Category" property in the string type. With the reference type defined, a C# script reads the pre-processed semantic information, instantiates each row as a new BIMObject instance, and documents all property values.

```
//Create BIMObject class
Public class BIMObject
    Public Semantic information names and data types
//Link semantic information to geometry
Import the semantic information file
For (all rows)
|   Create new BIMObject;
|       BIMObject ← semantic information[row];
|       If (ObjectID[row] == ObjectID[geometry])
|       |   BIMObject ← geometry name;
//Examples of functions enabled by information filtering
For (all BIMObjects)
|   If (Semantic information == criterion)
|   |   Geometry[BIMObject].SetActive = true/false;
|   |   Geometry[BIMObject].Material = given material;
//Examples of functions enabled by user input
If (UserSelected[BIMObject])
|   Geometry[BIMObject].highlight = active/inactive.
|   Text ← semantic information;
|   Canvas.location ← Geometry[BIMObject].location
|   Canvas.direction ← Reversed Users.direction (Vector3)
|   TextDisplay = true/false
```

Figure 4-4: Pseudocode for information integration and examples for function development in Unity3D

Instances are connected to geometries with a matching Object ID when an XR application is deployed. It ensures that data and filtering requests from XR functions can be processed promptly without decreasing the frame rate of the application. As a result, developers can design XR functions for objects with specific characteristics. For example, VR users in a design review application can modify the transparency of structural elements to get a better view of the Mechanical, Electrical, and Plumbing (MEP) systems. In this case, XR developers extract the Object IDs of all BIMObjects that have a "structural" value in their category property. The geometry of these objects can be found using object IDs, and transparent material can be applied to these objects. The process can also be reversed. For example, in an AR-based maintenance application, users can select a target object in view. Developers can obtain its object ID, activate the highlight function attached to its geometry, and display selected properties of the object on a text canvas.

Realistic lighting effects on building components play an indispensable role in aesthetic-related and simulation tasks, such as AR-based facade material comparison (Sangiorgio et al. 2021) and VR-based behavioral simulation for emergency evacuation (Ruppel and Schatz 2011, Zhang et al. 2021). Although an FBX file can contain light sources and simulations created by BIM, they are not fully interoperable with the illumination settings in Unity3D. As a result, light sources in BIM were not exported in FBX with model geometry. Instead, coordinates of light sources were extracted from semantic information. Developers manually added and adjusted these light sources to replicate the designed lighting conditions.

XR illumination can be achieved in three approaches, real-time lighting, baked lightmaps, and a mixed mode. A lightmap is a pre-calculated texture that displays the brightness of object surfaces under the preset illumination situation. For static models and light sources, building lightmaps before running the application is an effective approach for XR applications to handle large models and complex interactions without compromising frames per second (FPS). On the other hand, rendering lighting in real-time generally demands more computational power and enhances realism for dynamic light sources and objects. This paper selected the mixed mode for illuminating the GenXR model. In order to decrease the overall computational demand, all static light sources in the XR model were set on the "baked" mode. Dynamic light sources, such as emergency lights, were rendered in real-time. For specific XR applications that focus on lighting design and effects, developers can build multiple pre-calculated lightmaps, displaying various illumination designs using the same process (Keshavarzi, Caldas, and Santos 2021).

4.3.4 Automatic Update with BIM

The ability to rapidly and accurately update with BIM is a central function of the GenXR model. Figure 4-5 illustrates the workflow of the automatic update algorithm. The input for the algorithm comprised a dated GenXR model developed in earlier XR applications and an updated BIM. The semantic information in the updated BIM is extracted and processed into the same format as the GenXR model. A Python script then automatically pairs objects from the two semantic information files with the same Object ID and checks if the semantic information is identical. Objects from the GenXR model without a pair are recognized as “deleted objects”, while objects from the updated BIM without a pair are classified as “new objects”. The classification result is kept in the format of Object ID lists. Geometric features, such as objects’ bounding boxes and coordinates, are also compared for the difference in this step. Next, paired objects with identical semantic information are converted into point clouds to compare geometric similarity (see Han, Ma, and Leite (2021) for more detail on the point cloud-based algorithm). Figure 4-6 used pseudocode to demonstrate automatic model update procedures. The semantic information comparison step presented in this paper effectively decreases the computing demand on object comparison. Finally, the python script exports Object IDs into five categories in a text format, see Table 4-1.

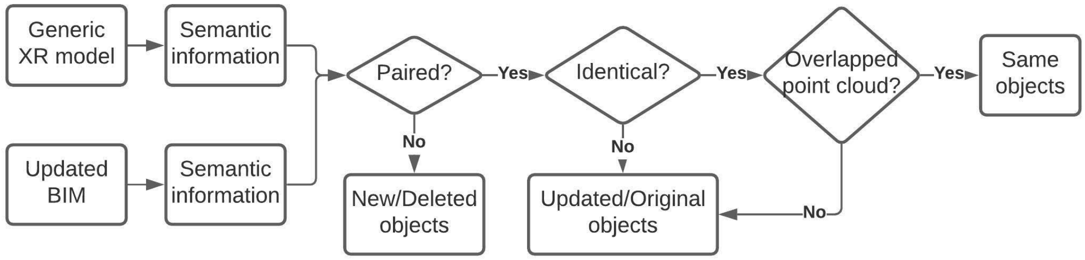


Figure 4-5: The workflow of automatically updating the GenXR model with BIM

Object origin	Not paired	Paired with the same semantic and geometric information	Paired with different semantic or geometric information
GenXR model	Deleted objects	Same objects	Original objects
Updated BIM	New objects	Same objects	Updated objects

Table 4-1: Classification results from the automatic model comparison

After the initial XR development, the automatic update function was applied in the following XR development process. Only new and updated objects experienced the BIM-to-XR process, and they were separately imported to XR development software systems, as described in section 4.3.2. On the other hand, deleted objects and original objects were deactivated and separately grouped based on Object IDs. As a result, the process realizes three key features of the GenXR model as follows.

- The GenXR model was automatically updated with a BIM;
- Identical BIM objects bypassed the traditionally time-consuming BIM-to-XR process; and
- The new XR model support version control of the project model.

```
//Pair Objects using Python
Import semantic information from the dated XR model
Import semantic information from Updated BIM
    For all ObjectID in [XR] and [BIM]:
        If (ObjectID [XR] == ObjectID [BIM])
            ObjectID → PairedList
        Else
            ObjectID[XR] → DeletedList
            ObjectID[BIM] → NewList
//Detect Changes using Python
For all PairedList:
    For all semantic information:
        If (XR[semantic information] != BIM[semantic information])
            ObjectID → UpdatedList
        Else
            ObjectID → OverlapTestList
//XR model update using C#
Import DeletedList and UpdatedList
New Archivefile
    For all DeletedList and UpdatedList:
        Object [XR] → Archivefile
        Disable Object [XR] → Archivefile
```

Figure 4-6: Pseudocode for the automatic model update procedures

4.3.5 Model Validation

This paper validated the applicability of the GenXR model via two case studies. The authors leveraged two BIMs, creating one VR, AR, and MR prototype for each case. In order to test the compatibility of the GenXR model with different types of BIM, the two BIMs involved in the case studies were developed by different companies for different project types. Only BIM-related operations and functions were performed in the case studies. For example, the function of overlapping a virtual model with reality was created to demonstrate that the GenXR model supported AR development. However, a localization function was not developed because it is an AR-specific function that does not relate to BIM. Table 4-2 summarizes XR functions developed in each prototype.

Case studies	VR applications	AR applications	MR applications
Academic building	Design review	Maintenance for the MEP system	Pipe routing
Infrastructure	Design review	Planning for schedule	Site planning

Table 4-2: XR functions realized in prototypes

4.4 CASE STUDIES

4.4.1 Project backgrounds

The first case study in this paper leveraged the BIM of a nine-story academic building composed of two towers and an auditorium. Architectural, Structure, Mechanical, Electrical, Plumbing, and Fire Protection systems of the building were modeled into six separate files by Autodesk® Revit®. The building was completed and in operation in Fall 2017. The authors utilized one floor in the south tower of the model to develop XR prototypes, see Figure 4-7. It is composed of 15 laboratories, three elevators, and a connecting bridge to the north tower. The selected area contains 5,278 objects.

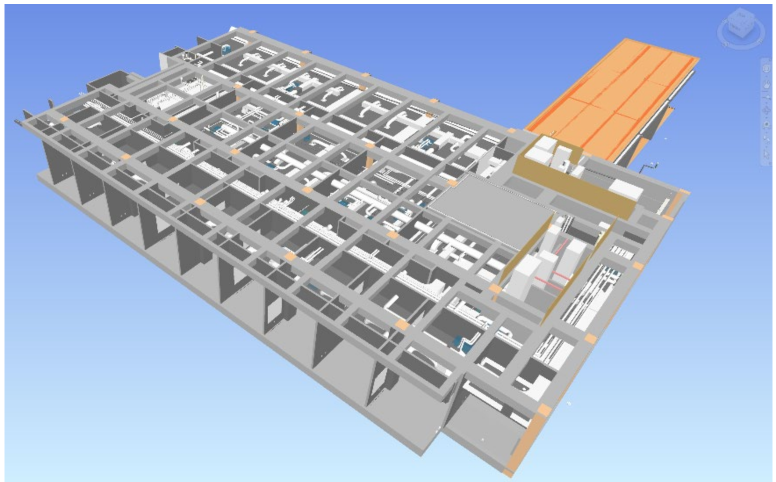


Figure 4-7: The BIM of an academic building used in case study one

The second case study used the BIM of a dam retrofit project developed by a different company, see Figure 4-8. In addition to structural elements and MEP systems, it also contains special equipment models and topography models created by drone-facilitated photogrammetry. The dam was modeled in Autodesk® Revit® with 1836 objects. However, unlike the academic building, the general contractor and subcontractors collaborated on a central model, and therefore, all objects were modeled in the same file. The dam project was under construction when the authors developed XR prototypes.

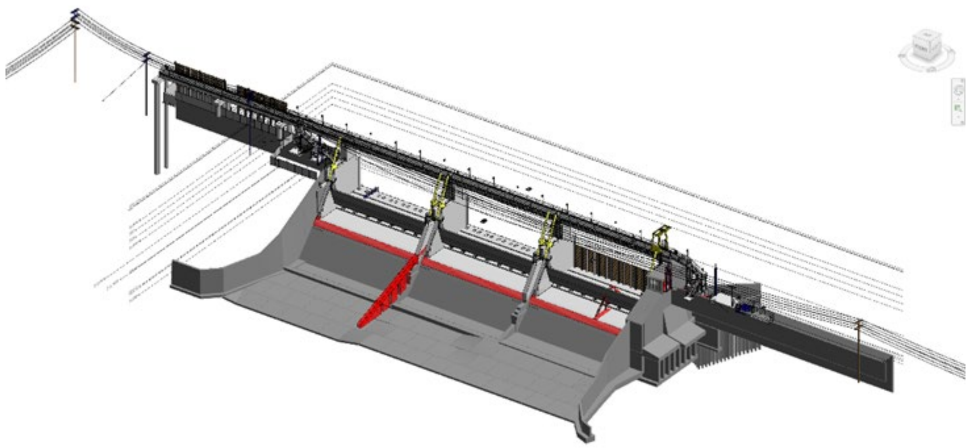
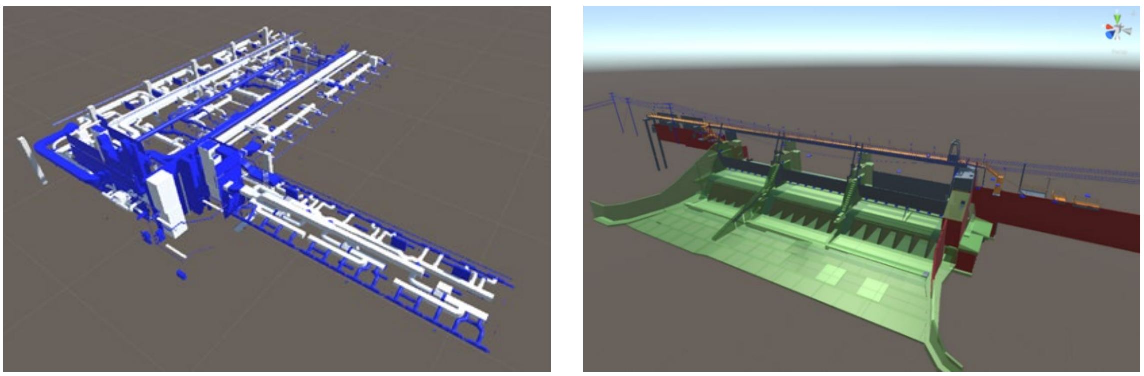


Figure 4-8: The BIM of a dam used in case study two

4.4.2 Prototype Development

VR, AR, and MR prototypes developed in this paper aim to validate the applicability of the GenXR model. Therefore, only model-related functions, such as overlapping virtual models with the real world and modifying 3D objects based on semantic information, were developed to an application level. Other technology-specific developments, such as indoor localization for AR and MR, are out of scope for this research.

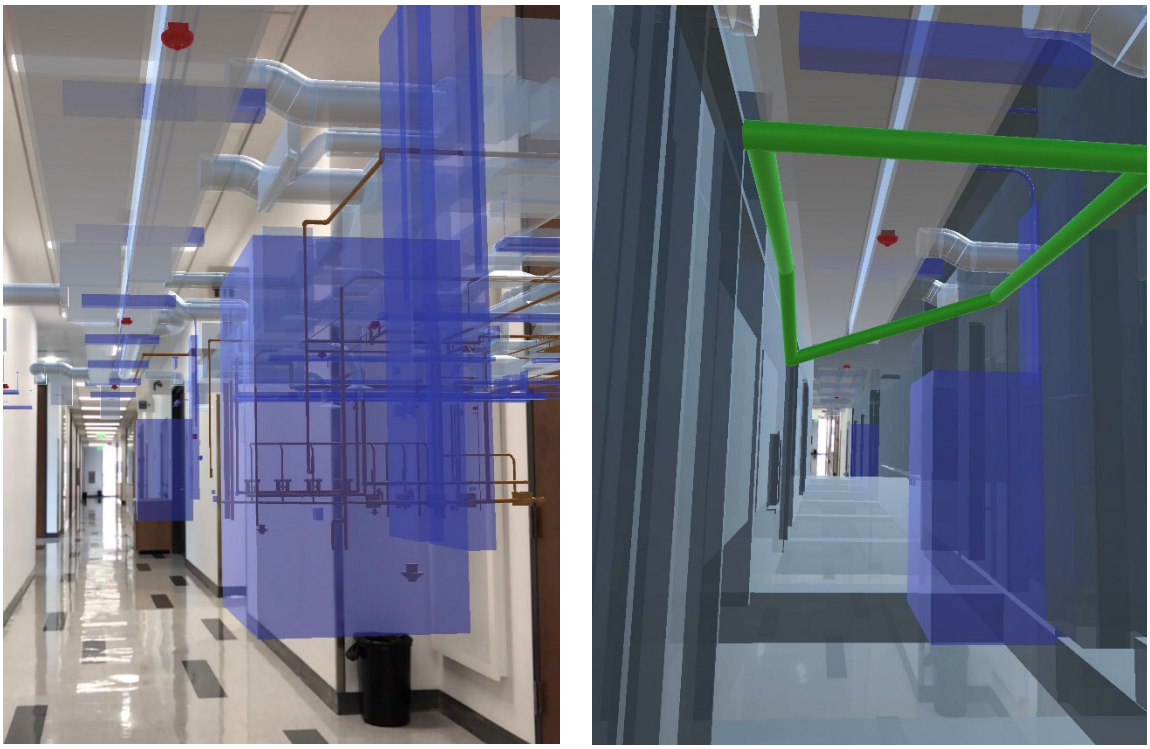
VR-based design review applications were developed in both case studies to validate the applicability of the GenXR model. The application had two essential functions. First, an avatar was added to connect the VR user with the virtual environment. The avatar was built based on SteamVR's player prefab. It realized the fundamental movement, controller-based input, and visualization functions in VR. Other player prefabs, such as the OVRPlayer prefab developed by Oculus, can also realize these functions. Next, specific functions for construction design review were created. Users gained control of 3D objects by accessing their semantic information. For example, they can activate only MEP systems in the academic building, as shown in Figure 4-9 (a), and mark the existing structure in a different material in the dam project, as shown in Figure 4-9 (b). In addition, users can take screenshots, teleport to pre-set locations and views, and access object semantic information in the prototype, as described by Han and Leite (2021b).



(a) (b)

Figure 4-9: VR functions realized by the GenXR model in case studies

AR and MR prototypes share the same function of overlapping the virtual model with reality. Therefore, AR and MR functions were developed in the same prototype. In the academic building, users can visualize the MEP systems occluded by the ceiling via an iPad, see Figure 4-10 (a). Similar to the VR application, XR effects on virtual objects can be modified by users according to their semantic information. For example, users can assign different colors or textures to the mechanical, electrical, and plumbing systems, respectively. In addition to AR functions, the authors realized interaction between the virtual model and the real world with the help of Unity3D's AR Foundation and ARKit packages. ARRaycastManager in the AR Foundation package was used to realize real-time surface recognition in the real world. Subsequently, the authors developed a function that allowed users to perform pipe routing work using an iPad onsite, see Figure 4-10 (b). The recognized real-world spot was illustrated on the iPad, and the users can simply click the start and end points to substantiate a pipe.



(a) (b)

Figure 4-10: AR and MR functions realized by the GenXR model in case study one

Considering that the dam project was under construction, its AR prototype was designed to help visualize the project design and plan for the construction schedule. Figure 4-11 demonstrates the effect when overlapping the dam model with its construction site. The activation status of objects, materials, and other visual effects can also be modified by the user based on semantic information. For example, users can activate objects step-by-step according to the pre-set construction schedule, replicating the planned construction process. The prototype shared the same surface recognition function as the academic building prototype in terms of XR functions. It allows users to create virtual models of construction equipment, such as mobile cranes, on appropriate locations selected in the real world.

Figure 4-11: AR functions realized by the GenXR model in case study two

4.4.3 Performance Measurement

4.4.3.1 Measurement Criteria

The performance of the GenXR model was measured by comparing the development durations for the six XR prototypes with and without the GenXR model. Considering that the GenXR model only streamlines the BIM-to-XR process, this paper only measured the development time for BIM-related activities. These activities include model transfer time from one software system to another, model modification time, as summarized in the literature review, and model-related development time, such as creating light effects. Application design, coding, and debugging are time-consuming activities in XR development. However, they were not considered at a project level because codes and effects for an XR application were likely to be developed at a company level and shared with multiple projects.

Manual input durations and automatic processing durations were separately measured to maintain rigor in results. The authors performed manual input activities three times in each application. The average duration was accepted if the differences were less than 5%. It is worth noting that the development process has been practiced several times before the measurement to mitigate the learning curve for the development. The automatic processing durations results were more objective and easier to replicate. Similar to the manual input practice, the authors executed each processing activity three times and presented the average duration when less than 5% deviation was observed. This paper validated the automatic update function by adding artificial changes to 10% of objects in the case study models. These changes included adding new objects, deleting existing objects, modifying the location and size of existing objects, and modifying semantic information. The performance of this algorithm was measured by identification accuracy. The manual input and computing time for the automatic update was included in the model performance measurements.

The desktop used to develop VR prototypes has an AMD® Ryzen® 3900x 12-core central processing unit (CPU), an NVIDIA® GeForce® RTX 2060 graphics processing unit (GPU), and 32 GB DDR4 random access memory. AR and MR prototypes were developed using a MacBook Pro that has an Apple M1 Chip with an Eight-Core CPU, an Eight-Core GPU, and 8GB unified memory. All XR prototypes were developed in Unity3D version 2021.1.10f1.

4.4.3.2 Measurement Results

Figure 4-12 shows XR prototype development durations in the academic building case study. Developing BIM-related activities in the VR, AR, and MR prototypes without the GenXR model took 7.75 hours, 7.49 hours, and 7.49 hours, respectively. In the initial cycle of XR development using the GenXR model, the prototype development took 7.92 hours overall, spending more manual operation time on the comprehensive information retrieval from BIM. However, on the following iterations, the overall development duration was reduced to an average of 2.53 hours when the model had around 10% updated objects. Overall, 66.7% of model-related development time was saved compared to independent XR development, including 75.1% manual operation time and 63.9% automatic computing time. Model transfer activities, from BIM to computer graphics programs and eventually to XR development platforms, benefited the most from the GenXR model. On the other hand, the automatic light-baking process was not shortened. In addition, all artificial modifications on the model were successfully detected by the automatic update function.

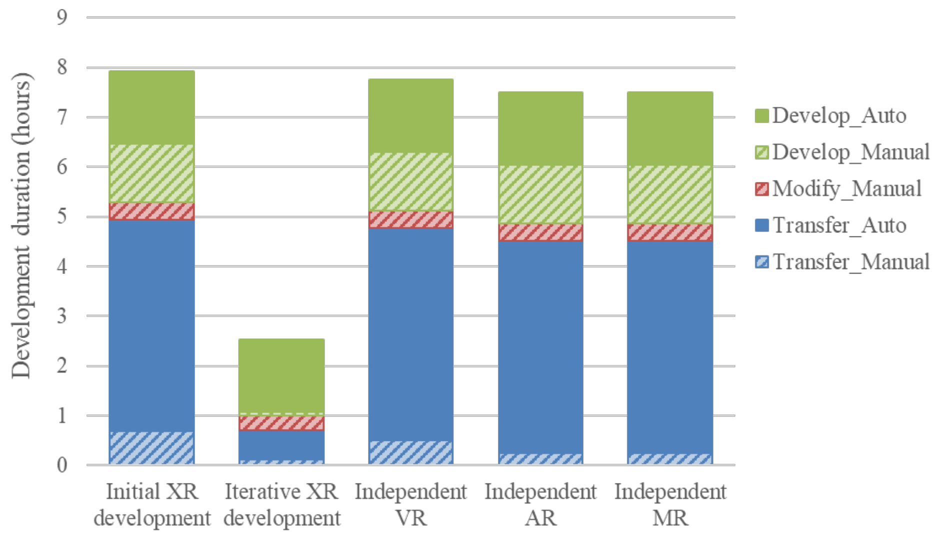


Figure 4-12: Prototype development durations with and without the GenXR model in case study one

The prototype development durations for the dam project are displayed in Figure 4-13. The automatic update function detected all model changes in the dam project as well. The overall development time was shorter than the academic building project because the dam model contains fewer objects. Similarly, using the GenXR model in the initial cycle took, on average, 12 minutes longer than developing VR, AR, and MR prototypes in the traditional method. The following iterations using the GenXR model were 63.8% faster than independent XR developments on average. In case study two, manual operation time was reduced by 71.9%, and automatic processing time was reduced by 63.6%.

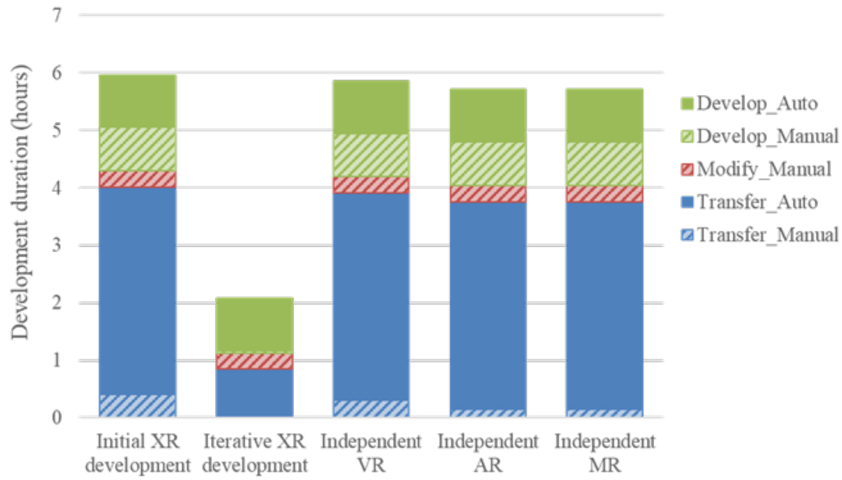


Figure 4-13: Prototype development durations with and without the GenXR model in case study two

4.5 Discussion

4.5.1 Applicability

The two VR prototypes demonstrated that the GenXR model could support diverse VR functions and applications in the AEC industry. First, design review applications could take full advantage of the ability to access semantic information and modify visualization effects accordingly. Beyond the changing material function demonstrated in prototypes, other review needs, such as construction schedule, sustainability design (Ayer, Messner, and Anumba 2016), and waste management (Guerra, Leite, and Faust 2020), can be achieved using the same programming logic. Second, the GenXR model realized functions of realistic illumination. This function supported a variety of AEC applications, including visibility analysis (Motamedi et al. 2017), emergency simulation (Lin et al. 2020, Lovreglio et al. 2018), and material selection (Sangiorgio et al. 2021).

The AR prototypes validated the applicability of the GenXR model in AR development for AEC use cases. As a fundamental function for AR, overlapping a virtual model with reality enabled diverse applications in a project's lifecycle, such as onsite Quality Assurance and Quality Control (QAQC). Meanwhile, the connection between geometry and semantic information supported advanced AR use cases. For example, construction progress can be visualized with the project's schedule, and maintenance information can be displayed directly to onsite workers with instructions on maintenance work (Chen, Lai, and Lin 2020). Although the prototype still needed AR-specific development, such as a localization function, before it could be applied in industry, these functions were independent of the model and have been developed in many research projects (Baek, Ha, and Kim 2019).

Although the virtual-real interaction enabled by MR was not widely implemented as VR and AR applications, the MR prototypes demonstrate many potential AEC use cases. The surface recognition function brought reference points in the real world to MR applications. Users can leverage these reference points, measuring distance or area in existing structures, placing construction equipment onsite for site management, and performing onsite pipe routing by placing pipes' start and end points. Currently, these MR functions, especially for reality recognition, heavily rely on advances in computer vision and artificial intelligence. However, the MR prototypes showed that the GenXR model realized model-related requirements and supported the deployment of these functions.

4.5.2 Performance

Measurements from the case studies showed that with the help of the GenXR model, the development time for XR applications slightly increased in the initial cycle and significantly decreased in the following iterations. The GenXR model only processed new and updated 3D objects in BIM after the first development, and both manual operations and automatic processing steps benefited from the model with fewer objects. It is worth mentioning that the automatic processing durations were more objective, while the manual operation durations may experience more variety due to differences in developers' skill levels. Considering that the developers' salary composed two-thirds of the XR investment, the result shows that the GenXR model could decrease the overall XR implementation cost when multiple XR applications are applied in the same project or when the XR model needs frequent updates.

In both case studies, the largest reduction in development time was observed in the automatic model transfer duration, followed by the manual development duration. The two activities are sensitive to the number of total or relevant objects in the model. On the contrary, the authors observed limited effectiveness in activities that are not influenced by the object number. For example, although semantic information for fewer objects was extracted from BIM in iterative XR developments, developers still underwent all manual operations for selection and exporting. Another activity that did not benefit from the GenXR model was creating Lightmaps. Updated 3D objects can affect the Lightmap for existing objects. Therefore, the Lightmap needs to be re-calculated for all objects after model updates.

Model features and modeling methods also caused different results in the same activities in the two case studies. First, XR iterations in case study two took a longer model transfer time (the solid blue bar in Figure 4-13) because the BIM was a central model used for collaboration among different stakeholders. Developers had to detach the model from the software's server and then process the model using the same workflow in case study one. The additional detaching process was necessary for each iteration. Second, model complexity can significantly impact the overall BIM-to-XR duration.

Although the dam project in the second case study has approximately one-third of objects compared to the academic building, it contains geographic objects with complex shapes. Therefore, the computing durations of model transfer and Lightmap creation per object were longer in case study two.

The reduction in overall development time not only realized the objective of reducing development cost. It also enabled new XR use cases. The AEC industry has already benefited from VR-based design review applications. However, VR currently cannot help design coordination use cases during construction, although the scenario is arguably similar to design review. In the current industry workflow in the US, design coordination meetings are held weekly or bi-weekly (Mehrbod et al. 2019b). A BIM coordinator would receive the BIM from different disciplines one day before the coordination meeting. The traditionally time-consuming VR development process prohibited creating a coordination environment in VR within the timeline. However, the GenXR model enabled the BIM coordinator or a specialized developer to fit the VR development process into the tight schedule of design coordination in construction. Therefore, all design coordination meetings could be held in VR, and the industry could expect a benefit similar to VR-based design review applications.

4.5.3 Limitations

The dependence on software systems is a major limitation of the proposed GenXR model. This paper only validated the BIM-to-XR information flow from Autodesk® Revit® to Unity3D. The GenXR model and workflow should prevail when other BIM, computer graphics, and XR development software systems are utilized. However, the information retrieval and processing methods might need tweaks to keep consistency with different software systems. As a result, the overall development time could vary from this paper's results.

Another limitation of this research can be found in the automatic update function. Decreasing the number of objects processed in the BIM-to-XR process is a central enabler for the shorter development time. Therefore, the effectiveness of the GenXR model could be decreased when the BIM experiences drastic changes. For example, if a general contractor decides to discard the designer's BIM and re-model the project, all objects in the construction BIM will be classified as new objects. The GenXR model cannot streamline the XR development in the designer-contractor interface. In this case, the GenXR model needs to experience the initial cycle for more than one time throughout the project lifecycle. The overall development time is supposed to increase accordingly.

Meanwhile, this paper only discussed a one-direction BIM-to-XR workflow using the GenXR model. However, after completing XR tasks, connecting XR results back to BIM is also essential in real-world practice. Theoretically, the GenXR model has the potential to complete the XR-to-BIM information flow. However, specific algorithms and tests are still lacking.

Finally, the manual input durations measured in each XR development activity can fluctuate with the developer's experience. The developer in this paper was proficient in development techniques for independent XR and the GenXR-enabled XR. Therefore, the result was observed in an ideal situation where no development errors or debugging time were included. Considering that the GenXR model utilizes an innovative and more complex workflow than the traditional method, industry professionals may spend more time coping with the learning curve. This process can also reduce the efficiency of the GenXR model.

4.6 Conclusions and Future Work

This paper identified the knowledge gap between XR applications in the AEC industry. The authors summarized information requirements from existing XR applications and developed a GenXR model accordingly. Geometry and sematic information are the two key components of the GenXR model. They were separately retrieved from BIM and connected via the Object ID. The BIM-to-XR workflow was also developed and automated in this paper. Specifically, the authors created an algorithm that automatically updated an existing XR model with an updated BIM. Consequently, only new and updated objects participated in the time-consuming BIM-to-XR process. The paper validated the GenXR model using six XR prototypes in two case studies. The result showed that the GenXR model supported the development of existing XR applications. Although XR development using the GenXR model in the initial cycle took 12 to 20 minutes longer than the traditional approaches, it saved from 63.8% to 66.7% BIM-to-XR model transfer time in the following iterations.

This paper contributed to the body of knowledge by proposing a GenXR model that connected BIM with XR development in the AEC industry. The knowledge helped standardize model-related information and, subsequently, formalized an efficient BIM-to-XR workflow that only processed new and updated objects in a BIM. Two major practical contributions can be expected from this paper. First, the reduced development time enabled more XR use cases in the AEC industry, especially during construction when XR applications were utilized with constant BIM updates. Second, the result showed that the GenXR model could significantly reduce XR development time when multiple XR applications were applied in the same project. From a business perspective, the reduction meant that XR implementation required less investment from construction companies, which could facilitate XR implementation in the AEC industry.

The authors would like to recommend three directions for future research in the area of BIM-to-XR workflow. First, exploring how different software systems and modeling logic impact the BIM-to-XR workflow could enhance the applicability of this work. It is not uncommon in the current AEC industry that designers, general contractors, and subcontractors use different modeling software systems in the same project. In this case, information retrieval and pre-processing for the GenXR model from different software systems become the key to the BIM-to-XR workflow. Second, case studies using the GenXR model would be the next step of performance measurement. The current result was observed in a lab environment with highly proficient developers. Before wide industry implementation, the GenXR model needs performance data observed in industry practice. A case study will provide the data and shed light on necessary modifications for industry uses. Last but not least, cloud-based XR model transferring, managing, and sharing can enable collaborations between developers and enhance application accessibility for remote users. More research efforts should be spent on replicating the current desktop-based GenXR model and the BIM-to-XR process on a server.

Chapter 5: Conclusions

5.1 Research Project Conclusions

This dissertation recognized and addressed three major engineering challenges in VR implementation in the AEC industry, especially for construction design review and coordination. Each challenge was encapsulated into one research question and addressed by a corresponding research project.

First, the actual performance of HMD-based VR was vague compared to 3D game engine-based alternatives. The dissertation answered the research question, " What is the impact of the Head-Mounted Display (HMD) on user performance in construction design review tasks when compared to desktop-based Virtual Reality (VR)?". A comparison framework that controlled more external variables was developed for users' performance measurement. Forty-eight industry experts and novices participated in a design review experiment. Statistical analysis revealed that VR significantly enhanced users' ability to detect design errors and plan for installation sequence, and the enhancement varied from 18% to 59%. However, such performance improvements were not applicable in the other two use cases, namely reviewing work package completeness and recalling the scope of work. Therefore, the benefit of VR applications only exists in specific use cases, and its industry implementation should be intentional. For construction tasks without existing experiment results, a construction company should follow the framework developed in research question 1 in this dissertation, evaluating VR effectiveness before implementation.

Next, occluded 3D objects are common components in BIMs. The lack of tools to visualize them in VR-based design review applications limited VR applicability and impeded its industry implementation. To answer the research question of " How can occluded building elements be automatically identified in 3D Models for VR-based construction design review applications?", this dissertation proposed a semi-automatic point cloud-based occlusion detection algorithm. The algorithm compared (a) point clouds converted from BIMs with (b) a point cloud generated by virtual scans of the BIM to determine the visibility status of 3D objects. This dissertation tested the algorithm using BIMs of an academic building and a gasoline refinery facility. In both case studies, the algorithm achieved over 90% recall rata for occluded objects. Therefore, the proposed point cloud-based algorism was applicable in occlusion detection tasks for BIMs, and the proposed scanning strategy, including a five-millimeter point interval and additional scanning density in narrow spaces, should be applied in relevant applications.

Last but not least, current XR development processes lack interoperability. Even though many XR applications retrieve information from the same BIM, the BIM-to-XR process needs to be repeated whenever the project BIM gets an update or a new XR application is needed. The third research question in this dissertation asked " How can a generic 3D model for BIM-based XR applications throughout the lifecycle of a construction project be developed?", aiming to streamline the BIM-to-XR process. Research question 3 summarized model-related functions in all existing XR development in the AEC research domain. The functions were then mapped into a list of model requirements. Next, the dissertation proposed a GenXR model that automatically updates. The applicability of the GenXR model was validated with six XR prototypes using BIMs of an academic building and a dam retrofitting project. Results show that the GenXR model supports model-related VR, AR, and MR development, and using the GenXR model saved over 65% of application development time.

5.2 INTELLECTUAL AND PRACTICAL CONTRIBUTIONS

The first research question contributed to the body of knowledge by (a) proposing a technology performance comparison framework that controls more external variables and (b) quantifying the impact of HMD on user performance in construction design review tasks. From an industry perspective, the knowledge created in this project provides quantitative references for decision-making on VR implementation.

The intellectual contribution from the second research question focuses on the proposed semi-automatic occlusion detection algorithm. This is the first algorithm in the AEC research domain that enables occlusion detection. Practically, the algorithm expanded the scope of VR-enabled construction design review from visible objects to all objects. A comprehensive design review opportunity enhanced the applicability of VR in related tasks. Meanwhile, the proposed algorithm has potential use cases in two broader research fields. Many other AEC VR applications that currently only focus on visible objects could benefit from this algorithm, such as VR-enabled training programs and behavioral simulations. In addition, general model comparison, such as a comparison between as-built and as-designed models, can be achieved by simple modifications to the proposed algorithms.

The third research question contributed to the body of knowledge in terms of (a) summarizing model requirements for AEC XR applications, (b) developing a GenXR model that supports all AEC XR development, and (c) quantifying the saved XR development durations using the GenXR model. In industry practices, the saved XR development duration can be interpolated into savings in XR investment. Therefore, the work facilitates implementing multiple XR applications in the same construction project. Meanwhile, the short overall development durations revealed new use cases for XR applications. For example, weekly design coordination meetings can be held in VR using the GenXR model.

5.3 LIMITATIONS

Two major limitations were identified in this dissertation work. First, all solutions proposed in three research questions relied on an available and up-to-date BIM. Although BIM implementation in the current United States AEC industry has already been widespread, high-quality BIMs are not always accessible for many reasons. For example, the current legal document for construction projects is still 2D drawings. As a result, issues with model-drawing consistency and certain subcontractors refusing to use BIM are not uncommon, and these issues could impair the effectiveness of VR-based design reviews. Next, the proposed models, methods, and applications were only tested with models that have at most 5,000 3D objects. The current mainstream desktop computers may not be able to support BIMs of complex buildings and infrastructure facilities. This limitation was addressed by creating sections in BIM and reviewing the project in VR section-by-section. In other words, reviewing the complete model of complex buildings and infrastructure facilities in VR is still challenging.

In addition, each research question has its own limitations. The VR performance measurement framework still includes non-technical variables, such as participants' industry experience, age, and VR experience. Recruiting more participants to the experiment could address this issue, but recruiting a large number of industry experts can be challenging. In addition, the performance-oriented scoring system provided strong support for industry decision-making. However, it could not explain the variety of user performance in different tasks or provide guidance for VR use case selection. In research question 2, the algorithm is semi-automatic because it still needs manual input on virtual scan locations. Selecting these locations relies heavily on the practitioner's experience. The lack of standardized criteria may cause variations in scanning quality when implementing the algorithm in the AEC industry. At the same time, the work detected a tradeoff between the recall rate of the algorithm and the computing duration. An algorithm that can intelligently distribute or sample the scanned and converted point clouds based on the size of an object is still lacking. Finally, the GenXR model only realized the BIM-to-XR model and information transfer. However, in practice, exporting results from XR back to BIM is also essential to realize the full benefits of XR applications. In addition, research question 3 only tested the GenXR model using one set of software systems. However, contractors from different disciplines may use different modeling software systems in a real-world construction project, and there are also many commercial XR software systems for AEC development. The GenXR model may need minor adjustments for additional software systems.

Chapter 6: Future Work

This dissertation research revealed several future research directions for XR technology and implementation in the AEC industry. First, the author recommends exploring the workflow of using reality capture technologies to create XR models. The starting point of the dissertation work is BIM. However, many existing buildings, structures, and infrastructure systems do not have an available BIM or general 3D model. Re-creating a BIM can be a labor-intensive process. Reality capture technologies, such as Unmanned Aircraft Systems (UAS), laser scanning, and Light Detection and Ranging (LiDAR), are under fast development, together with data processing algorithms, such as Structure from Motion (SfM). Combining these technologies has the potential to perform fast and realistic modeling for XR applications. Potential use cases for reality capture-enabled XR include but are not limited to the preservation and adaptive reuse of heritage buildings (Lee et al. 2019), skill and safety training for labors (Pedro, Le, and Park 2016), and behavioral simulations (Cao, Lin, and Li 2019). Currently, these VR applications can only model the building environment in BIM and then transfer the model into XR.

Then, the exploration of key contributing features of XR technologies to construction scenarios could benefit both technology developers and industry professionals. The first research question in this dissertation demonstrated a systematic approach to comparing technology performance in certain use cases. Such experiments can also be implemented at the technological feature level. For example, using VR headsets with different fields of view in an RQ1 environment could reveal the impact of the field of view on user performance. Such experiments are recommended to be performed repetitively on various AEC use cases. A meta-analysis of the performance data could provide scientific proof of correlations between technological features and the observed performance improvement. With the rapid advances in information and communication technologies, AEC practitioners would be able to use the knowledge and select appropriate technologies for a given task with a scientific basis. On the other hand, technology developers could be more intentional in hardware and software development.

Another future research direction is to explore model optimization algorithms specifically for AEC models. As discussed in the limitation section, it is still challenging to handle complex BIMs using current mainstream desktop computers. Considering that most AEC elements have regular shapes, such as boxes and tubes, specific model optimization algorithms should be able to decrease the number of polygons used to represent a building element. Optimizing 3D meshes could significantly decrease the required computing power, allowing XR applications to handle larger models. In addition, mesh optimization could significantly benefit standalone devices, such as untethered VR HMD and MR headsets. These types of equipment provide better portability but have limited computing power, especially in graphic processing. Creating XR models that represent construction objects with fewer polygons could facilitate the implementation of standalone XR devices and, thereby, supports more on-site construction use cases.

Finally, creating XR-specific requirements for building information models could help the AEC industry reap more benefits from XR technologies. This dissertation, along with many existing research projects on XR implementation in the AEC industry, utilized building information models in the same way as desktop-based applications. As discussed in Chapter 3, the MEP systems were modeled in the LOD of 400, and the trivial objects complicated the occlusion classification process. Similar challenges could be solved with less effort during BIM development comparing to addressing them in XR development software systems. Therefore, summarizing XR-specific requirements for BIM and implement them during the modeling phases could be a complementary approach to saving XR development time in construction projects.

Appendices

Appendix A – Abbreviations List

Appendix A contains a list of abbreviations used throughout this dissertation:

AEC – Architectural, Engineering, and Construction

ANOVA – Analysis of Variance

API – Application Programming Interface

AR – Augmented Reality

BIM – Building Information Modeling

CPU – Central Processing Unit

CSV – Comma Separated Values

FBX – Filmbox

FME – Feature Manipulation Engine

FOV –Field of View

FPS – Frames Per Second

GenXR – Generic Extended Reality

GIS – Geographic Information System

GPU – Graphics Processing Unit

HCI – Human-computer Interaction

HMD – Head-Mounted Display

ICT – Information and Communication Technology

ifcXML – Industry Foundation Classes Extensible Markup Language

IRB – Institutional Review Board

IVR – Immersive Virtual Reality

LiDAR – Light Detection and Ranging

LOD – Level of Development

MEP – Mechanical, Electrical, and Plumbing

MEPF – Mechanical, Electrical, Plumbing, and Fire Protection

MR – Mixed Reality

QA – Quality Assurance

QC – Quality Control

RAM – Random Access Memory

RFI – Requests for Information

SD – Standard Deviation

SfM – Structure from Motion

SME – Subject-Matter Expert

TOF – Time-of-flight

UAS – Unmanned Aircraft Systems

UUID – Universally Unique Identifier

VR – Virtual Reality

XML – Extensible Markup Language

XR – Extended Reality

APPENDIX B – BIM-TO-VR WORKFLOW

Appendix B displays step-by-step model transfer procedures and settings for the VR-based design review application presented in Chapter 2.

B.1 Model Export from BIM

The BIM used in Chapter 2 research was a federated model created by Autodesk® Navisworks® Manage 2020. The model was exported into an FBX file using the build-in exporter in Navisworks Manage with settings shown in Figure B-1. Key parameters and reasons for the export setting are as follows.

- Textures should be "embedded" in the FBX model to avoid losing texture information or losing connections between textures and objects in the following activities.
- The author does not recommend including lights and cameras in the FBX model. It can be easier for the developer to directly use lights and cameras provided by XR development software systems.
- Polygon limiting is not recommended because it may cause unexpected deletion of 3D objects in the model.
- Many different units and FBX versions work for this purpose. However, it is important to keep consistency during model transfer and VR development.

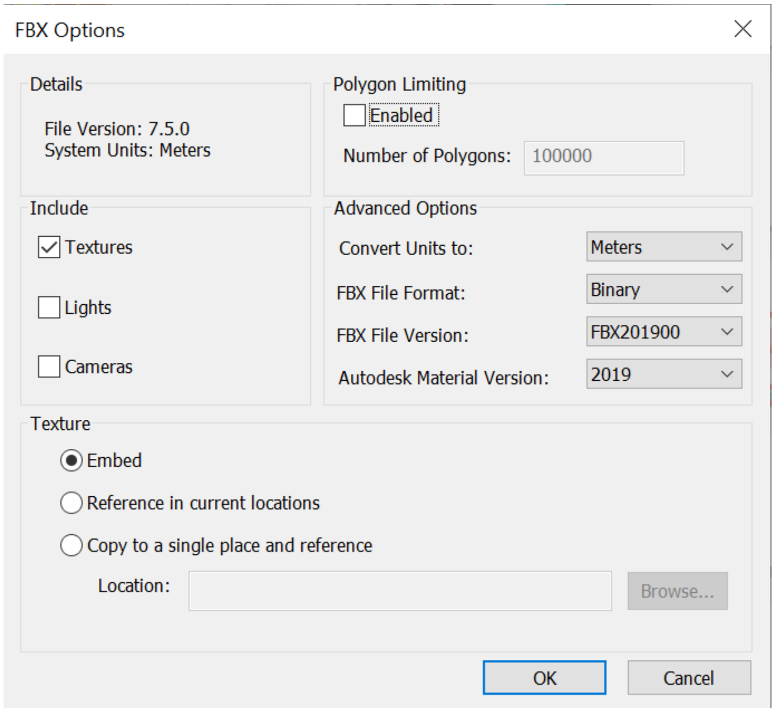


Figure B-1: FBX output settings

B.2 Optimize the FBX in Computer Graphics Software Systems

The exported FBX file was then optimized for VR development in computer graphics software systems before importing to VR development software systems. Autodesk® 3ds Max® 2020 was used for this purpose. The FBX model was imported to 3ds Max using the settings shown in Figure B-2.

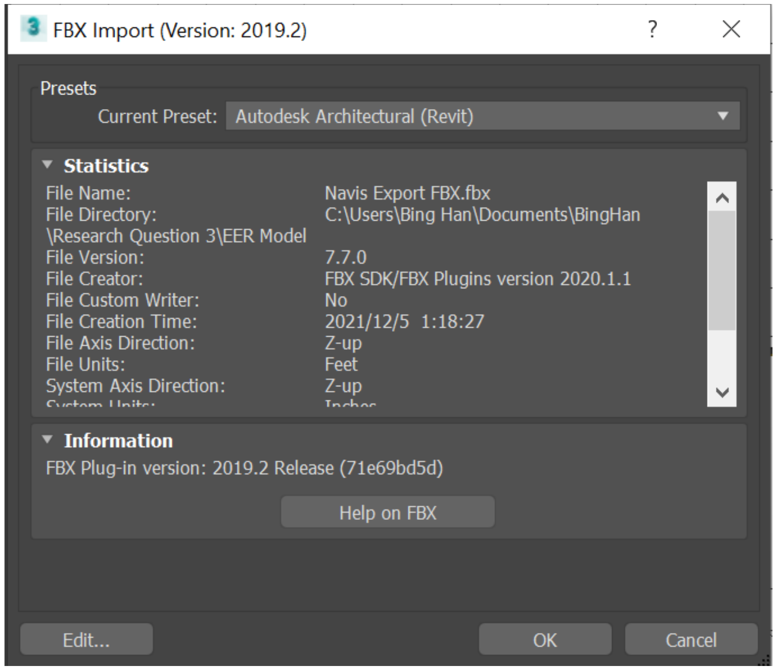


Figure B-2: FBX input settings for 3ds Max

The optimization was composed of three major activities. First, irrelevant objects, including empty objects, reference points, and 2D drawings, should be deleted. The hierarchy of objects and systems could be complex after directly importing the FBX into 3ds Max, see Figure B-3. Therefore, the hierarchy of objects could be streamlined while cleaning up irrelevant objects. Last but not least, for all objects in the FBX model, their pivots were located at the center of the whole model. In order to achieve coordinate-drive object movement in VR, object pivots were reset to the center of each object using the "Adjust Pivot" function in 3ds Max, see Figure B-4.

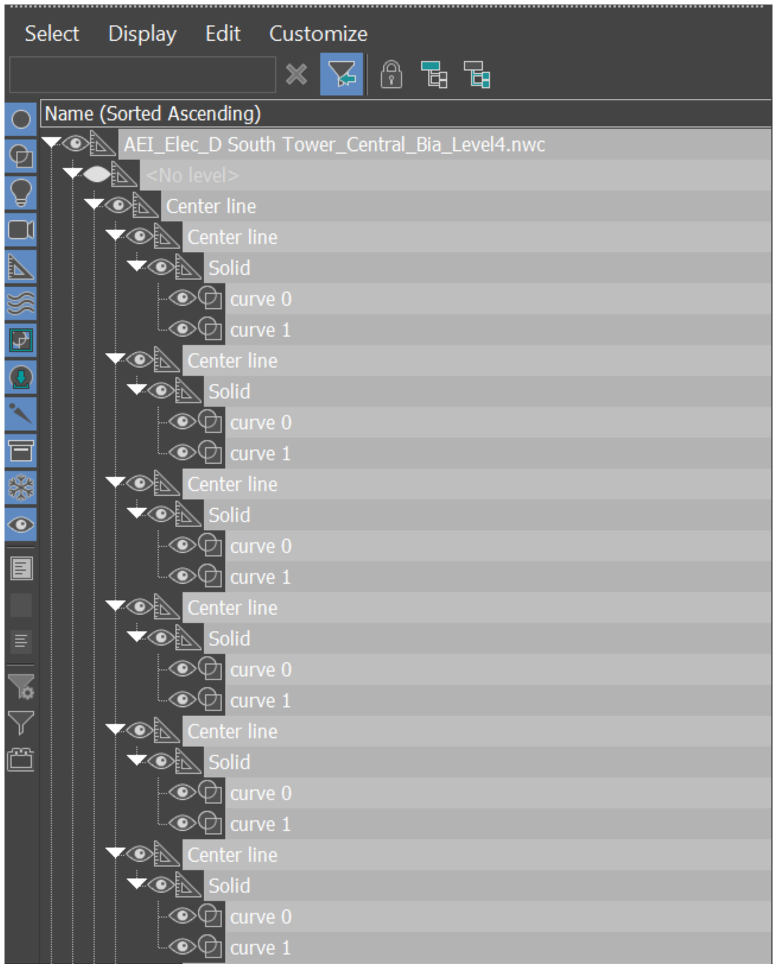


Figure B-3: An example of model with irrelevant objects and a complex hierarchy

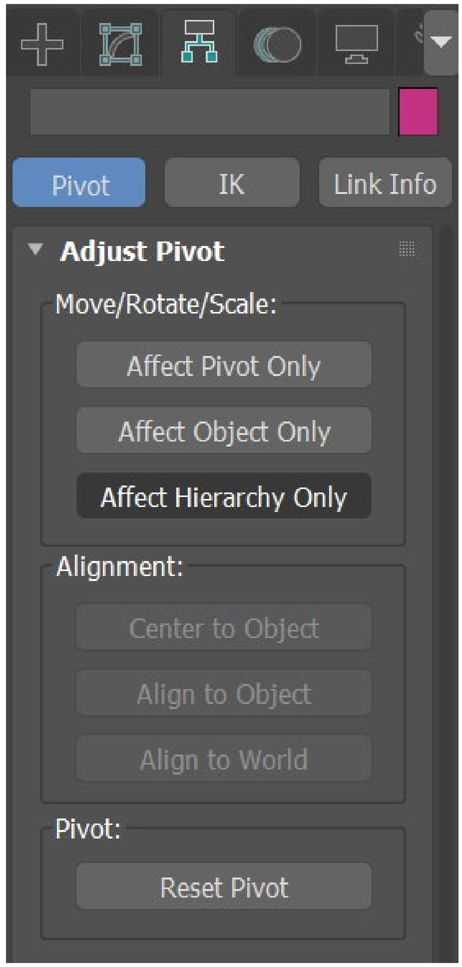


Figure B-4: Change all objects' centers of pivots from the center of the model to the center of the object.

Eventually, the optimized model was exported to a FBX file again using the built-in exported in 3ds Max. Figure B-5 demonstrates the export settings. As mentioned before, cameras and lights are not included in the FBX file. Millimeters is recommended but not required for the scene unit because it enables better maneuverability in VR development.

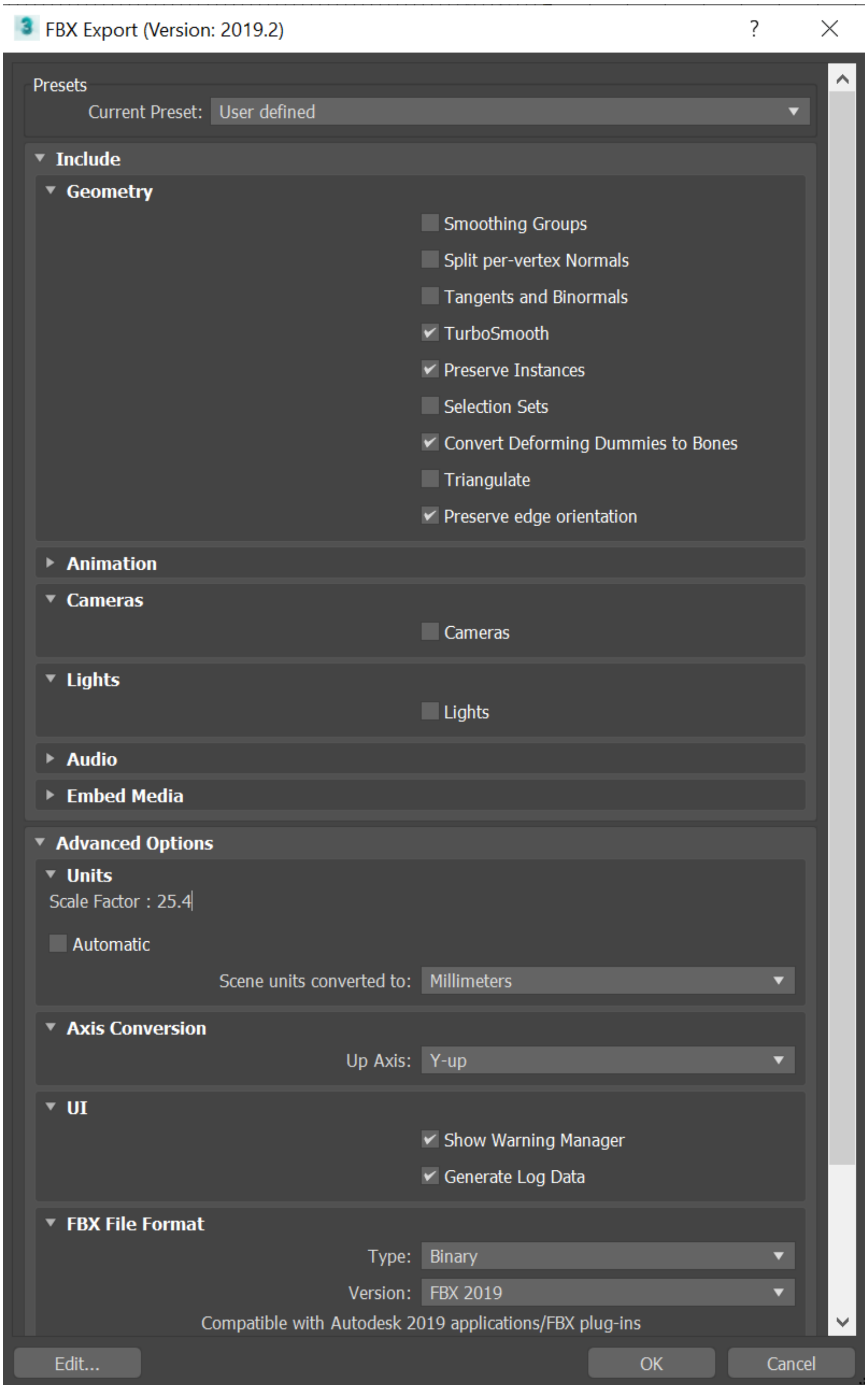


Figure B-5: Export settings from 3ds Max.

B.3 VR Development

All VR functions were developed using Unity3D 2018.4.12f1. The optimized FBX model was imported into Unity3D using the function “Import New Asset”. The model has the type of a “Prefab” in Unity3D and was unpacked completely for operations at an object level.

The author imported “Oculus Integration” and used “OVRPlayerController” to create an Avatar in the virtual environment. The “360 screenshot capture” package was added to the VR development to enable the user make screenshots. Figure B-6 uses pseudocode to demonstrate the process of visualizing work packages and installation sequences.

All human-computer interactions, including virtual moving, work package visualization, and taking 360 screenshots, were connected to buttons on VR controllers as well as keyboard keys.

```
//Group objects based on work packages
Public GameObject WorkPackage
    For all WorkPackage:
        For all Objectname:
            If Object[i].name == Objectname:
                Object[i] → WorkPackage
//Visualize or hide work packages
Public int Step = 0
If (user input == next step):
    i = i + 1
    For all WorkPackage[j]
        If (j > i):
            WorkPackage[j].setActive = false
        Else
            WorkPackage[j].setActive = true
If (user input == previous step):
    i = i - 1
    For all WorkPackage[j]
        If (j > i):
            WorkPackage[j].setActive = false
        Else
            WorkPackage[j].setActive = true
```

Figure B-6: Pseudocode for the automatic model update procedures

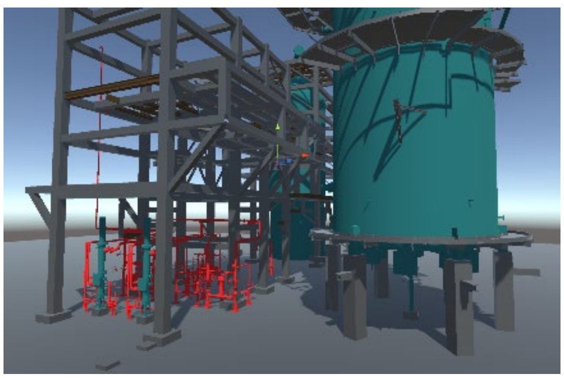
Appendix C – VR Performance Data Collection

C.1 Questionnaire after User Test

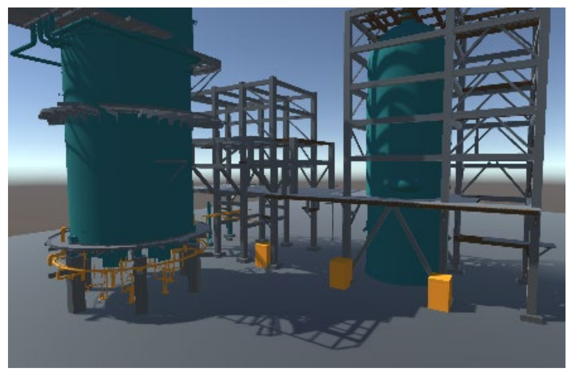
The IWPs have been adjusted to adequate amount of work, as shown in Figure C-1.

a. Please provide applicable sequence for these IWPs.

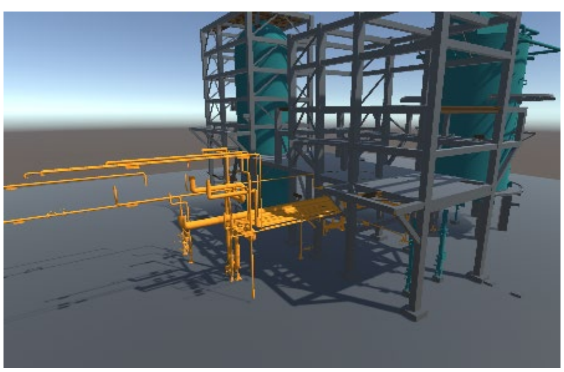
b. If there are 2 crew available in this project, please provide a fast track IWP sequence, assuming each IWPs will use exactly 1 week to install.



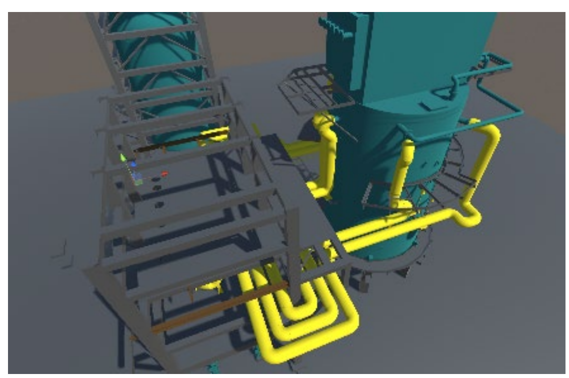
(a)



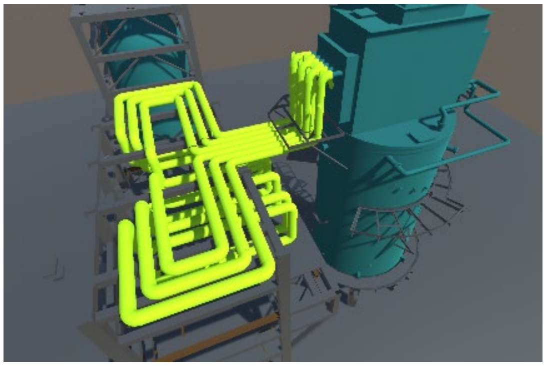
(b)



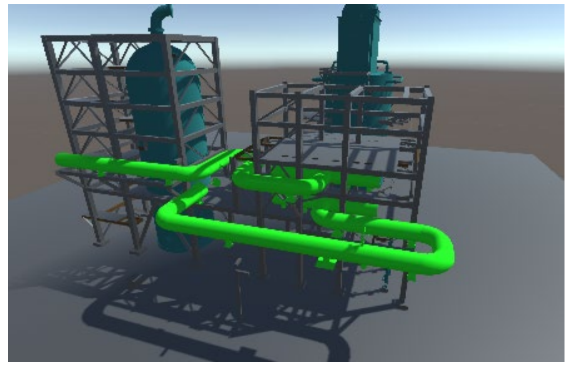
(c)



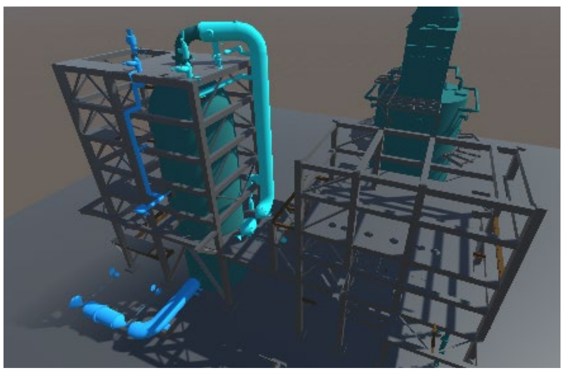
(d)



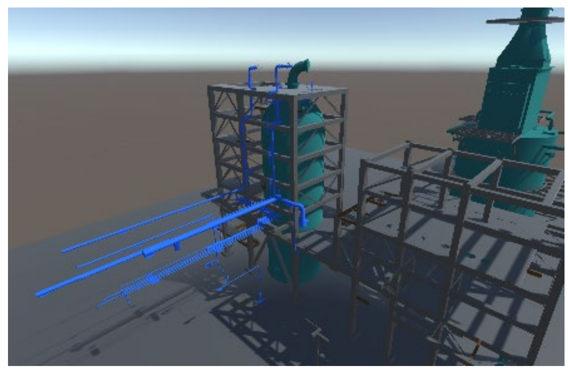
(e)



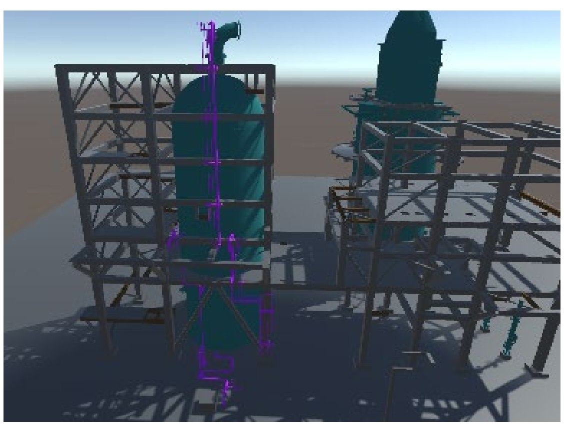
(f)



(g)



(h)



(i)

Figure C-1: Work packages shown to experiment participants

C.2 Questionnaire for Recall Test

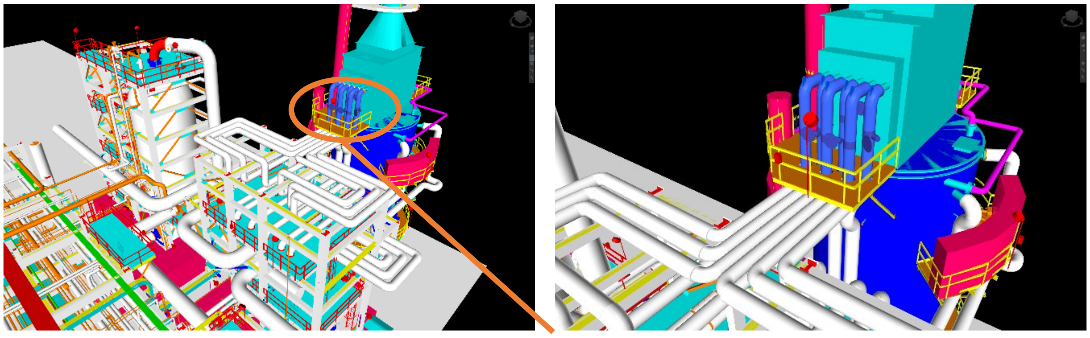
This is a follow-up questionnaire to test memory retention of Virtual Reality. Please follow the instructions of each question based on your memory and send back in the same day you received this questionnaire. If you have any questions or comments, please contact hannbingg16@gmail.com. Please note that this is not a competition to get high score, all of your feedback and data are valuable for this research project. Really appreciate your time and efforts.

1. Please identify if the components and errors shown in Figure C-2 are inside the work packages of your company. The components are shown in blue, and two images are used for each question to provide large context and detailed components. Please provide you answers by putting "√" in Table C-1. Correct answers will get 2 points, not sure answer will get 1 point and wrong answer will get 0 point.

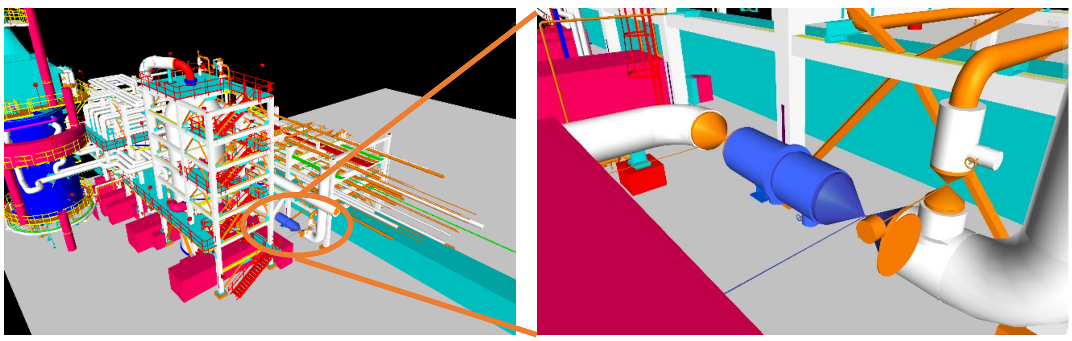
	Yes, they are part of my packages.	No, they are not part of my packages.	I am not sure about this question.
Q1			
Q2			
Q3			
Q4			
Q5			
Q6			
Q7			
Q8			
Q9			
Q10			

Table C-1: Response table to the memory retention test.

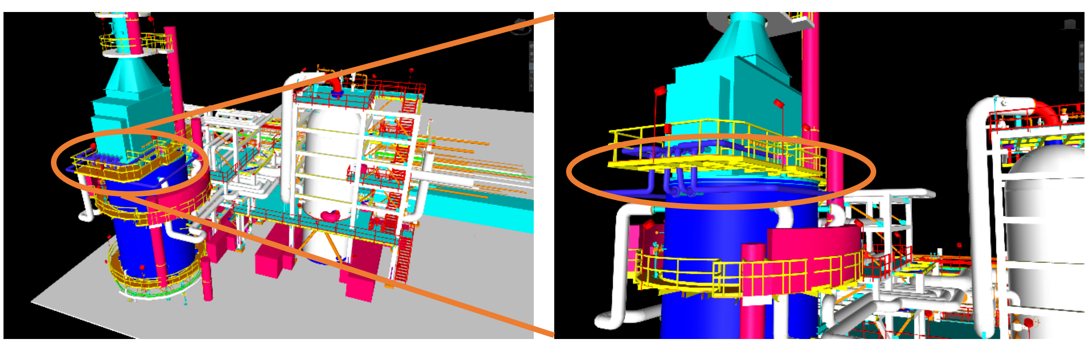
Q1:



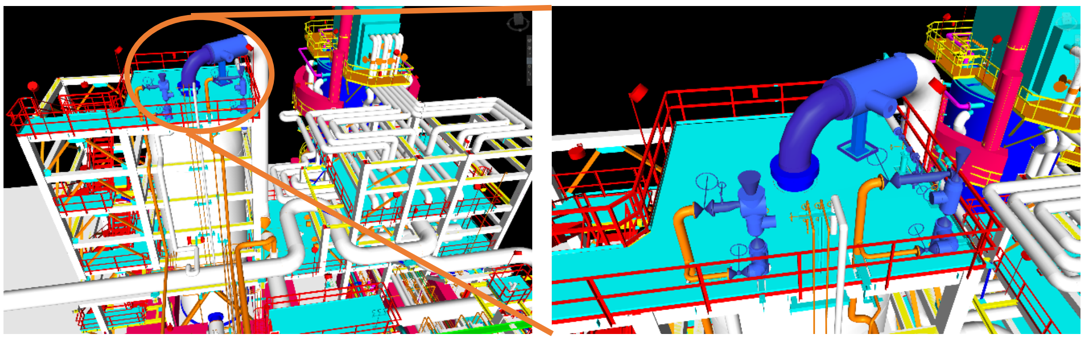
Q2:



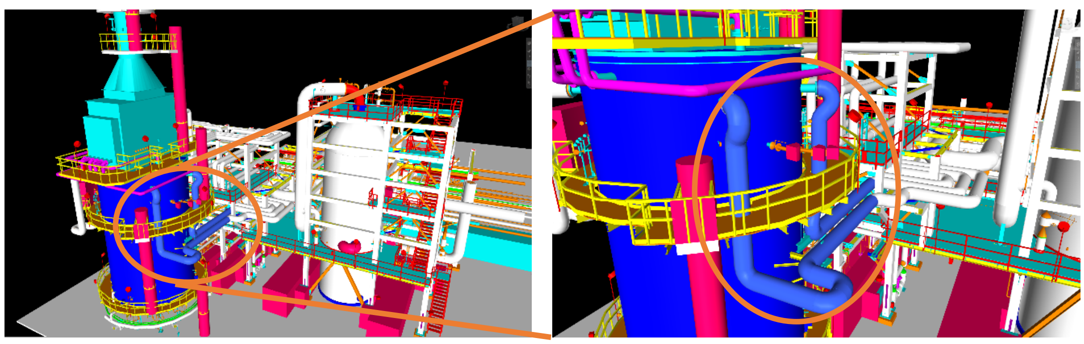
Q3:



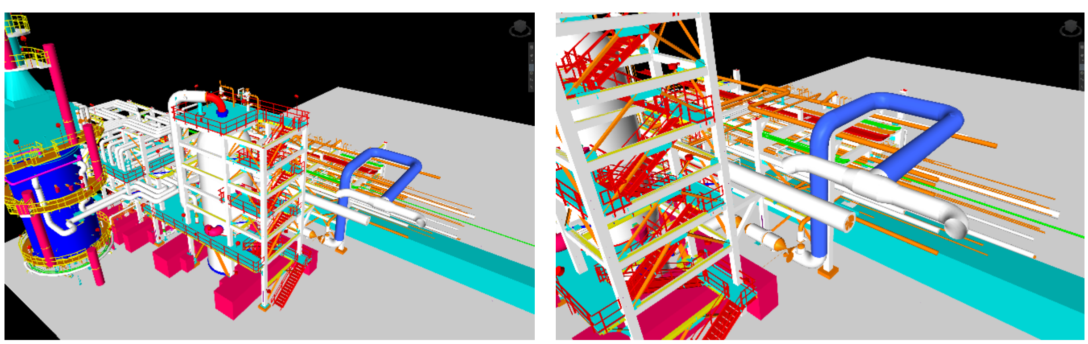
Q4:



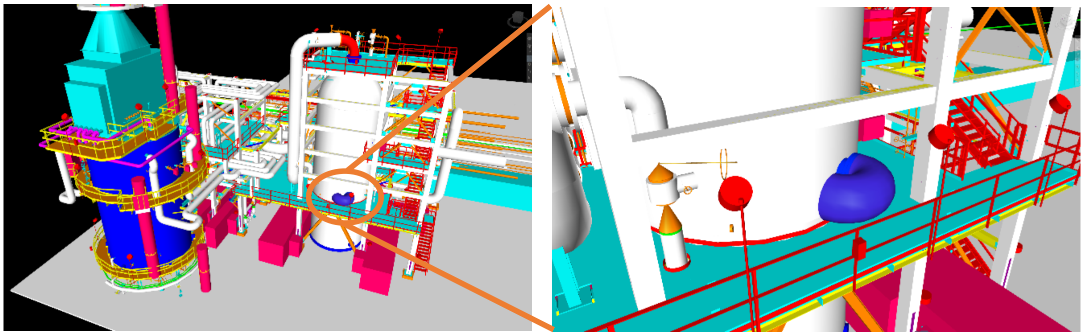
Q5:



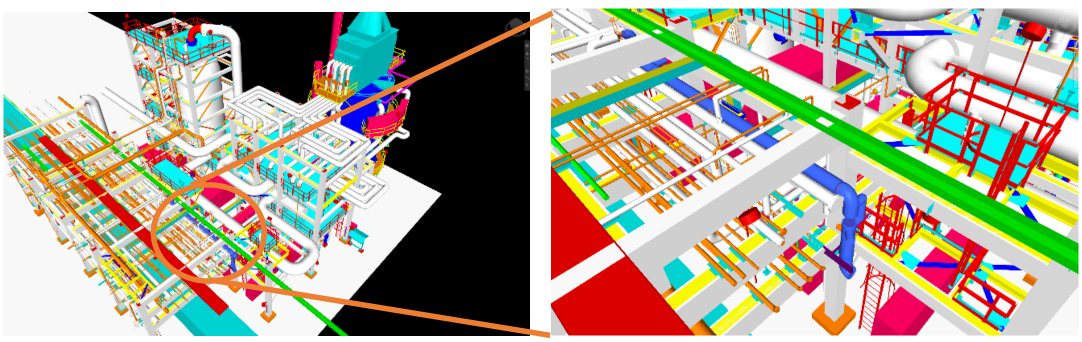
Q6:



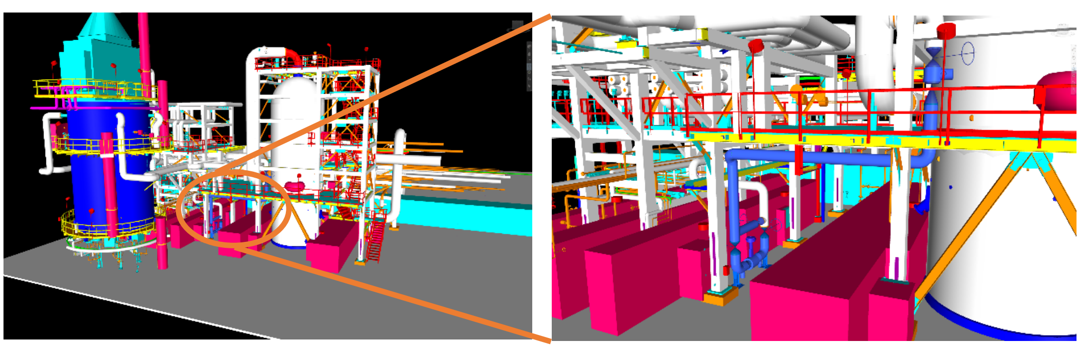
Q7:



Q8:



Q9:



Q10:

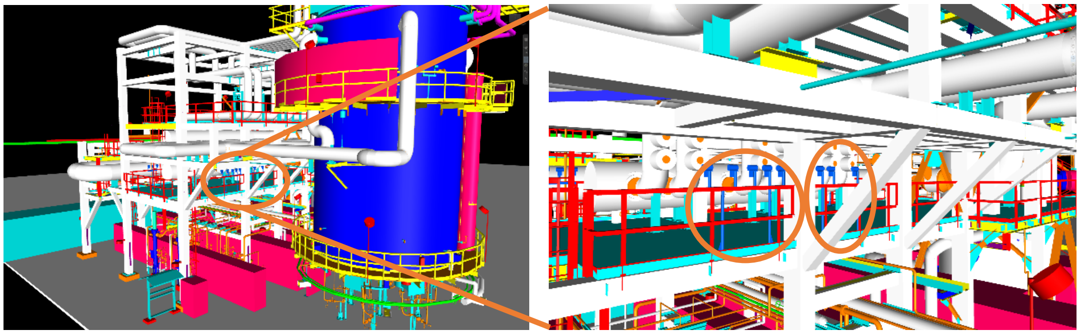


Figure C-2: Memory retention tests questions

2. Please identify possible improvements for your user test experience. (e.g., navigation methods, functions, model quality)

3. Please identify functions that are (or you think might be) helpful to your performance.

4. (For VR users only) Please identify features of VR which have influence (positively and negatively) on your performance in these tasks and shortly explain the reasons.

5. Do you have any other feedback, concerns, suggestions or opinions on this user test you want to share?

6. What background knowledge and experiences do you have concerning this user test?

Year(s) of industrial experiences (including internships for students):

Year(s) of industrial project experiences (including internships for students):

Gaming experiences (Yes/No):

VR experiences (Yes/No):

APPENDIX D – SEMI-AUTOMATIC OCCLUSION DETECTION ALGORITHM

D.1 Virtual Scan in BlenSor Settings

In research question 2, Blensor was used to perform a virtual scan to Building Information Models. Figure D-1 presents key scanner settings for this task. Each scan result was converted into a NumPy file. The author used Python 3.8 together with its NumPy library to automatically combine the data into one CSV file.

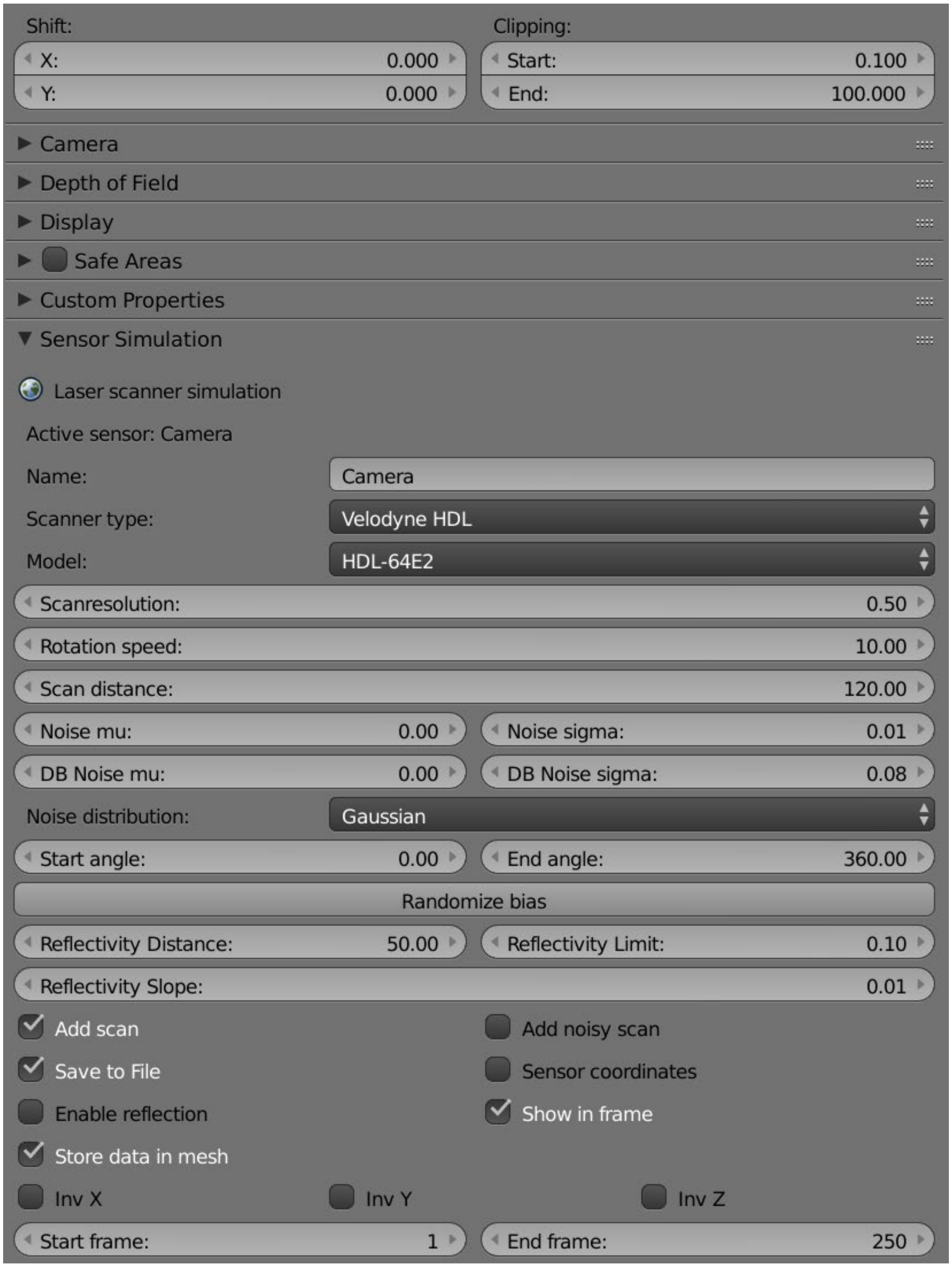


Figure D-1: Key scanner settings for virtual scans of BIM

D.2 Creating Potential Point Clouds

As described in Chapter 3, creating potential point clouds for all converted point clouds played an important role in decreasing the computing demand. Figure D-2 uses pseudocode to demonstrate the process of creating these potential point clouds. This activity was achieve using Python 3.8, Python's NumPy library, and Python's Pandas library.

```
//Create potential point clouds
For all ConvertedPointClouds:
 | New CSV file PotentialPointCloud[a]
 | x_max = max(x); y_max = max(y); z_max = max(z);
 | x_min = min(x); y_min = min(y); z_min = min(z);
 | For all points in ScannedPointClouds:
 | | If (x_min <= x[i] <= x_max and y_min <= y[i] <= y_max and
 | |     z_min <= z[i] <= z_max)
 | |   | Point[i] → PotentialPointCloud[a]
```

Figure D-2: Pseudocode for creating potential point clouds

D.3 Automatic Comparison between Scanned and Converted Point Clouds

The comparison between scanned and converted point clouds also used Python 3.8, Python's NumPy library, and Python's Pandas library. Figure D-3 presents the logic of the algorithm using pseudocode.

```
//Set parameters
Float SamplingThreshold
Float Tolerance
Int DirectPassThreshold
Float DirectPassPercentage
//Sample PerfectPointClouds
For all PerfectPointClouds:
    If len(PerfectPointCloud > SamplingThreshold)
        For i in range (SamplingThreshold)
            Point[round(i * len(PerfectPointCloud) / SamplingThreshold)]
                → PerfectPointCloud
//Test visibility
For all PerfectPointClouds:
    Int Visible = 0
    For i in range(len(PerfectPointCloud)):
        For j in range(len(PotentialPointCloud)):
                If (abs(PerfectPointCloud[i][x] - PotentialPointCloud[j][x]) < Tolerance and
                    abs(PerfectPointCloud[i][y] - PotentialPointCloud[j][y]) < Tolerance and
                    abs(PerfectPointCloud[i][z] - PotentialPointCloud[j][z]) < Tolerance):
                     Visible = Visible + 1
                Break
        If (Visible > DirectPassThreshold or Visible / len(PerfectPointCloud) >
           DirectPassPercentage)
            PerfectPointCloud → Visible
        Else
            PerfectPointCloud → Occluded
```

Figure D-3: Pseudocode for visibility analysis

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