Data-Driven Immersive Optimization - Enhancing Architectural Design using Virtual Reality and Computer Vision

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DOCTORAL THESIS

Data-Driven Immersive Optimization - Enhancing Architectural Design using Virtual Reality and Computer Vision

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Declaration of Authorship

I, Fabian JARRIN, declare that this thesis titled, "Data-Driven Immersive Optimization - Enhancing Architectural Design using Virtual Reality and Computer Vision" and the work presented in it are my own. I confirm that:

- This work was done wholly or mainly while in candidature for a research degree at this University.
- Where any part of this thesis has previously been submitted for a degree or any other qualification at this University or any other institution, this has been clearly stated.
- Where I have consulted the published work of others, this is always clearly attributed.
- Where I have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely my own work.
- I have acknowledged all main sources of help.
- Where the thesis is based on work done by myself jointly with others, I have made clear exactly what was done by others and what I have contributed myself.

Signed:

Date:

"The time will come when diligent research over long periods will bring to light things which now lie hidden. A single lifetime, even though entirely devoted to the sky, would not be enough for the investigation of so vast a subject... And so this knowledge will be unfolded only through long successive ages. There will come a time when our descendants will be amazed that we did not know things that are so plain to them... Many discoveries are reserved for ages still to come, when memory of us will have been effaced."

Seneca, Natural Questions

KYUSHU UNIVERSITY

Abstract

Graduate School of Human-Environment Studies
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Doctor of Engineering

Data-Driven Immersive Optimization - Enhancing Architectural Design using Virtual Reality and Computer Vision

by Fabian JARRIN

The Architecture, Engineering, and Construction (AEC) industry faces critical challenges in aligning precision, sustainability, and stakeholder engagement in design workflows, compounded by limited adoption of advanced technologies. This study addresses the gap by proposing the Data-Driven Immersive Design Optimization (DIDO) framework, which integrates Data-Driven Building Design (DBD), Virtual Reality (VR), and Computer Vision (CV) to enhance decision-making and optimize architectural practices. This study investigates the question on how immersive and data-driven technologies can bridge computational optimization with user-centered design goals in diverse architectural contexts. A mixed-methods approach was employed to validate the DIDO framework. Two applications were explored: 'Site Layout Planning' (SLP) and 'Facade Complexity Analysis'. In the SLP application, VR simulations were used to enhance stakeholder engagement and decision-making accuracy, aligning multi-objective optimization (MOO) recommendations with user preferences. In the facade complexity analysis, the Computational Image Complexity Analysis (CICA) system integrated CV and VR to quantify complexity and analyze user preferences across historical, contemporary, and experimental datasets. Data from experiments involving 17 participants in SLP and 26 participants in facade analysis provided quantitative and qualitative insights. The results demonstrated DIDO's transformative potential. In SLP, VR immersion improved decision-making accuracy by an average of 48.3%, reducing deviations between stakeholder selections and MOO recommendations (Chapter 4). For facade complexity analysis, the CICA system revealed a clear preference for moderate complexity (mean CICA score: 4.05/10), with 40% of participants selecting designs near this score, underscoring its utility in balancing intricate and simple designs (Chapter 5). The study also highlighted the importance of aligning analytical rigor with user experience, fostering sustainable and culturally responsive design practices. The findings suggest significant implications for architectural workflows. DIDO bridges performance-based metrics with immersive technologies, enhancing collaboration, sustainability, and decision-making precision. It addresses challenges in both macro-level urban planning and micro-level design optimization, contributing to innovative design methodologies in the AEC industry. Limitations include sample size constraints, VR system usability variations, and CICA's focus on 2D facade analysis, suggesting areas for refinement. Future research should expand DIDO's applications to broader datasets, explore real-world adoption scenarios, and integrate emerging technologies such as Mixed Reality (MR) to bridge virtual and physical design experiences. By addressing its limitations and extending its capabilities, DIDO has the potential to reshape architectural practices, enabling sustainable, user-aligned, and technologically advanced design solutions.

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List of Abbreviations

AI	**A**rtificial **I**Intelligence
AEC	**A**rchitecture, **E**ngineering, and **C**onstruction
AHP	**A**nalytical **H**ierarchy **P**rocess
AR	**A**ugmented **R**eality
BIM	**B**uilding **I**nformation **M**odeling
BPS	**B**uilding **P**erformance **S**imulation
CICA	**C**omputational **I**mage **C**omplexity **A**nalysis
CV	**C**omputer **V**ision
DBD	**D**ata-Driven **B**uilding **D**esign
DIDO	**D**ata-**D**riven **I**mmersive **D**esign **O**ptimization
HCI	**H**uman-**C**omputer **I**nteraction
IOT	**I**nternet **O**f **T**hings
LOD	**L**evel **O**f **D**etail
MCDM	**M**ulti-**C**riteria **D**ecision-**M**aking
MOO	**M**ulti-**O**bjective **O**ptimization
OBPD	**O**n-Site**B**uilding **P**erformance **D**ata
SLP	**S**ite **L**ayout **P**lanning
VR	**V**irtual **R**eality
XR	**E**xtended **R**eality

Dedicated to my parents and family. . . .

Chapter 1

Introduction

Chapter 1 introduces the thesis by highlighting the transformative potential of advanced technologies in architectural design, focusing on the Data-Driven Immersive Design Optimization (DIDO) framework as a novel approach to integrate Data-Driven Building Design (DBD), Virtual Reality (VR), and Computer Vision (CV). The chapter establishes the research background, emphasizing the growing need for precision, sustainability, and stakeholder engagement in the AEC industry. It identifies key challenges, including resistance to adopting advanced tools and the limitations of traditional heuristic-based methods, framing the problem statement around the lack of an integrated framework to bridge computational rigor and human-centered goals. The research objectives detail the development and validation of DIDO through applications in 'Site Layout Planning' (SLP) and 'Facade Complexity Analysis', showcasing its ability to enhance decision-making and align user preferences with optimized design outcomes. The chapter underscores the significance of the study in advancing sustainable, data-driven architectural practices, aligning with evolving industry needs, and positions the research as a critical contribution to the discourse on technology-enabled design innovation.

1.1 Background

The integration of advanced technologies into architectural design has opened new frontiers in how buildings are conceived, planned, and executed. Rapid advancements in Building Information Modeling (BIM), parametric design, and digital fabrication are enabling architects to approach design with unprecedented precision and flexibility. BIM supports cross-disciplinary collaboration by providing a centralized repository for all project data, improving coordination and reducing errors [1]. Parametric design introduces adaptive flexibility through algorithmic processes, allowing complex forms to be generated based on specific design criteria [2]. Digital fabrication, meanwhile, automates the materialization of these forms, supporting efficient and accurate construction. As AI and robotics advance, digital fabrication's role will continue to grow, fostering a deeper integration between human creativity and computational efficiency in the construction process, with machines increasingly taking on construction tasks guided by data-driven models [3].

Among these technological advancements, Data-Driven Building Design (DBD) optimization has emerged as a powerful approach, enabling the systematic exploration of multiple design alternatives based on quantitative performance metrics. Moving beyond traditional prescriptive design methods, which rely heavily on set standards and personal intuition, DBD optimization offers a pathway to solutions optimized for factors such as energy efficiency, sustainability, and functional performance [4]. By leveraging multi-objective optimization (MOO) algorithms, designers can evaluate alternatives that balance aesthetic, functional, and environmental criteria, enhancing both the quality and feasibility of architectural projects. DBD optimization thus represents a shift toward a more analytical and data-supported design practice, facilitating decision-making that aligns with diverse project objectives.

Virtual Reality (VR) is another transformative tool in architectural design, offering immersive and interactive environments that enable stakeholders to experience building models at a human scale. By visualizing complex data within a realistic spatial context, VR makes it easier for users to engage with design elements, enhancing their understanding and contributing to more intuitive decision-making. In architectural applications, VR serves as a bridge between technical data and human perception, allowing optimized designs to be evaluated based on functional requirements and user preferences. Furthermore, VR enables collaborative engagement by allowing multiple stakeholders to interact with and provide feedback on design models, leading to more accepted and informed design outcomes [5].

Computer Vision (CV) is a relatively unexplored tool in architectural design when compared to the more prominent technologies like BIM, parametric design, and VR. While often employed in background roles within automation and decision-making processes, CV holds significant potential for architectural analysis, especially in evaluating visual and structural complexity [6]. By processing images to assess patterns, textures, and structural features, CV algorithms can provide detailed insights into design elements like facades, interior design or even urban networks, allowing architects to balance intricate visual details to enhance both functionality and appeal. Although CV is less frequently highlighted in design practices, its role in supporting detailed analysis and objective decision-making makes it a valuable asset for more data-informed and aesthetically aligned architecture.

These technologies collectively reflect a trend toward data-driven, user-centered approaches in the Architecture, Engineering, and Construction (AEC) industry. With continued advancements in AI, robotics, and digital fabrication, the integration of human and computational creativity will only strengthen, establishing a collaborative design process where both machine intelligence and human insight play critical roles. By leveraging DBD, VR, and CV in tandem, this research highlights the transformative potential of these technologies to contribute to a more integrated design process, aligning technical performance with user satisfaction and shaping a new era of innovative, sustainable, and functional architecture.

1.2 Problem Statement

The Architecture, Engineering, and Construction (AEC) industry is under growing pressure to meet demands for precision, sustainability, and efficiency in building design. Despite advancements in technology, such as Building Information Modeling (BIM), parametric design, and digital fabrication, the industry continues to rely heavily on traditional, heuristic-based methods and 2D drawings [7]. These outdated approaches hinder the integration of cutting-edge technologies like Virtual Reality (VR), Computer Vision (CV), and Data-Driven Building Design (DBD), which have demonstrated potential to enhance design precision, stakeholder collaboration, and sustainability.

This resistance to adopt advanced technologies stems from multiple barriers, including perceived high implementation costs, steep learning curves, and concerns about disrupting established workflows [7]. Many professionals worry that adopting these tools might compromise creativity or require significant operational adjustments. Yet, evidence suggests that the long-term benefits far outweigh these initial challenges. For example, a McGraw-Hill Construction survey (2008) revealed that 48% of firms tracking BIM's return on investment (ROI) reported substantial gains, with returns ranging from 140% to as high as 39,900% [7]. This indicates that technological adoption can significantly improve outcomes when properly implemented.

Even with these demonstrated benefits, the industry lacks a cohesive framework that integrates DBD, immersive visualization, and computational analysis to address the growing complexity of architectural workflows. Key challenges include insufficient stakeholder engagement, inadequate tools to quantify and balance design complexity with user preferences, and limited integration of sustainability goals into decision-making processes. These gaps result in design solutions that fail to align technical performance with user-centric and environmental priorities, leading to suboptimal project outcomes.

To address these issues, this research introduces the Data-Driven Immersive Design Optimization (DIDO) framework, an innovative methodology that combines DBD with immersive VR and CV technologies. By leveraging VR for real-time stakeholder interaction and CV for quantifying facade complexity, DIDO bridges computational precision with intuitive user engagement. This framework aims to optimize decision-making in areas such as 'Site Layout Planning' (SLP) and 'Facade Complexity Analysis', demonstrating its versatility across diverse architectural challenges.

The DIDO framework provides a practical solution for integrating advanced technologies into architectural workflows, fostering better alignment between technical metrics, user preferences, and sustainability goals. Through its applications, this research seeks to enable the AEC industry to transition toward data-driven, user-centered, and environmentally responsible design practices, addressing current limitations and establishing a foundation for innovation and efficiency in architectural design.

1.3 Research Objectives

The overarching goal of this research is to develop, validate, and apply the 'Data-Driven Immersive Design Optimization' (DIDO) framework, an innovative methodology that integrates data-driven building design (DBD) principles with immersive visualization technologies such as Virtual Reality (VR) and Computer Vision (CV). By combining computational rigor with stakeholder-centric tools, DIDO seeks to bridge the gap between technical optimization and user-centered design, enhancing decision-making in architectural workflows and fostering collaboration across diverse stakeholders.

This research validates the applicability of the DIDO framework through two focused case studies: 'Site Layout Planning' (SLP) and 'Facade Complexity Analysis'. The first case study investigates the potential of VR to enhance stakeholder engagement in SLP, aiming to align data-driven optimization with user preferences. The second case study integrates CV with DBD and VR to establish a framework for assessing facade complexity, linking computational metrics to user perception and exploring the implications for historical and contemporary architectural contexts.

Through these applications, the study contributes to the AEC industry by advancing sustainable, efficient, and user-focused architectural design. The following objectives outline the primary goals and specific tasks within each case study.

Primary Objectives:

1. **Explore the integration of immersive and computational tools in architectural design:** Investigate how DBD, VR, and CV technologies can enhance user engagement and improve decision-making in design workflows.
2. **Develop and validate the DIDO framework:**
   - Establish a unified approach that combines performance-based metrics with immersive visualization tools.
   - Demonstrate DIDO's ability to align computational optimization with stakeholder collaboration for cohesive, user-driven design outcomes.
3. **Assess the impact of immersive technology on stakeholder engagement:**
   - Evaluate how VR and CV can simplify complex architectural data, making it accessible to non-expert stakeholders.
   - Measure the effectiveness of immersive experiences in fostering engagement, eliciting collaborative feedback, and enabling informed decision-making in architectural processes.
4. **Evaluate DIDO's practical applications and limitations:**
   - Conduct case studies in SLP and facade complexity analysis to assess the framework's adaptability, robustness, and potential as a standardized tool.
   - Identify limitations in integrating these methodologies and provide actionable insights for refining the DIDO framework to broaden its application in the AEC industry.

DIDO for SLP-Specific Objectives:

1. Optimize 'Site Layout' decisions through the integration of Multi-Objective Optimization (MOO) and Data-Driven Building Design (DBD), improving precision, efficiency, and sustainability in layout planning.

2. Assess VR's role in enhancing stakeholder engagement and decision accuracy during 'Site Layout' evaluations.
3. Measure the impact of immersive, data-driven design workflows on achieving optimized 'Site Layout' that align with stakeholder priorities.

DIDO for Facade Complexity Analysis-Specific Objectives:

1. Develop and validate the 'Computational Image Complexity Analysis' (CICA) system as a CV-based tool within the DIDO framework, integrating VR to facilitate real-time stakeholder interaction and decision-making.
2. Quantify and analyze facade complexity across historical, contemporary, and experimental datasets, establishing correlations with user preferences to inform designs that balance intricate detailing with simplicity.
3. Expand the application of the CICA system to urban streetscapes, leveraging its insights to analyze facade complexity across diverse architectural contexts, and develop actionable recommendations for urban renewal and contemporary design practices.
4. Evaluate the CICA system's effectiveness in predicting and optimizing facade complexity by benchmarking it against user feedback, identifying discrepancies, and refining its metrics to enhance both aesthetic and functional outcomes.

1.4 Significance of the Study

This study contributes to the evolving discourse on integrating advanced technologies in architectural practice. At its core is the development and validation of the Data-Driven Immersive Design Optimization (DIDO) framework, a novel approach that combines Virtual Reality (VR), Computer Vision (CV), and Data-Driven Building Design (DBD) to support decision-making in architectural design. By merging these technologies, DIDO addresses critical gaps in the Architecture, Engineering, and Construction (AEC) industry's approach to adopting new tools. Through this integration, the research advances both performance-based optimization and user-centered design, promoting a cohesive and effective workflow that aligns computational precision with human-centered design goals.

In fulfilling these goals, the study contributes to several key areas that emphasize both innovation and practical impact:

- *Bridging Technology Gaps in the AEC Industry:* By introducing the DIDO framework, this research addresses the industry's resistance to adopting advanced tools. DIDO responds to this resistance by offering a unified platform that aligns technical objectives with the user-centered design process and aesthetic goals, reducing reliance on traditional heuristic approaches while promoting evidence-based decision-making.

- *Enhancing Stakeholder Engagement:* VR technology within DIDO improves communication and decision-making by allowing stakeholders to experience design models in real time, fostering a more intuitive understanding of complex data. The study demonstrates how immersive VR simulations bridge data-driven recommendations with user experience, as evidenced by 48.3% improvement in decision accuracy in Site Layout Planning (SLP) (see Chapter 4, Section 4.4). This approach strengthens the alignment between technical performance and stakeholder preferences, advancing participatory design.

- *Promoting Sustainable and Precise Architectural Design Solutions:* DIDO's data-driven optimization promotes sustainability by enabling precise simulations and calculations that minimize waste and enhance energy efficiency. This positions DIDO as a method that not only improves design quality but also contributes to environmentally responsible practices in the AEC industry. The ability to integrate VR and CV ensures an adaptable and future-oriented approach for sustainable design workflows.

- *Providing a Practical and Adaptable Framework for Industry Application:* DIDO's adaptability across diverse applications, including SLP and facade complexity analysis, exemplifies its versatility, as detailed in Chapters 4 and 5. Its integration of data analytics and immersive environments positions it as a standardized tool for enhancing workflows and improving project outcomes across the AEC industry.

- *Enhanced Decision-Making in Site Layout Planning (SLP):* Through the implementation of immersive VR simulations, DIDO highlights VR's potential to transform stakeholder engagement and decision-making in SLP. By reducing deviations between user-selected layouts and optimization model recommendations (Section 4.4), DIDO bridges the gap between heuristic insights and data-driven planning, enhancing project precision and efficiency. This approach positions VR as a valuable tool in collaborative site planning processes, offering intuitive insights into optimized spatial arrangements.

- *Quantifying Aesthetic and Functional Complexity in Facade Design with CV:* DIDO introduces the Computational Image Complexity Analysis (CICA) system, which quantifies facade complexity through CV algorithms, enabling a balance between aesthetic appeal, functionality, and user preferences. This contribution is particularly significant for sustainability, as the ability to quantify intricate design through a facade complexity score could theoretically establish an optimal range of intricacy that enhances the aesthetic and cultural value of buildings. By creating more memorable and appreciated facades, CICA supports the design of buildings that are less likely to face demolition, thereby contributing to long-term sustainability through the preservation of architectural heritage and reduced construction waste. The alignment of CICA-based evaluations with user preferences (mean score 4.05) in facade complexity experiments (Section 5.4.2, Chapter 5) underscores its utility in guiding future facade design practices.

In summary, this research establishes a holistic approach to integrating advanced technologies within architectural design, positioning DIDO as a versatile framework with applications that extend beyond this study's immediate scope. By emphasizing adaptability, sustainability, and user-centered design, DIDO aligns closely with the AEC industry's commitment to environmentally responsible practices and modernized workflows.

These contributions offer the AEC industry innovative methodologies that not only improve design processes but also enhance project outcomes. Ultimately, this research underscores the transformative potential of immersive, data-driven tools in shaping a more collaborative, efficient, and sustainable future in architecture.

1.5 Overview of Structure of the Thesis

This thesis is organized as follows:

- **Chapter 1: Introduction** - This chapter provides the foundation of the research, detailing the background, problem statement, objectives, and significance of the study. It introduces the thesis title, *"Enhancing Architectural Design through Data-Driven Building Design using Virtual Reality and Computer Vision"*, emphasizing the integration of these technologies within the Data-Driven Immersive Design Optimization (DIDO) framework. Additionally, it outlines the structure of the thesis and its relevance to architectural workflows.

- **Chapter 2: Literature Review** - This chapter reviews the theoretical foundations of DBD, VR, and CV in architecture and their applications in the AEC industry. It discusses key concepts such as multi-objective optimization, user-centered design, and facade complexity analysis, identifying research gaps that the DIDO framework aims to address.

- **Chapter 3: Data-Driven Immersive Design Optimization (DIDO) Framework and Methodology** - This chapter introduces the DIDO framework, integrating data-driven insights, immersive VR environments, and CV algorithms to optimize architectural workflows. It elaborates on the methodology, detailing the development of VR and CV systems, the CICA system for facade analysis, and tools used for data collection and analysis.

- **Chapter 4: Implementation of Virtual Reality-based Site Layout Planning for Building Design** - This chapter applies the DIDO framework to Site Layout Planning (SLP), exploring the role of VR in enhancing stakeholder engagement and decision-making accuracy. It evaluates the effectiveness of VR-enhanced multi-objective optimization (MOO) in reducing decision-making deviations, with quantitative results showing a 48.3% improvement in alignment with MOO recommendations (Section 4.4).

- **Chapter 5: Implementation of VR and Computer Vision-based Facade Complexity Analysis for Building Design** - This chapter explores the application of the DIDO framework in facade complexity analysis using the Computational Image Complexity Analysis (CICA) system. It quantifies complexity across historical, experimental, and urban streetscape datasets, aligning computational metrics with user preferences (mean CICA score of 4.05). The chapter highlights the system's capability to inform both contemporary design practices and urban renewal strategies.

- **Chapter 6: Conclusions, Contributions, Limitations, and Future Work** - This chapter synthesizes the main findings of the thesis, emphasizing the transformative potential of the DIDO framework in enhancing architectural workflows. It addresses limitations, such as participant demographics and technological constraints, and proposes future research directions, including the exploration of volumetric complexity and cultural adaptation of facade designs. The chapter concludes with reflections on the broader implications of the research for sustainable, user-centered architectural practices.

Chapter 2

Literature Review

The literature review for this thesis examines the theoretical and technological foundations that support the Data-Driven Immersive Design Optimization (DIDO) framework. In recent years, the Architecture, Engineering, and Construction (AEC) industry has experienced a rapid evolution in design and construction methodologies due to advancements in digital tools. Building Information Modeling (BIM), parametric design, digital fabrication, Virtual Reality (VR), and Computer Vision (CV) have expanded how architects approach design and stakeholder engagement. In today's era of rapid technological advancement, digitization is a key factor shaping the construction industry. The use of BIM, ISO 19650 standards, and technologies like VR, Augmented Reality (AR), Virtual Design and Construction (VDC), and Common Data Environment (CDE) enhances efficiency, improves design quality, and reduces project costs and timelines [8]. Despite this progress, the integration of these tools within a cohesive, adaptable framework remains limited, particularly when attempting to align technical optimization with user-centered design.

This chapter systematically reviews the major technologies influencing modern architecture, focusing on Data-Driven Building Design (DBD), VR, and CV, which together form the core of the DIDO framework developed for this study. These technologies reflect a trend toward data-driven, user-centered approaches in the AEC field, where precision, efficiency, and adaptability are increasingly prioritized. By addressing the intersections and gaps between these advancements, this review establishes the rationale for the DIDO framework and identifies specific challenges that the methodology aims to resolve.

2.1 Data-Driven Building Design (DBD) in Architecture

Data-Driven Building Design (DBD) marks a significant evolution in architectural practice, moving from conventional, intuition-based methodologies toward a data-centric, performance-oriented approach. This transformation aligns architecture with other fields increasingly shaped by digitalization, where operational and strategic decisions rely heavily on real-time data and advanced analytics [4]. Traditional design processes, which typically depend on subjective expertise and static standards, are now increasingly supplemented—and, in many cases, replaced—by quantitative performance metrics that enable more precise, adaptable decision-making. These data-driven methods allow architects to assess design alternatives across multiple criteria, such as energy efficiency, sustainability, and cost, contributing to more targeted, high-performance building outcomes.

Digitalization has not only enhanced data accessibility but has fundamentally altered the design and construction landscape by enabling continuous data flow across platforms and disciplines. This change is driven by advances in Internet of Things (IoT) technology, cloud computing, data mining, and machine learning [4]. In architecture, these tools allow the integration of on-site building performance data (OBPD) into the design process, supporting iterative, data-backed decision-making that improves alignment between design intent and actual building performance [9]. As Tian et al. (2021)notes, accumulated OBPD has proven invaluable in closing the performance gap between simulations and real-world outcomes, making DBD a crucial component in building high-performance structures that meet both functional and environmental standards [9].

Central to DBD is Multi-Objective Optimization (MOO), which allows architects to evaluate a spectrum of design options based on diverse, often competing objectives. By leveraging big data and advanced analytics, MOO enables designers to navigate complex trade-offs [10], balancing criteria such as energy efficiency, structural integrity, and cost-effectiveness. For example, data-driven modeling can assess energy performance more accurately than traditional simulations, as OBPD provides insights into actual usage patterns, environmental conditions, and system efficiency [9]. This approach not only enhances design quality but also supports architects in achieving more sustainable, cost-efficient outcomes.

As data-driven methodologies reshape the design process, they also introduce new collaborative demands on architects, data scientists, and engineers. Cantamesa et al. (2020) highlights the need for cross-functional teams with overlapping technical and analytical skills to interpret complex data and translate insights into actionable design improvements [4]. Designers are now expected to work closely with data analysts and other specialists, moving away from isolated, discipline-specific workflows to integrated, interdisciplinary frameworks. This collaboration enhances the depth and precision of design decisions, as data scientists gain insights into architectural goals, while designers become proficient in interpreting data-driven analyses to support functional and aesthetic design elements (see Figure 2.1).

Despite its advantages, DBD still faces challenges related to data accessibility, model scalability, and industry adoption. Tian et al. (2021) [9] underscore the need for more extensive OBPD databases and models that address specific design features, such as building envelopes, insulation, and ventilation. Practical applications of DBD in industry remain limited, although initiatives like the US Department of Energy's Building Performance Database are paving the way for broader adoption by providing tools to compare energy use across building types. Moving forward, the AEC industry must focus on creating data-driven frameworks that are adaptable to various building contexts, fostering a balance between technical optimization and user-centered design.

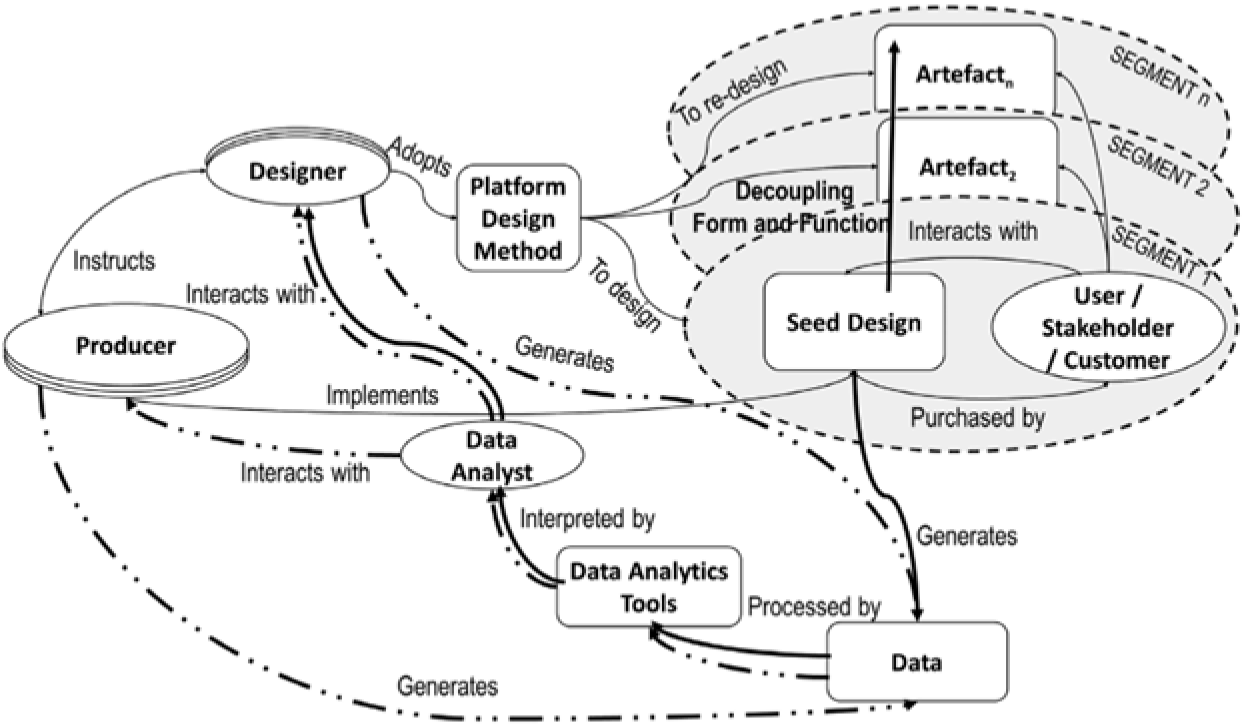


FIGURE 2.1: The data-driven design paradigm in product development. This figure illustrates the interactions among designers, data analysts, producers, and end users within a data-driven design framework. Source: Cantamesa et al. (2020) [4].

2.1.1 DBD's Role in Transforming Architectural Design and Applications

Data-Driven Building Design (DBD) has redefined architectural decision-making by integrating real-time data and performance metrics into every stage of the design and construction process. By basing decisions on material efficiency, building systems, and user behavior, DBD enables a data-driven, iterative design process that aligns closely with key performance goals. Furthermore, DBD applications extend beyond the initial design phase, incorporating lifecycle considerations—from material durability and maintenance costs to environmental impact—supporting a comprehensive approach to architectural planning that promotes resilience and adaptability.

In modern architecture and the AEC industry, data-driven methodologies significantly contribute to improving efficiency, sustainability, and user comfort in building design. While applications often address multiple objectives simultaneously, they are generally categorized by their primary focus. Key categories include:

- Energy Efficiency
- Spatial Optimization
- Urban Planning and Infrastructure Optimization
- Material Selection and Structural Analysis
- Predictive Maintenance and Lifecycle Management

These categories illustrate DBD's versatility and impact across various scales and objectives in architecture. Each application contributes uniquely to the development of resilient, sustainable, and user-aligned architectural environments.

DBD Applications in Energy Efficiency

DBD models simulate building energy performance, allowing architects to design more sustainable buildings by optimizing insulation, orientation, and material properties. These models enable the testing of different scenarios to identify energy-saving strategies that align with sustainability goals, ensuring that buildings meet both user needs and environmental standards.

For example, Yesilyurt et al. employed machine learning to predict energy consumption in a university office, integrating air conditioning demand as a new parameter to improve model accuracy [11]. Similarly, Zhang et al. applied a multi-objective optimization framework to address energy efficiency while accounting for urban heat island effects, achieving a 54% improvement in building energy optimization [12]. These studies underscore DBD's role in sophisticated energy modeling that adapts to local environmental factors and sustainability objectives.

DBD Applications in Spatial Optimization

DBD facilitates spatial optimization by enabling architects to balance functional and aesthetic requirements, especially critical in high-density urban areas. These data-driven approaches ensure efficient use of space while meeting design and performance standards.

For instance, Fan et al. utilized a multi-objective optimization framework based on genetic algorithms and neural networks to optimize gymnasium layouts, achieving notable reductions in cooling energy consumption and solar radiation exposure, as well as improved thermal comfort. This framework highlights the potential of algorithm-driven layout design to enhance environmental performance in early design stages [13].

Similarly, Zhou et al. developed an integrated data-driven and knowledge-based approach for optimizing residential space layouts with a focus on health and comfort performance. Their method, which incorporates parameters like adjacency preference and noise score, offers a generative design tool that provides multiple layout alternatives, ultimately enhancing decision-making in spatial planning [14].

These studies exemplify how spatial optimization through data-driven methods can address various performance objectives—ranging from energy efficiency to occupant well-being—reinforcing DBD's versatility in creating adaptable, high-performance and user-centered spaces.

DBD Applications in Urban Planning and Infrastructure

DBD's influence extends to urban planning, where data-driven models contribute to energy-efficient urban environments and sustainable land-use planning. By integrating technologies like image recognition, light sensors, and big data, DBD provides real-time insights that guide urban space allocation, thermal management, and ecological preservation.

Huang and Li, for example, implemented a thermal energy optimization model using image recognition and light sensors, dynamically adjusting building energy usage based on outdoor light changes to support urban green environment planning. This approach not only reduces energy consumption within individual buildings but also serves as a scalable model for creating energy-efficient, low-carbon city zones [15]. By adjusting building energy usage according to real-time light data, the study supports sustainable urban green environment planning, highlighting DBD's potential for broader applications in urban energy optimization.

In another example of DBD in urban contexts, Mohammadyari et al. implemented a hybrid simulated annealing-genetic algorithm to optimize land-use allocation within an urban watershed in Ilam, Iran. By integrating ecosystem services (ES) such as water yield, sediment retention, and habitat quality, the model optimizes land allocation for sustainable landscape planning[16]. The study's findings reveal that optimizing land allocation with ES not only preserves ecological functions but also supports the efficient distribution of urban green spaces and natural resources. These studies demonstrate DBD's capability to balance urban infrastructure with environmental needs, ensuring a balanced coexistence of urban infrastructure and natural ecosystems.

DBD Applications in Material Selection and Structural analysis

Data-driven methods play an essential role in optimizing material selection to enhance sustainability and efficiency in architectural projects. By analyzing properties like durability, lifecycle costs, and environmental impact, architects can make informed choices that ensure both cost-effectiveness and environmental responsibility. For instance, Zhong et al. (2024) developed a low-carbon design method that optimizes material usage alongside factors like daylight and carbon emissions. This approach enabled a greenhouse design that reduced carbon emissions by 23% while significantly improving daylight performance, demonstrating the potential of data-driven, multi-objective optimization for sustainable material selection [17]. Such methods allow architects to evaluate multiple factors simultaneously, balancing structural requirements with ecological impacts for optimized, resilient building designs.

In structural analysis, DBD is capable of producing high-performance solutions by leveraging advanced modeling and optimization techniques. For example, Li et al. applied multi-material topology optimization to the design of the "Xiong'an Wings" building, focusing on structural performance and material efficiency. Their methodology resulted in a design that lowered material costs while improving both static and dynamic structural performance [18]. This research underscores the potential of data-driven structural analysis to enhance architectural innovation by supporting complex geometries and minimizing material waste, particularly for challenging architectural forms.

DBD Applications in Predictive Maintenance and Lifecycle Management:

DBD has broadened its scope to predictive maintenance and lifecycle management, essential for optimizing long-term building performance. By leveraging data analytics, sensors, and advanced modeling, predictive maintenance identifies potential failures, reducing unexpected repairs and ensuring operational efficiency.

DBD approaches have extended beyond initial design and construction phases to include predictive maintenance and lifecycle management, essential for optimizing building performance over time. By leveraging data analytics, sensors, and advanced modeling, predictive maintenance helps identify potential system failures before they occur, minimizing unexpected repairs and ensuring continuous operational efficiency. Lifecycle management, on the other hand, uses simulation tools to anticipate and plan for the future environmental and economic impacts of buildings, guiding decision-makers in both new construction and retrofit projects.

For instance, Satola et al. explored lifecycle optimization in the context of multifamily housing in India, emphasizing the importance of integrating sensitivity analysis and multi-objective optimization to reduce lifecycle greenhouse gas emissions and lifecycle costs. Their findings reveal substantial reductions in both lifecycle GHG emissions (62–75%) and lifecycle costs (40–54%) by optimizing critical design parameters such as mechanical ventilation and renewable energy use [19].

Similarly, Motalebi et al. presented a framework that combines Building Information Modeling (BIM) with Life Cycle Assessment (LCA) for energy retrofits in existing buildings. Their study demonstrates how integrating mathematical optimization with lifecycle cost and environmental impact analysis can guide decision-makers towards sustainable retrofit measures. This approach achieved a reduction in global warming impacts by over 45% and lowered lifecycle costs through optimized energy efficiency upgrades [20].

These examples illustrate DBD's value in supporting sustainable, long-term building operations, highlighting its role beyond initial design phases.

2.1.2 Multi-Objective Optimization in Architecture

Multi-Objective Optimization (MOO) is essential in Data-Driven Building Design (DBD) as it enables architects and designers to balance multiple, often competing objectives, such as cost, environmental impact, and aesthetic quality. By integrating various performance metrics, MOO offers a structured approach to achieving balanced, high-performance design outcomes across different stages of architectural planning.

MOO is part of the broader *Multi-Criteria Decision-Making* (MCDM) framework, which aims to assess and select optimal solutions based on multiple criteria [21]. MCDM methods are widely applied across diverse fields. As shown in Figure 2.2, MCDM methods are especially popular in disciplines closely related to architecture and construction, such as engineering and energy. This widespread use highlights the relevance of MOO techniques in addressing complex decision-making needs in the Architecture, Engineering, and Construction (AEC) industry, where balancing numerous, often conflicting objectives is essential. In DBD, MOO allows designers to evaluate an expansive decision space with infinite possible solutions, adapting to the complexities of architectural requirements. Unlike single-objective optimization, MOO accounts for multiple, sometimes conflicting objectives, requiring trade-offs between design variables.

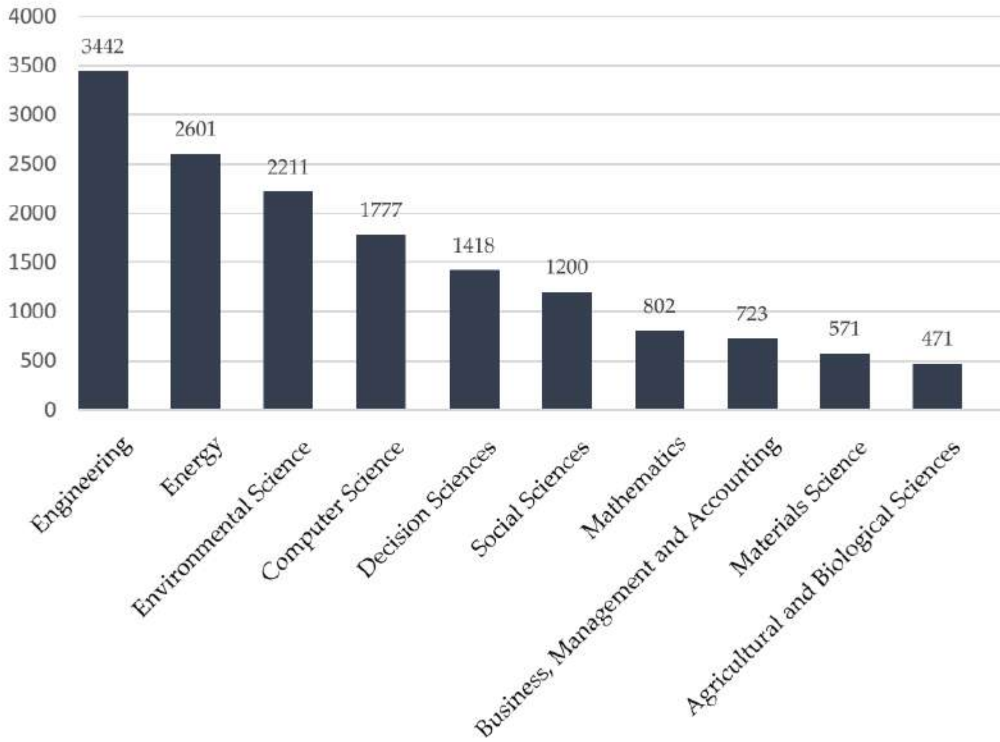


FIGURE 2.2: Subject Areas in MCDM Studies—Number of Articles based on Subject Area, 2012–2021. Source: Taherdoost and Madanchian (2023) [21] MCDM methods are utilized in various fields, with the highest number of applications in engineering and energy, directly aligning with the goals of DBD in the AEC industry.

Two primary MOO methods, 'Pareto Optimization' and 'Scalarization', are frequently applied in architecture to facilitate these trade-offs. The Pareto method keeps solution components independent, creating a 'Pareto Optimal Front' (POF), which represents a set of 'non-dominated' solutions where one objective cannot be improved without compromising another [10]. This approach offers decision-makers a range of compromise solutions, each representing a different balance among objectives, from which they can select based on their specific priorities. Pareto Optimization is particularly suitable for complex architectural projects where multiple stakeholders may prioritize objectives differently. It enables visual trade-off analysis, allowing stakeholders to make informed decisions based on a broad spectrum of feasible solutions.

In contrast, the Scalarization method simplifies multi-objective problems by combining them into a single weighted objective function, producing a streamlined optimized solution. This method's computational efficiency makes it ideal for cases with fewer objectives or when a single, prioritized solution is needed, such as in projects with clear objectives [10]. Scalarization also allows designers to assign specific weights to objectives, tailoring the solution to meet project-specific goals. This approach is particularly advantageous for tasks like material selection, where factors such as cost or durability can be directly prioritized without extensive trade-off analyses.

MOO's applications in architecture span a range of design challenges, from energy-efficient building design to dynamic construction planning. For instance, Zavari et al. (2022) applied a multi-objective optimization framework to optimize construction site layouts dynamically, using Building Information Modeling (BIM) and Geospatial Information Systems (GIS) data to enhance on-site safety and reduce travel distances for personnel [22]. Similarly, Pilechiha et al. (2020) developed an MOO model for office window design, balancing energy efficiency, daylight access, and quality of views [23]. By employing a Pareto frontier, their approach demonstrates MOO's capability to address multiple design criteria within a unified framework, giving architects a comprehensive view of feasible solutions.

The integration of MOO into DBD represents a significant shift towards data-driven design practices, enabling architects to navigate complex interdependencies between design factors. As MOO techniques continue to evolve, future applications may focus on incorporating human-centered and experiential factors, bridging the gap between quantitative performance metrics and user-centered design elements [21].

2.1.3 Challenges and Limitations in DBD

Data-Driven Building Design (DBD) holds tremendous potential to improve building performance and support sustainable, user-centered design. However, there are many challenges and limitations to DBD's implementation, which impinge upon its effectiveness and general uptake in industry. This chapter addresses, in detail, these challenges facing data quality and accessibility, barriers to integration, computational requirements, skill shortages, limitations of human-centered design, and the requirements for future research.

Data Quality and Accessibility

High-quality data is the basic requirement for any successful DBD, but the burden of collecting complete and consistent data remains a challenge. Such variability in data and gaps may impact the reliability of the predictive models, creating discrepancies between the simulated and real outcomes. On the other hand, where data completeness or consistency is missing, the decision-making process—especially in projects involving historical or real-time inputs of data—is undermined [4].

The use of sensitive information in architectural design, such as occupancy trends and energy consumption, raises high privacy and security issues. Satola et al. (2020) emphasize the protection of this information, especially in lifecycle management, where detailed data is gathered on building performance and maintenance schedules [19]. With the increasing use of data in DBD, these privacy and security issues will have to be addressed with much higher urgency.

Interoperability and Integration

One of the most critical issues in implementing DBD is interoperability between various software tools. Zavari et al. (2022) point this out in their work on integrating BIM and GIS data for dynamic site layout planning, where limitations in data exchange between platforms affect the optimization process [22]. Issues with interoperability impede the seamless flow of information, specifically when several tools are used throughout various design and construction stages.

One of the major integration barriers lies in a lack of standardized data formats across the AEC industry. Zawada et al. (2024) points out that standardization—especially in BIM—could further encourage collaboration and data exchange between project stakeholders [8]. Industry-wide standards in data exchange have to be realized for DBD applications to be scalable and interoperable.

The scaling of DBD solutions across diverse architectural projects requires adaptable frameworks that can respond to project size and complexity. Based on this consideration, Gunantara (2018) argues that the presence of 'multi-objective optimization' (MOO) problems may limit DBD to applications in small projects only due to computational limitation and increased variability in project requirements [10].

Computational Complexity and Resource Demand

Data-driven models, in particular, those embracing complex simulations such as MOO, are typically computationally expensive, especially when environmental factors are taken into consideration [12]. Furthermore, with the increasing number of large projects that quite often require energy-intensive simulations, the environmental cost of high-performance computing is beginning to raise concern.

Implementing DBD can be costly, especially for smaller firms that may lack the resources to invest in advanced software and computational infrastructure. Taherdoost and Madanchian (2023) point out that the cost of implementing 'multi-criteria decision-making' (MCDM) methods, which are often integral to DBD, is a significant barrier to adoption [21]. These costs not only include software but also the expenses related to training and computational resources.

Skill Gaps and Industry Resistance

Specialized skills are in demand because DBD requires a wide range of skills, from architecture to data science and computational optimization. Today architects are expected to understand data analytics and simulation methods; this represents a radical change from traditional design practices [4]. The rarity of professionals with the required skills prevents the general adoption of DBD across the industry.

Within the AEC sector, a significant opposition exists against the incorporation of novel technologies, such as DBD, since this typically necessitates alterations in established workflows. Such was the case for embracing Building Information Modeling (BIM) due to the anticipated disruptions to operational practices, a concern that similarly pertains to DBD [7]. Furthermore, the challenges associated with reconciling objectives among interdisciplinary teams, especially when navigating complex MOO processes that necessitate collaboration among stakeholders with varying priorities [10].

Limitations of Human-Centered Design and User Experience

While DBD excels in quantitative assessment, it usually struggles to incorporate qualitative considerations, which in many cases include occupant comfort and aesthetic considerations. For example, Pilechiha et al. (2020), on their study of MOO framework for designing office windows, emphasize the challenge of balancing energy efficiency with qualitative considerations—such as daylight quality and aesthetic views—of the built environment [23]. More technically optimal designs may come out of such limitations, but those may fail to translate in terms of appeal or user comfort.

DBD models may introduce biases unintentionally, especially if data used are either incomplete or not representative. According to Taherdoost and Madanchian (2023) , MCDM methods tend to focus on the quantitative indicators often leading to over-optimization of the measurable fields at the expense of the human-centric concerns [21]. This risk of over-optimization can result in designs that meet technical standards but fail to address occupant needs effectively.

Research Gap and Future Directions

With developments in real-time data collection and integration capabilities, DBD could use increasingly responsive and adaptive design methodologies. As Tian et al. (2021) suggest that incorporating real-time building performance data into DBD models could significantly improve the accuracy of decision-making [9]. What's more, future studies should highlight the need for reconciliation of the quantitative performance indicators with the qualitative aspects of user experience.

For bridging the skill gap, training in architecture, data science, and engineering has to be created and realized that would stress interdisciplinary knowledge to fully realize the potential of

BIM within DBD frameworks [8]. Such training should at least partially prepare the next generation of architects for the skills needed to work with data-driven methodologies.

2.2 Virtual Reality (VR) in Architectural Design

This section explores the evolution and impact of VR in architectural design, examining its applications, benefits, and limitations. Virtual Reality (VR) has emerged as a transformative technology in the Architecture, Engineering, and Construction (AEC) industry, offering immersive environments that bridge the gap between traditional design methods and modern, data-driven approaches. Initially limited to wireframe models in the 1960s, VR has significantly evolved due to advancements in graphics hardware, real-time rendering, and innovative tracking technologies [5]. This progression has enabled VR to provide architects, designers, and stakeholders with intuitive, interactive tools for understanding complex architectural models, thereby enhancing decision-making and collaboration. As the AEC industry seeks to address challenges of precision, efficiency, and stakeholder engagement, VR plays a pivotal role in reshaping how buildings are conceptualized, reviewed, and executed [5].

Initially constrained by technological limitations, VR has transitioned from simple wireframe visualizations to highly realistic, immersive environments. This evolution has been powered by advances in graphics processing units (GPUs), motion tracking, and real-time rendering software, enabling unprecedented levels of interactivity and spatial awareness. Recent developments include the real-time synchronization of Building Information Modeling (BIM) data with zero latency and cloud-based multiuser VR headset systems, facilitating seamless remote collaboration and project communication [24]. These innovations have expanded VR's applications from visualization to active participation in design reviews, collaborative decision-making, and user feedback collection. By enhancing visualization, collaboration, and coordination, VR continues to solidify its role as a cornerstone technology in modern architectural workflows.

Traditional design methods, including 2D drawings and static 3D models, often fall short in conveying the spatial nuances and dynamic interactivity needed for comprehensive stakeholder comprehension. These methods lack the immersive experience required for stakeholders to fully engage with a proposed design, making it challenging to visualize spatial relationships, proportions, and scale [25]. Misunderstandings arising from these limitations can lead to misaligned expectations, and suboptimal outcomes. Furthermore, traditional tools offer limited interactivity, restricting stakeholders from exploring design variations in real-time. These conventional approaches are often costly and time-consuming for iterative design revisions, particularly when physical models are involved [25]. In contrast, VR allows users to experience design concepts at a human scale, providing a tangible sense of depth, proportion, and functionality [5]. This capability makes VR a powerful tool for refining layouts, visualizing performance metrics, and facilitating stakeholder feedback, while ensuring that spatial designs align more closely with both technical goals and user preferences.

The adoption of VR in the AEC industry has accelerated in recent years, driven by advancements in hardware, software, and integration with tools like Building Information Modeling (BIM) [24]. VR is now used for immersive design visualization, allowing architects and clients to interact with 3D environments and explore projects in detail. It facilitates remote collaboration, enabling teams to review designs in real time, regardless of location, and enhances client presentations by offering realistic walkthroughs before construction. VR also supports simulations to optimize factors like lighting and acoustics, virtual prototyping for testing design options, and interactive showrooms to help clients make informed decisions. Additionally, it plays a growing role in training, providing virtual construction site experiences for professionals. These applications highlight VR's transformative impact on architectural practices, improving collaboration, decision-making, and client engagement [5].

Despite its transformative potential, several challenges hinder the widespread adoption of VR in the AEC industry. High upfront costs for VR hardware and software, as well as the need for specialized skills to create VR content, present significant barriers, particularly for smaller firms [24]. Additional concerns include hardware compatibility issues, data security, and privacy risks, as well as user comfort challenges like motion sickness, which can impact the overall VR experience. Resistance to change among professionals accustomed to traditional workflows further limits VR integration into mainstream design practices [24]. Overcoming these obstacles requires a multifaceted approach that includes targeted training programs, technological advancements to improve hardware compatibility and usability, and cost-reduction strategies to make VR more accessible [26]. Moreover, establishing standardized workflows and industry guidelines is essential for facilitating seamless integration of VR into AEC practices.

By delving into VR's ability to enhance stakeholder engagement, enable performance optimization, and support data-driven design decisions, we aim to highlight its role as a cornerstone technology for modern architectural practices. Additionally, the section addresses the challenges that must be overcome to unlock VR's full potential, positioning it as a key component in frameworks like Data-Driven Immersive Design Optimization (DIDO), where it bridges computational rigor with intuitive user experiences. Despite the recognized potential of immersive VR simulations and real-time feedback in bridging the gap between heuristic and data-driven processes, limited attention has been paid to their impact within the context of Site Layout Planning (SLP) and Facade Complexity Analysis; this topic is covered in detail in the literature review sections of their dedicated chapters, Chapter 4 and Chapter 5, respectively.

2.3 Computer Vision (CV) in Architectural Design

Computer Vision (CV) has emerged as a transformative technology in the Architecture, Engineering, and Construction (AEC) industry, enabling the automated analysis of visual data to enhance design precision, functionality, and efficiency. By leveraging advanced algorithms, CV extracts valuable data from construction sites, tracks project progress, enhances safety monitoring, and improves communication among stakeholders. It complements Building Information Modeling (BIM) by providing real-time data and visual insights, ultimately supporting decision-making processes throughout the construction lifecycle [27]. These capabilities position CV as a vital tool for bridging the gap between conceptual design and practical implementation, driving innovation and efficiency in modern architectural practices.

The evolution of Computer Vision (CV) in the AEC sector has been driven by advancements in artificial intelligence (AI), machine learning, and computational power. Initially employed in basic tasks such as safety control and object detection, CV has expanded to address more complex challenges, including operation process monitoring, productivity analysis, and scene recognition [28]. This progression has been facilitated by the transition from traditional visual representations to digital formats, enabling the explicit modeling and simulation of human vision for analyzing architectural drawings, recognizing design decisions, and developing intelligent tools to enhance architectural design processes [29]. Furthermore, the advent of large-scale datasets and refined convolutional neural networks (CNNs) has enabled scalable and accurate applications, significantly contributing to automation and efficiency in the AEC industry.

Traditional methods of analyzing architectural designs, such as manual evaluations of plans, sections, and elevations, often rely on subjective heuristics and static models, which can be inconsistent, time-consuming, and prone to errors [30]. These approaches lack real-time adaptability to changing environmental or project conditions and often fail to provide the cognitive insights necessary for optimizing designs [29]. For instance—topics explored in detail in subsequent chapters—, assessing elements like facade complexity or urban layouts, covered in subsequent chapters, through manual methods may lack the precision required to align technical goals with aesthetic aspirations. Computer Vision (CV) addresses these limitations by automating the evaluation of patterns, and proportions, enabling more systematic, repeatable, and data-driven analyses [29]. Additionally, by offering real-time insights into critical factors such as thermal energy distribution and environmental monitoring, CV empowers modern architects to optimize designs for energy efficiency, occupant comfort, and sustainability [30]. This automation reduces human error, enhances decision-making, and provides architects with actionable insights, bridging the gap between traditional design representations and forward-thinking architectural practices.

Applications of CV in architecture have expanded significantly, encompassing a diverse range of functions that improve both design efficiency and project management. Architects now leverage CV to analyze building layouts, optimize material usage, and evaluate energy efficiency, enabling more informed and sustainable decision-making [30]. Additionally, CV facilitates real-time construction monitoring, automating progress tracking and safety analysis to prevent hazards and ensure compliance with project timelines [28]. The integration of CV with virtual and augmented reality technologies further enhances design visualization, allowing clients to experience immersive simulations of projects prior to construction [28]. Moreover, CV supports facility management by automating the detection of structural defects and maintenance needs, demonstrating its utility throughout a building's lifecycle. These advancements highlight CV's transformative role in architectural practices, offering solutions that improve aesthetic appeal, structural performance, and operational efficiency.

Despite its transformative potential, the adoption of CV in the AEC industry faces notable challenges. A significant barrier is the dependency on high-quality, diverse datasets to ensure accuracy in architectural contexts, as inconsistent lighting, weather conditions, and camera angles can degrade algorithmic performance [28]. Additionally, the computational intensity and resource demands of developing CV technologies tailored to architectural processes deter smaller firms, exacerbating scalability issues for large or multi-site projects [28]. Aligning algorithmic outputs with user-centered and culturally sensitive design goals remains complex, as architects must interpret CV-generated insights within broader design narratives, often hindered by the limited interpretability of results for non-technical users [29]. Furthermore, seamless integration into existing workflows, alongside ethical concerns related to data privacy and compliance with regulations such as GDPR, creates additional hurdles [28]. Addressing these challenges will require investment in standardized datasets, user-friendly interfaces, targeted training programs, and collaborative efforts between AEC professionals and technology experts.

Beyond architecture, CV's integration with emerging technologies like the Internet of Things (IoT), Artificial Intelligence (AI), and data analytics drives advancements in real-time visual data processing, predictive modeling, and immersive user experiences [30]. These synergies enable smarter decision-making and automation across industries, reinforcing CV's transformative potential.

As part of the 'Data-Driven Immersive Design Optimization' (DIDO) framework, Computer Vision (CV) plays a pivotal role in enhancing computational precision and supporting immersive visualization technologies like Virtual Reality (VR). By quantifying design elements, CV complements VR's ability to present intuitive visual simulations, enabling architects to bridge technical analysis with experiential design. Together, these technologies foster a cohesive workflow that integrates data-driven optimization with user-centered design, ensuring architectural practices are both innovative and responsive to stakeholder needs. In Chapter 5, DIDO's application to facade complexity analysis is explored in detail, illustrating how CV and VR work in tandem to translate complex computational analysis into accessible, immersive simulations, showcasing their combined capability to redefine modern architectural practices.

2.4 Existing Research in Bridging Gaps in Data-Driven and Immersive Architectural Research

The rapid evolution of digital technologies in architecture has transformed the way design and construction are conceptualized, analyzed, and executed. Tools such as Data-Driven Design (DBD), Virtual Reality (VR), and Computer Vision (CV) have each introduced significant advancements, enabling optimization, immersive visualization, and automated analysis. However, prior studies often explore these technologies in isolation or within narrowly defined contexts, resulting in fragmented methodologies that fail to fully exploit their synergistic potential.

This section explores key studies that have sought to bridge these gaps by integrating DBD, VR, and CV into architectural workflows. By examining immersive visualization frameworks [31], site safety monitoring using CV [27], and hybrid approaches for energy efficiency and design optimization [30], this review identifies recurring limitations in existing research. These include the lack of cohesive integration across technologies, limited support for iterative and interactive feedback, task-specific methodologies that hinder generalization, and accessibility gaps in presenting results to stakeholders.

The Data-Driven Immersive Design Optimization (DIDO) framework developed in this research addresses these challenges by unifying DBD, VR, and CV into a seamless and adaptable workflow. By providing real-time, interactive feedback and translating complex data into intuitive visualizations, DIDO bridges the gap between technical precision and stakeholder collaboration. This section positions DIDO within the context of prior research, emphasizing its innovative contributions to advancing architectural design and decision-making.

Analysis of Existing Studies

a. Immersive and Data-Driven Frameworks

The study by Seyed et al. (2022), titled *"Data-Driven Design Exploration with Immersive Visualization,"* explores the integration of Virtual Reality (VR) and Data-Driven Design (DBD) methodologies to address the limited evaluation of design options during architectural simulation processes [31]. The authors aim to enhance decision-making by linking performance metrics, such as structural performance and spatial daylight autonomy, with immersive visualization, thereby facilitating a more comprehensive exploration of complex design spaces [31].

This research utilizes VR to create interactive and immersive environments, coupled with DBD methodologies for performance optimization. These technologies are integrated within a workflow that connects multi-objective optimization results to a dynamic VR environment, enabling stakeholders to engage with design options and visualize associated performance metrics in real time [31].

A notable strength of this study lies in its development of an early-stage prototype that effectively combines immersive visualization with efficient communication of design options. By enabling users to interact directly with design parameters within a VR setting, the research underscores the potential of immersive technologies in enhancing understanding and improving decision-making processes in architectural design [31]. This contribution represents a significant advancement in architectural research, particularly in demonstrating the application of VR and DBD to facilitate data-driven exploration of architectural solutions [31].

Despite its contributions, the study presents certain limitations. It focuses primarily on specific building typologies, such as detached classrooms, potentially restricting the generalizability of its findings to other architectural contexts [31]. Additionally, while the proposed workflow promotes interaction between users and performance metrics, it lacks a robust mechanism for iterative feedback, which is critical for refining design options in user-centered approaches [31]. Furthermore, challenges related to the interoperability between tools, such as Building Information Modeling

(BIM) and VR, remain insufficiently addressed, limiting the practical application of the proposed methodology [31].

The results are presented through immersive and interactive environments that allow stakeholders to visualize complex relationships effectively. However, the accessibility of these insights may be limited for users without a fundamental understanding of the underlying performance metrics [31]. Nonetheless, the study contributes to the field by establishing a foundational framework for integrating immersive technologies with data-driven, performance-based design methodologies [31]. Its methodologies hold potential for broader generalization and adaptation to diverse design challenges within the architecture, engineering, and construction (AEC) industry [31].

Although the study successfully combines VR and DBD, it does not adequately address the need for iterative feedback mechanisms or seamless interoperability between multiple technologies [31]. The DIDO framework extends these foundations by incorporating Computer Vision (CV) alongside VR and DBD, establishing a more comprehensive and integrated workflow. Unlike the static evaluation of design options presented in the study, DIDO introduces real-time, immersive feedback loops that allow iterative refinement based on user input. Furthermore, DIDO's application scope spans a broader range of design tasks, including facade complexity analysis and site layout planning, addressing the narrow focus observed in the study. This positions DIDO as a more adaptable and holistic framework for addressing contemporary challenges in architectural design.

b. Computer Vision in Construction Safety Monitoring

The study by Kulinan et al. (2024), titled *"Advancing Construction Site Workforce Safety Monitoring through BIM and Computer Vision Integration,"* addresses critical challenges related to ensuring workplace safety on dynamic and hazardous construction sites [27]. Specifically, it focuses on integrating Building Information Modeling (BIM) and Computer Vision (CV) technologies to enhance real-time monitoring of workforce safety and to identify potential hazards, thereby improving site safety management practices [27].

The technologies employed in this research include BIM for 3D modeling and CV for real-time visual data analysis. These tools are integrated into a cohesive workflow that also incorporates Internet of Things (IoT) sensors for supplementary data collection. This integration facilitates continuous monitoring of construction sites, enabling real-time data visualization that enhances safety management practices [27].

A primary strength of the study is its novel approach to combining BIM with CV to improve situational awareness for safety managers. This integration allows for proactive hazard management, significantly reducing accident rates on construction sites [27]. By leveraging real-time technology, the study advances traditional safety management practices, offering valuable insights into the effectiveness of combining digital tools for enhanced site management [27].

Despite its contributions, the study identifies several limitations. The effectiveness of computer vision algorithms is highly dependent on environmental factors, such as lighting conditions and occlusions, which can affect accuracy [27]. Moreover, the study focuses on specific use cases and does not comprehensively explore the broader application of the integrated technologies across different construction project types [27]. Another notable gap is the lack of iterative feedback mechanisms or user-centered design approaches that would allow for refinement based on real-world input from workers and safety managers [27].

The study addresses integration challenges by proposing a framework that emphasizes interoperability standards between BIM and CV, ensuring seamless data exchange without loss of context [27]. The results are presented through interactive dashboards, providing safety managers with accessible real-time data alongside static graphs that outline safety trends over time [27]. This dual presentation ensures that the insights are both actionable and easy to interpret for stakeholders, including project managers and safety officers [27].

While Kulinan et al. (2024) effectively integrate BIM and CV for safety monitoring, the study's scope is limited to specific use cases, and it lacks a broader application framework that could encompass diverse design and construction challenges [27]. The DIDO framework builds upon these foundations by expanding the application of CV beyond site safety to include architectural design analysis and optimization. Unlike the static safety dashboards presented in this study, DIDO employs immersive technologies, such as Virtual Reality (VR), to create real-time, interactive environments that enhance stakeholder engagement. Furthermore, DIDO introduces iterative feedback mechanisms, enabling continuous refinement of design and safety parameters based on user input, bridging the gap between computational precision and experiential insights [27]. By integrating VR, CV, and DBD, DIDO provides a unified framework that extends the applicability of advanced technologies across multiple facets of the AEC industry.

c. Hybrid Approaches: Integrating Data-Driven Design, VR, and Computer Vision in Energy Optimization

The study by Zhang Hui [30], *"Image Acquisition Based On Computer Vision Technology For Optimizing Thermal Energy In Building Environments And Simulating VR Interior Design"*, tackles the critical challenge of increasing energy consumption in urbanized environments, with a specific focus on optimizing thermal energy management in buildings. This issue is addressed through the integration of advanced technologies, including computer vision (CV), virtual reality (VR), and deep learning algorithms. By employing these technologies, the study aims to enhance energy efficiency and occupant comfort while bridging the gap between traditional design practices and modern data-driven approaches.

To achieve its objectives, the study utilizes CV for thermal energy monitoring, enabling the identification of inefficiencies through heat map generation. VR is incorporated to simulate interior designs, providing immersive environments where stakeholders can visualize the impacts of energy optimization strategies. Deep learning algorithms are employed to process the data acquired through CV, offering actionable insights for thermal energy management. These technologies are integrated into a cohesive workflow, wherein real-time data from CV directly informs VR simulations, creating an iterative process for optimizing both energy use and design outcomes [30].

The primary strength of this study lies in its innovative integration of CV, VR, and deep learning, resulting in a seamless workflow that enhances both the technical accuracy of energy management and the experiential quality of design visualization. By merging performance data with immersive simulations, the study advances architectural research and demonstrates the potential for interdisciplinary applications in building design. It also makes a notable contribution to sustainable practices by addressing the pressing challenge of energy consumption in urbanized contexts [30].

However, several limitations are identified. The study's focus on specific building types restricts the generalizability of its findings across broader architectural contexts. The reliance on high-cost CV equipment may pose barriers to adoption in practice. Additionally, while VR supports user-centered design, the study lacks a robust mechanism for iterative feedback, which could further enhance the workflow through real-world user engagement [30].

In terms of integration challenges, the study establishes workflows to facilitate real-time data sharing between CV and VR technologies. This interoperability streamlines the design process, ensuring alignment between computational precision and user-centered goals. Results are presented through interactive VR environments, supplemented by heat maps that effectively communicate thermal energy dynamics. Although the presentation is accessible to a range of stakeholders, a basic understanding of architectural and energy management principles may be required to fully interpret the insights [30].

The study contributes significantly to the broader field of architecture, engineering, and construction by demonstrating the potential of integrating advanced technologies to optimize energy efficiency and improve occupant comfort. While its framework is focused on specific applications, it offers a foundation that could be adapted for use in other architectural contexts, showcasing the potential for interdisciplinary methodologies in performance-driven design [30].

Despite its contributions, this study leaves gaps that the Data-Driven Immersive Design Optimization (DIDO) framework seeks to address. First, the study's narrow focus on specific case studies limits its scalability and generalizability, whereas DIDO provides a structured framework adaptable to various building contexts. Second, while the study integrates CV and VR effectively, it lacks an emphasis on iterative feedback mechanisms. DIDO addresses this by incorporating user-centered iterative refinement, enabling continuous improvement of design solutions based on stakeholder input. Additionally, DIDO extends the integration of technologies by incorporating multi-objective optimization frameworks, allowing for the evaluation of competing priorities such as energy efficiency and spatial aesthetics. Finally, DIDO enhances stakeholder engagement through immersive simulations that facilitate collaboration and ensure that design outcomes meet both technical requirements and user expectations. By building upon the foundations established by Zhang Hui [30], DIDO presents a comprehensive solution for integrating data-driven methodologies and immersive technologies in architectural design.

2.5 Summary

This summary section combines the information derived from exploring the roles of Data-Driven Building Design (DBD), Virtual Reality (VR), and Computer Vision (CV) in architectural design, and the existing research on methods for integrating advanced technologies in the architectural design process. We have traced the contributions, challenges, and transformational potential of each technology, outlining how these innovations are reshaping architectural practice. The main findings are reiterated in this section with a focus on their overall importance in addressing contemporary challenges facing the AEC industry. Additionally, we highlight critical deficiencies of existing applications and show how the 'Data-Driven Immersive Design Optimization' (DIDO) framework overcomes these deficiencies by combining these technologies in one, new workflow.

Summary of Keypoints

Data-Driven Building Design (DBD):

DBD is a huge advancement in the architecture field, moving from an intuition-based practice to a data-based and performance-based approach. State-of-the-art technologies like VR, CV, and the Internet of Things(IoT) give architects the possibility to make better decisions based on real-time information. DBD uses Multi-Objective Optimization techniques to compare design options against conflicting objectives, such as energy efficiency and cost-effectiveness. Effective collaboration among architects, data analysts, and different experts is required in DBD for the interpretation of complex data sets and the enhancement of design outcomes. Despite its transformation potential, DBD faces challenges in data availability, model scalability, and industry-wide adoption, meaning there is a need for flexible data-driven frameworks to enable innovation in architectural practices. Ultimately, DBD represents a shift towards more precise and adaptable design processes that rely on quantitative data and performance metrics, marking a significant evolution in architectural practice.

Virtual Reality (VR):

VR has transformed stakeholder engagement by offering immersive, interactive environments that have revolutionized how architectural designs are visualized and understood. Allowing for navigation of design models at a human scale, VR empowers architects and stakeholders with a much better understanding of spatial relationships and design implications. Its dynamic visualization capabilities make complex architectural data more accessible, fostering clear communication and informed decision-making among project participants. Compared to traditional forms of architectural representation, VR offers dynamic interactivity that reduces misunderstanding and improves feedback, supporting effective iterative design processes. Despite challenges such as high costs, technical complexity, and resistance to change, advancements in hardware like VR headsets and specialized architectural software continue to expand its potential. With the constant development of hardware components, and software platforms developed specifically for architectural applications, VR will definitely play a critical role in changing architectural practices by revolutionizing spatial perception, design visualization, collaboration, and interactive design evaluation.

Computer Vision (CV):

CV has become a substantial transformative force within the AEC industry by automating design analysis and enabling real-time insights to improve both accuracy and operational efficiency. Contrary to traditional approaches, often based on subjective assessments and static models, CV provides reliable data-driven evaluations of elements like patterns, proportions, and even thermal performance when applied for energy calculations. Applications range from optimizing material consumption to monitoring construction progress and improving safety and facility management, demonstrating its adaptability throughout a building's entire life cycle. Furthermore, CV combines with Virtual Reality and Augmented Reality (VR/AR) technologies to create immersive simulations for improved client engagement and informed decision-making. However, widespread CV adoption faces obstacles in the requirements for high-quality datasets, considerable computational needs, and challenges in aligning algorithmic outputs with broader design narratives. In the context of Data-Driven Immersive Design Optimization (DIDO), CV helps to complement VR by connecting technical analysis with intuitive user experiences, showing its pivotal role in innovative, responsive, and sustainable architectural practices.

Common Limitations in Existing Research

While considerable development has been achieved in DBD, VR, and CV, most are typically implemented in isolation in the AEC industry. Although DBD is especially good at optimizing designs according to quantitative metrics, it often lacks intuitive methods of engaging stakeholders. Similarly, the immersive visualization abilities of VR have increased the understanding of stakeholders, although most are based on static or heuristic-driven design models that do not make full use of real-time data-driven insights. CV, while powerful in automating complex analysis like facade evaluations or safety monitoring, is yet to be widely integrated into workflows that balance computational efficiency with user-centered decision-making, leaving its potential not fully explored. This fragmented approach constrains the possible influence of these technologies, as the lack of interoperability hinders seamless collaboration, real-time feedback, and alignment of technical precision with design objectives.

The review of prior studies reveals recurring limitations that hinder the full potential of integrating advanced technologies in the Architecture, Engineering, and Construction (AEC) industry. These limitations include fragmentation of technologies, a lack of iterative processes, task-specific frameworks, and accessibility gaps. By examining studies presented in Section 2.4 ([31], [27], and [30]), these issues are contextualized to highlight their implications for innovation and implementation in the AEC industry.

A key limitation across existing research is the isolated application of technologies like Data-Driven Design (DBD), Virtual Reality (VR), and Computer Vision (CV). For instance, while Kulinan et al. (2024) [27] integrates Building Information Modeling (BIM) and CV to enhance safety monitoring, it neglects the potential contributions of VR, missing opportunities for immersive visualization and enhanced stakeholder interaction. Similarly, Zhang Hui (2024) [30] demonstrates the integration of CV and VR for energy optimization but does not extend this approach to include DBD or broader project contexts. The fragmented application of these technologies restricts opportunities for comprehensive data integration, collaborative decision-making, and holistic project management. This fragmentation limits the ability of studies to address the multifaceted challenges of AEC projects, reducing the potential for unified solutions that could streamline processes, improve efficiency, and drive innovation.

A recurring issue in the reviewed studies is the insufficient incorporation of iterative feedback mechanisms. While Zhang Hui (2024) [30] incorporates real-time monitoring for energy optimization, it falls short of establishing interactive feedback loops for refining design workflows dynamically. Similarly, Kulinan et al. (2024) [27] focuses on real-time hazard identification but does not emphasize iterative stakeholder engagement for continuous improvement. This absence of real-time, interactive workflows limits stakeholder involvement, reducing their ability to provide immediate feedback and collaborate effectively throughout project lifecycles. The rigidity of these approaches hinders adaptability to changing conditions or user input, potentially compromising project outcomes and reducing stakeholder satisfaction.

Many studies focus narrowly on specific use cases, resulting in frameworks that lack versatility. For example, Kulinan et al. (2024) [27] centers on workforce safety monitoring, while Zhang Hui (2024) [30] prioritizes energy management. This specialized focus, while effective within its context, restricts the adaptability of these methodologies to a broader range of tasks. The lack of generalizable frameworks prevents the transfer of successful strategies across diverse project types or challenges, limiting the capacity for cross-disciplinary innovation. In turn, this narrow scope diminishes the potential for holistic approaches that address the interconnected complexities of modern architectural and construction processes.

Accessibility of results remains a significant barrier in existing research. Studies such as Seyed et al.(2022) [31] often present findings in technically dense formats, which may alienate non-technical stakeholders. Similarly, Zhang Hui (2024) [30] relies on heat maps and VR visualizations that, while intuitive, require a foundational understanding of architectural and energy concepts to interpret effectively. These presentation formats hinder collaboration and limit the usability of insights, as non-specialists may struggle to engage with the results or provide valuable feedback. The lack of clarity in conveying findings ultimately reduces the practical application of the insights and inhibits effective implementation in real-world scenarios.

These limitations—fragmentation of technologies, lack of iterative workflows, task-specific frameworks, and accessibility challenges—underscore the need for a more integrated, adaptable, and accessible approach in the AEC industry.

The Contribution of DIDO

The Data-Driven Immersive Design Optimization (DIDO) framework addresses the critical gaps identified in prior research by providing a comprehensive and integrated solution that combines advanced technologies, iterative workflows, and stakeholder-centric design principles. Through its innovative approach, DIDO enhances the usability, adaptability, and effectiveness of data-driven architectural and construction processes.

Integration: A Unified Workflow for DBD, VR, and CV

The DIDO framework unites Data-Driven Design (DBD), Virtual Reality (VR), and Computer Vision (CV) into a cohesive, interactive workflow, effectively addressing the fragmented approaches observed in prior studies [31, 27, 30]. Unlike frameworks that use these technologies in isolation, DIDO ensures interoperability and dynamic data exchange between tools. For example, CV-generated insights are directly integrated into VR environments, allowing for real-time visualization of performance metrics. This unified approach bridges the gaps between computational precision, immersive visualization, and actionable insights, enabling holistic project management and decision-making across the Architecture, Engineering, and Construction (AEC) industry.

Iterative Feedback: Real-Time Refinement in Interactive Environments

One of DIDO's core contributions is its emphasis on iterative feedback mechanisms. By leveraging immersive VR environments, stakeholders can engage in real-time interactions with design parameters, providing immediate feedback and refining outcomes collaboratively. This capability addresses the rigidity of static workflows in previous studies, such as those by Kulinan et al. (2024) [27] and Zhang Hui (2024) [30], by introducing dynamic feedback loops. The iterative nature of DIDO enhances adaptability to evolving project requirements and user preferences, ensuring that design solutions remain responsive and stakeholder-driven throughout the project lifecycle.

Generality: Versatility Across Diverse Applications

DIDO demonstrates adaptability across a broad range of architectural and construction tasks, addressing the limitations of task-specific frameworks identified in previous research. While earlier studies focused narrowly on use cases like energy management or safety monitoring, DIDO applies its integrated approach to diverse challenges, including facade complexity analysis and site layout planning. This generality allows DIDO to be deployed across various scales and project types, fostering cross-disciplinary innovation and improving overall project performance in both design and construction contexts.

Enhanced Usability: Intuitive VR Simulations for Stakeholder Collaboration

A significant strength of DIDO is its ability to translate complex data into intuitive VR simulations, making insights accessible to both technical and non-technical stakeholders. By visualizing performance metrics and design implications in immersive, interactive environments, DIDO fosters effective collaboration and informed decision-making. This enhanced usability overcomes the accessibility gaps noted in studies like Seyed et al.(2022) [31] and [30], where technical presentation formats limited stakeholder engagement. By bridging the gap between technical complexity and stakeholder engagement, DIDO ensures that participants with varying levels of expertise can actively engage in the design and optimization process. This inclusivity fosters enhanced communication, collaborative decision-making, and improved project outcomes.

By addressing the key limitations of prior research—fragmented technologies, static workflows, task-specific applications, and accessibility barriers—DIDO represents a significant advancement in the AEC field. Its integration of DBD, VR, and CV into a unified framework, emphasis on iterative feedback, adaptability across diverse tasks, and focus on usability position it as a transformative solution for modern architectural and construction practices. DIDO not only bridges the gaps identified in earlier studies but also sets a new standard for leveraging advanced technologies to optimize design, enhance collaboration, and achieve sustainable, user-centered outcomes.

Through the integration of real-time data analysis, intuitive visual representations, and user-centered feedback mechanisms, DIDO effectively connects heuristic methodologies with data-driven design approaches. Successive chapters will reveal core components and guiding principles of DIDO, complemented by the practical examples showing its potential for transformative effect in tasks such as site layout planning and facade complexity analysis; highlighting its capacity to redefine workflows in the AEC industry.

Chapter 3

Data-Driven Immersive Design Optimization (DIDO) and Methodology

This chapter details the research design and methodology used to explore how data-driven optimization can be integrated with immersive technologies, particularly Virtual Reality (VR) and Computer Vision (CV), in the process of architectural design. It introduces the 'Data-Driven Immersive Design Optimization' (DIDO) framework, an innovative strategy developed to align performance-based metrics with user-oriented visualization tools, facilitating better decision-making throughout the design process. The chapter discusses the essential elements of the DIDO framework, explaining the technologies and five core components of methodology. These include: *'3D Modeling', 'Data-Driven Process' (DBD, Multi-Objective Optimization (MOO), and CV integration), 'VR Integration', 'Data Analysis', and 'Optimization and Refinement'*. It also describes data collection and analysis methods used in evaluating the effectiveness of DIDO. Finally, it provides a brief overview of two practical applications of the DIDO framework—'Site Layout Planning' (SLP) and 'Facade Complexity Analysis'—selected as case studies, detailed in subsequent chapters, to illustrate DIDO's potential in real-world architectural settings.

3.1 Introduction to the DIDO Framework

The Data-Driven Immersive Design Optimization (DIDO) framework is a comprehensive approach designed to enhance architectural design through the integration of data-driven methodologies and immersive technologies. At its core, DIDO aims to unite the precision of computational optimization with the intuitive understanding fostered by immersive experiences. By bridging these two domains, DIDO enables architects and designers to make more informed, holistic decisions that consider both performance metrics and user-centered goals. This approach is particularly suited to the Architecture, Engineering, and Construction (AEC) industry, where there is increasing demand for sustainable, efficient, and adaptable design solutions that engage a diverse array of stakeholders.

The DIDO framework is built on three foundational elements: Data-Driven Building Design (DBD), Virtual Reality (VR), and Computer Vision (CV). Each component contributes distinct capabilities that collectively address the multifaceted challenges of architectural design:

1. **Data-Driven Building Design (DBD):** focuses on optimizing various performance criteria, such as energy efficiency, material usage, and environmental impact, through quantitative analysis. As described on the 'Literature Review' (Section 2.1), DBD provides a structured, objective foundation that allows architects to explore and balance competing objectives, aligning the design process with measurable performance outcomes.

2. **Virtual Reality (VR):** was chosen for its unique ability to create immersive, experiential environments, allowing stakeholders to interact with design models at a human scale. Unlike traditional 2D plans or static 3D models, VR enables users to 'walk through' and explore

spaces, bridging the gap between technical data and human perception. This immersive quality enhances stakeholder engagement, especially for non-experts, by making complex spatial and design concepts more accessible and understandable. In Site Layout Planning (SLP), for example, VR allows users to visualize spatial configurations and circulation paths, fostering a collaborative decision-making process that integrates user feedback, reduces misunderstandings, and helps align design choices with stakeholder expectations early on. This interaction with the design in a simulated environment fosters deeper engagement, bridging the gap between technical data and human perception. VR empowers users to visualize, manipulate, and understand complex design decisions in real-time, enhancing collaboration and decision-making.

3. **Computer Vision (CV):** was integrated into DIDO for its capacity to analyze visual data and quantify aesthetic and functional aspects of design that are often subjective, such as facade complexity, symmetry, and spatial organization. CV enables architects to turn these traditionally qualitative elements into measurable data points, supporting more precise optimization aligned with sustainability goals and user preferences. For instance, in facade design, CV can quantify levels of visual complexity, balancing aesthetic appeal with functional requirements like energy efficiency. By embedding CV in the DIDO framework, architects can achieve a data-informed approach to design that captures both functional outcomes and user-centered attributes, enhancing the quality and adaptability of architectural solutions. By processing visual data, CV helps transform subjective aspects of design—such as aesthetics—into quantifiable metrics, enabling data-informed assessments of design elements that would otherwise rely on personal judgment.

Guiding the integration of these technologies into the Architectural and Construction process required elaborating a set of modules that combined to create the DIDO framework. This methodology, detailed in 'Section 3.2', encompasses five core components (Figure 3.2): '3D Modeling', 'Data-Driven Processing for Multi-Objective Optimization (MOO) and CV Integration', 'VR Integration', 'Data Analysis', and 'Optimization Refinement'. Each element contributes a distinct function within the DIDO framework, collectively supporting a streamlined workflow that integrates computational precision with immersive user interaction. These core components guide the structured implementation of DIDO, ensuring that optimized design solutions are both performance-driven and aligned with stakeholder needs.

Together, these components support a data-driven, user-centered design process that enhances both technical precision and experiential quality. The DIDO framework is structured to foster a cohesive architectural workflow, where optimized designs are functional, sustainable, and aligned with stakeholder expectations. However, implementing this framework presented challenges, such as ensuring compatibility across different software platforms and managing real-time data processing. In order to resolve such issues, custom Python scripts and tools like Unity and Blender were employed so that the data preparation process could be automated simply, making integration seamless between models. Additionally, the Multi-Objective Optimization (MOO) model was linked directly with the VR platform in Unity, in order for optimization results to be updated in real time within the immersive environment. These integration steps, along with the challenges they addressed, will be discussed in detail in the following sections.

The DIDO framework demonstrates its adaptability by addressing a wide range of architectural challenges, from large-scale logistical planning to intricate aesthetic considerations. This thesis highlights two key applications of DIDO—Site Layout Planning (SLP) (Chapter Chapter 4) and 'Facade Complexity Analysis' (Chapter 5)—to showcase DIDO's versatility. These case studies exemplify the framework's capacity to optimize technical performance while integrating user feedback, effectively bridging computational precision with experiential design. Section 3.6 introduces these applications, while subsequent chapters provide a detailed exploration of their

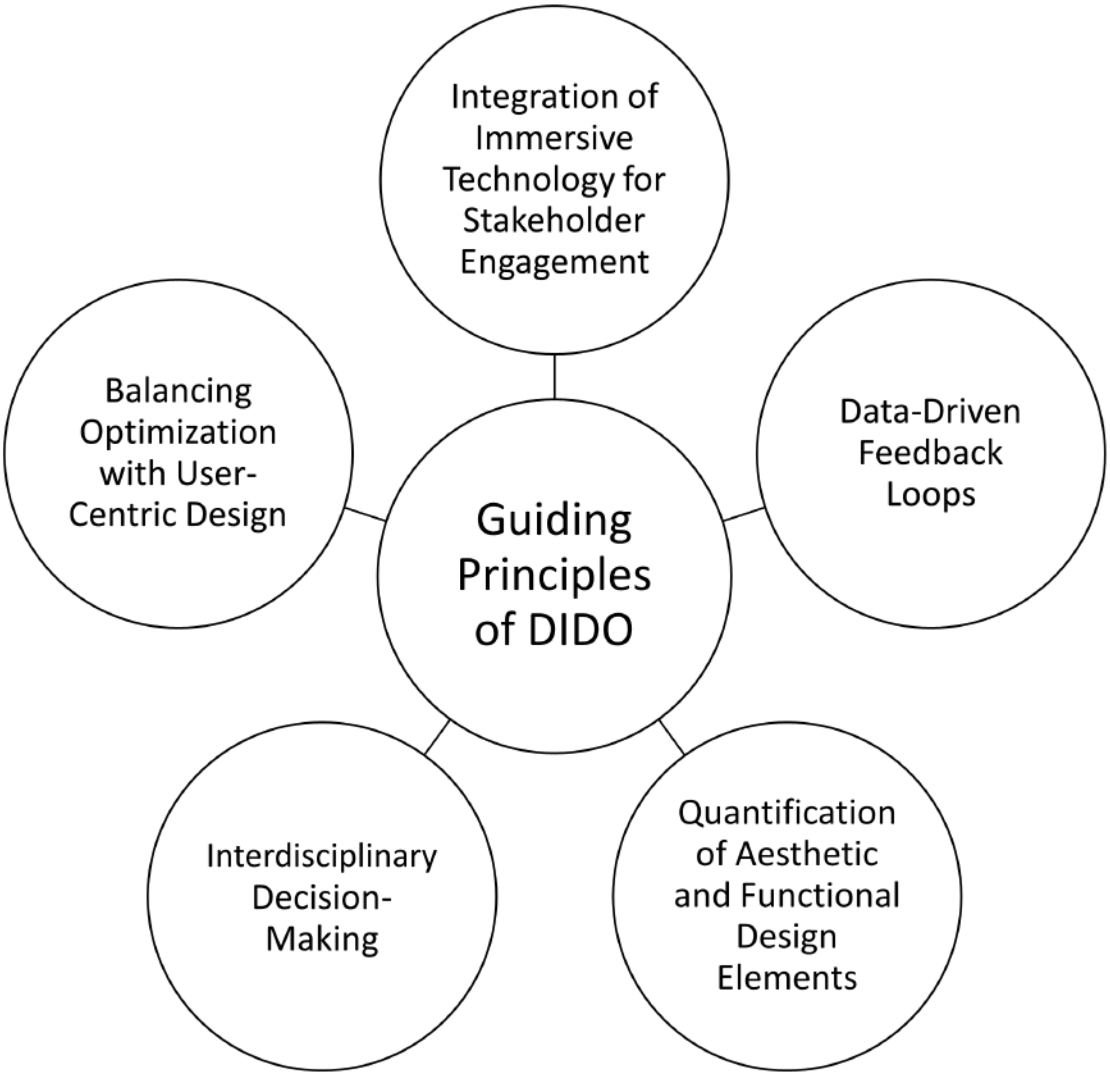


FIGURE 3.1: Flowchart illustrating the 5 Guiding principles of Data-Driven Immersive Design Optimization (DIDO).

development, demonstrating how DIDO adapts to diverse challenges and delivers innovative, context-specific solutions.

3.1.1 Guiding Principles of DIDO

The DIDO framework is guided by five core principles that drive its methodology and application (see Figure 3.1):

1. *Integration of Immersive Technology for Stakeholder Engagement:* VR technology is central to DIDO's mission of translating complex, data-driven outcomes into intuitive, immersive experiences. By allowing stakeholders to interact with designs directly, VR helps bridge the gap between raw data and human intuition, offering a platform where non-experts can engage meaningfully with the design process. This engagement is particularly beneficial for visualizing complex spatial configurations and performance metrics, making data-driven designs more accessible and comprehensible.

2. *Data-Driven Feedback Loops:* DIDO employs multi-objective optimization (MOO) and CV analysis to create real-time, iterative feedback loops. This approach enables continuous refinement of design elements based on user interactions and feedback, enhancing both the aesthetic appeal and functionality of the final design. The feedback loops ensure that computational models are not static but evolve in response to user engagement, a crucial factor in fields like architecture where balancing aesthetic and functional criteria is essential.

3. *Quantification of Aesthetic and Functional Design Elements:* Traditionally, aspects such as visual complexity have been evaluated subjectively. Through CV and other data-driven techniques, DIDO allows for the quantification of these design elements, providing architects with objective metrics for assessing aesthetics and functionality. For instance, in facade complexity analysis, CV can quantify visual patterns, allowing for a balanced approach that enhances both the aesthetic appeal and the sustainability of designs. This principle aligns design decisions with both user satisfaction and performance goals.

4. *Interdisciplinary Decision-Making:* The DIDO framework supports collaborative, interdisciplinary decision-making, facilitated by VR, which allows for real-time engagement from diverse stakeholders, including architects, clients, and engineers. This collaborative approach ensures that the design process incorporates a range of perspectives and requirements, particularly relevant in areas such as Site Layout Planning (SLP), where functional, logistical, and user-centered considerations intersect. By fostering an inclusive environment, DIDO aligns design outcomes with practical, aesthetic, and environmental needs.

5. *Balancing Optimization with User-Centric Design:* DIDO emphasizes that achieving optimal design is not solely about meeting computational objectives; user-centric validation is equally crucial. By integrating VR-based user feedback into the optimization process, DIDO ensures that final design solutions align with both data-driven insights and user expectations. This approach advocates for a harmonious balance between quantitative targets and qualitative user experiences, underscoring the importance of user-centered validation in achieving designs that are both high-performing and intuitively satisfying.

In summary, the DIDO framework presents a structured methodology that combines the rigor of data-driven optimization with the immersive potential of VR and the analytical power of CV. Through these core principles, DIDO supports the creation of resilient, sustainable, and user-aligned architectural solutions that address the complex demands of modern design.

3.2 Core Components of the DIDO Framework

The DIDO framework's functionality relies on a series of core components that together create a cohesive, data-driven approach to architectural design. Each component serves a distinct purpose within the workflow, integrating computational precision with immersive, user-centered experiences. These components—3D Modeling, Data Processing and Multi-Objective Optimization (MOO), VR Integration, Data Analysis, and Optimization Refinement—work in tandem to enable a seamless and adaptable design process (Figure 3.2).

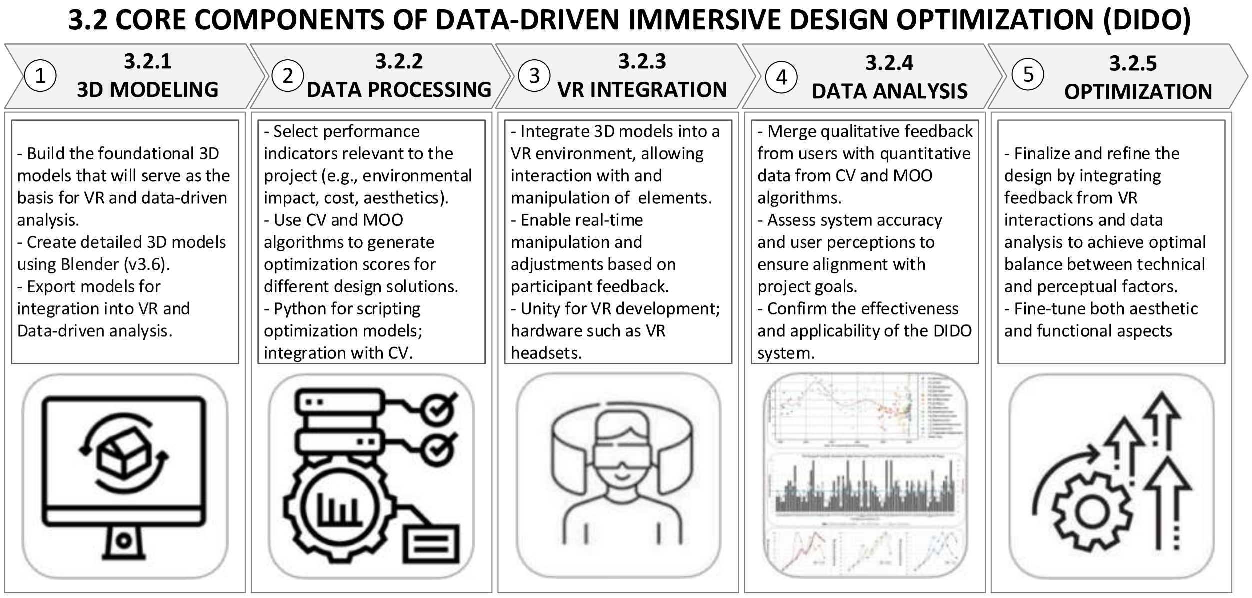


FIGURE 3.2: Methodology Flowchart illustrating the sequential steps of theory behind the Data-Driven Immersive Design Optimization (DIDO) approach.

3.2.1 3D Modeling

In the DIDO framework, 3D modeling serves as the foundation for VR immersion and data-driven analysis, creating detailed and adaptable representations of architectural designs. These models are essential for visualizing, manipulating, and optimizing architectural elements, providing the baseline for both quantitative performance analysis and immersive stakeholder interaction (Figure 3.3).

The 3D modeling workflow begins with conceptual design creation, where initial drafts are developed using tools like AutoCAD or Rhino to capture the project's key architectural elements. Next, detailed 3D modeling is undertaken using software like Blender or Revit, ensuring the inclusion of critical design details such as spatial configurations, material properties, and facade intricacies.

A crucial aspect of this process is the refinement of the Level of Detail (LOD), which ensures that models strike the right balance between visual accuracy and computational efficiency. For instance, models with higher LOD are used for immersive VR interactions, while those with lower LOD facilitate efficient performance analysis. Overly simplified models risk diminishing stakeholder engagement, while excessive detail can strain computational resources.

Following the modeling stage, the process involves exporting and converting models into compatible formats (e.g., .fbx or .obj) to enable seamless integration with VR platforms and data-processing workflows. During this step, geometry, material properties, and spatial organization

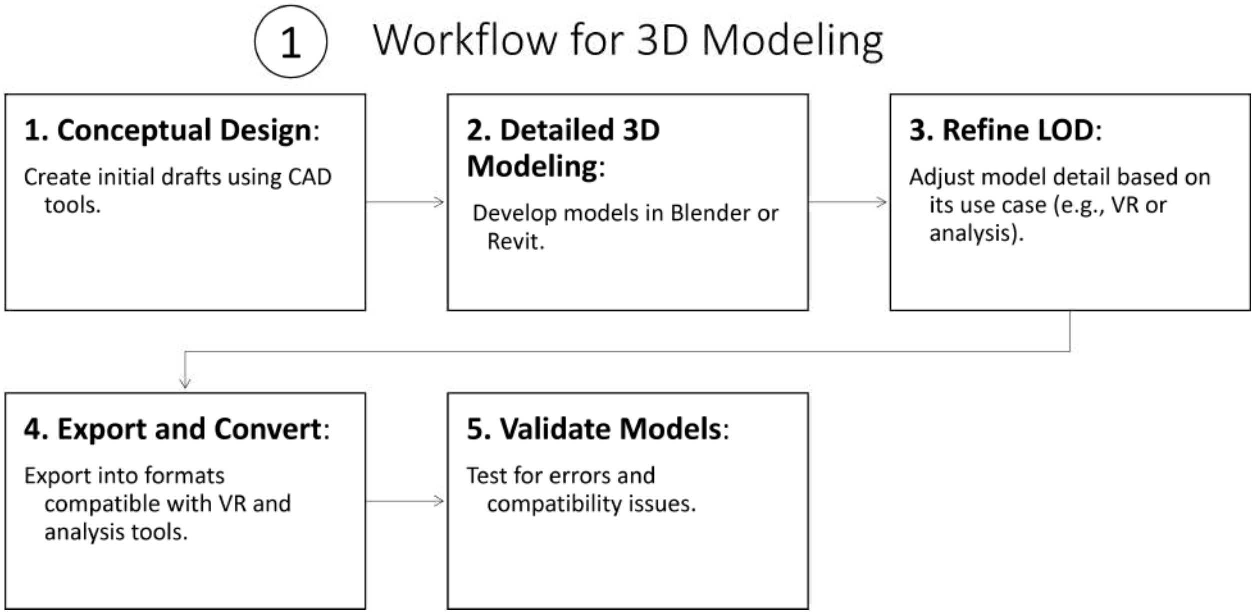


FIGURE 3.3: Workflow for Computer Vision (CV) Integration within the Data-Driven Immersive Design Optimization (DIDO) framework. The flowchart outlines the sequential stages enabling CV to enhance architectural design processes across various tasks.

must be optimized to maintain model fidelity across platforms. Finally, model validation and testing ensure that exported models meet the requirements of the DIDO framework, identifying and addressing any issues related to geometry, rendering, or usability.

By aligning model development with these structured stages, the DIDO framework ensures a cohesive workflow where design choices are visually compelling, computationally robust, and aligned with both stakeholder expectations and performance criteria.

3.2.2 Data-Driven Processes in the DIDO Framework: Data Processing, Multi-Objective Optimization (MOO) and CV Integration

This module serves as the analytical backbone, processing raw data and balancing multiple design objectives to inform optimal architectural solutions. This section covers the data processing workflows, the application of the MOO method for handling competing objectives, and the use of CV for quantifying aesthetic and functional attributes (Figure 3.4).

Together, these components create a dynamic, iterative system within DIDO that manages complex, multidimensional design data. This data-driven process ensures that design outputs are rigorously optimized and aligned with both quantitative performance goals and qualitative user preferences.

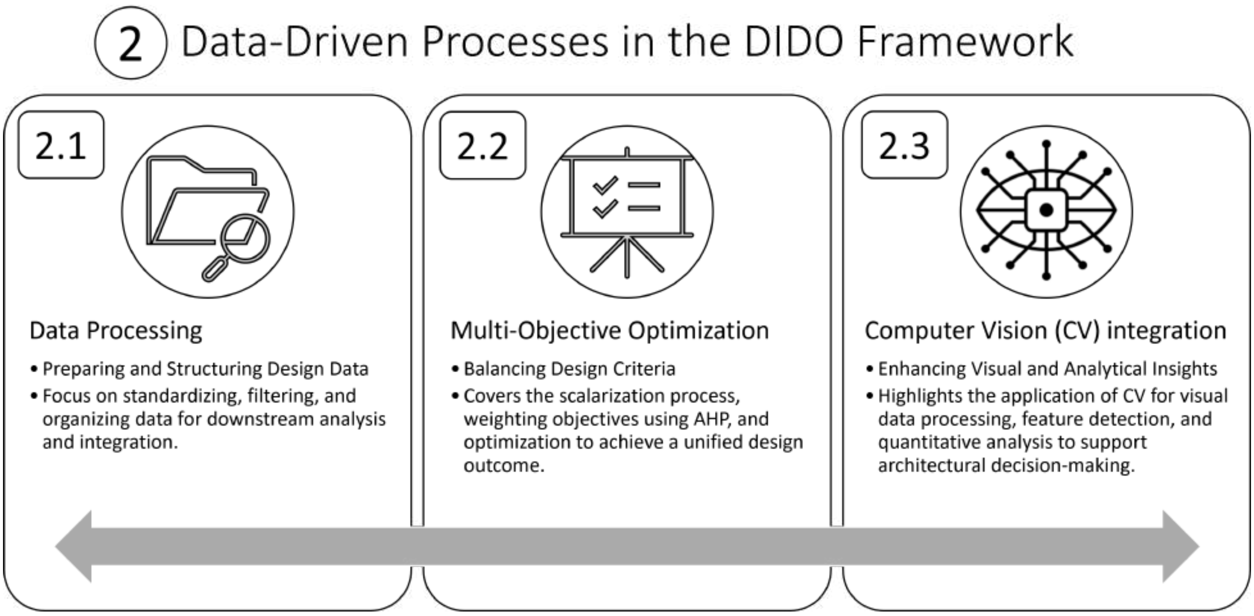


FIGURE 3.4: Data-Driven processes flowchart: it illustrates the interplay between data processing, multi-objective optimization (MOO), and computer vision (CV)integration, forming the core data-driven processes of the DIDO framework. Each component contributes unique functionalities that collectively enhance architectural design precision and user engagement.

3.2.2.1 'Data Processing' for MOO and CV

'Data Processing' is an essential preparatory step that structures raw data for effective use in the Multi-Objective Optimization (MOO) and Computer Vision (CV) processes. This subcomponent refines and organizes incoming data to ensure accuracy and consistency, creating a robust foundation for optimization and analysis. In architectural design, where diverse data sources—including environmental, structural, aesthetic, regulamentory and economic metrics—must converge, efficient data processing is critical for achieving meaningful and accurate optimization results.

The 'Data Processing' workflow includes several key stages (Figure 3.5):

1. *Data Collection and Filtering:* Relevant design data is collected from various sources, such as 3D models, energy analysis outputs, material specifications, local regulations, standards and user preferences. This data often arrives in various formats, requiring a structured filtering process to standardize entries, remove outliers, and verify accuracy. Filtering is crucial, as it eliminates redundant or irrelevant data points, enhancing the quality of the dataset used for MOO and CV applications.

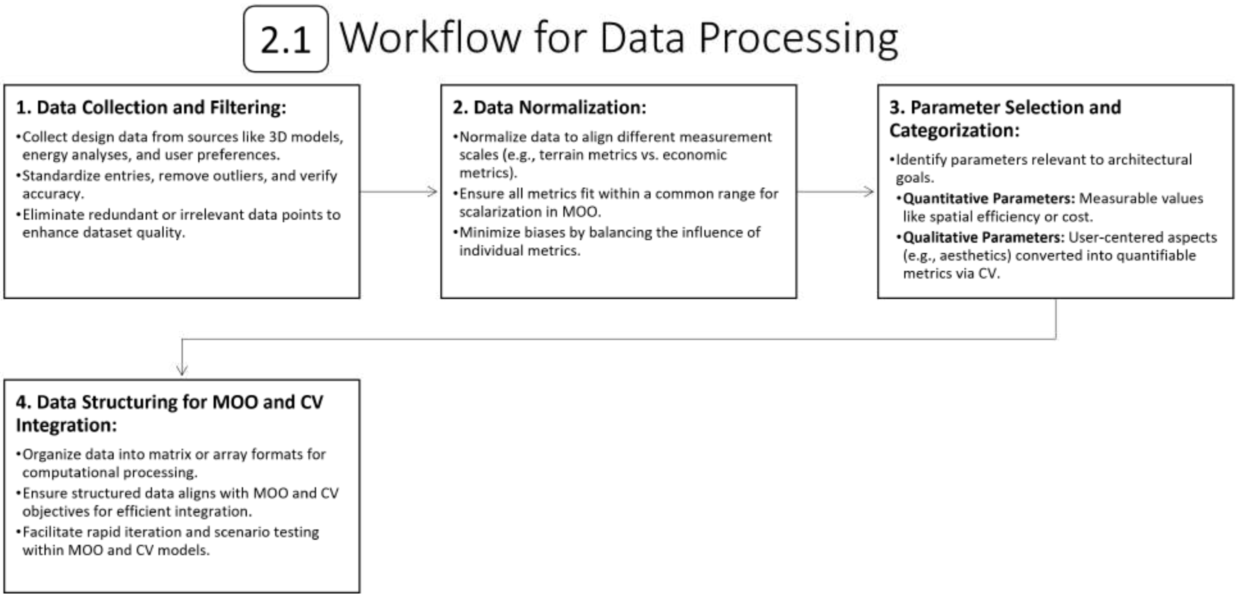


FIGURE 3.5: 'Data Processing' Workflow illustrating the key stages required to prepare and structure data for integration into the Data-Driven Immersive Design Optimization (DIDO) framework. The process ensures compatibility and readiness for Multi-Objective Optimization (MOO) and Computer Vision (CV) analysis.

2. *Data Normalization:* Once collected and filtered, data is normalized to ensure compatibility across different measurement scales. For example, terrain metrics (e.g., topography, earthwork analisys) may require different scaling from economic metrics (e.g., cost, ROI). Normalization adjusts the scales of all metrics to fit within a common range, making it easier to apply the scalarization method in MOO and enabling a balanced comparison of objectives. Normalization also minimizes biases in the optimization process by preventing any single metric from disproportionately influencing the results.

3. *Parameter Selection and Categorization:* Parameters that will be used in the MOO and CV analysis are carefully selected based on their relevance to the architectural goals. In DIDO, parameters are categorized into two main groups:

   - Quantitative Parameters: These include measurable values such as spatial efficiency, and cost. Quantitative parameters serve as the objective foundation of the optimization process.
   - Qualitative Parameters: These are often derived from visual or user-centered data, such as facade aesthetics or spatial layout preferences. These may be interpreted via CV and then converted into quantifiable metrics to be included in the optimization framework.

4. *Data Structuring for MOO and CV Integration:* The final step in the data processing workflow involves structuring the data for direct integration into the MOO and CV models. Structured data is organized into matrix or array formats, facilitating efficient computational processing. This organization supports rapid iteration within the MOO model, particularly when testing various design scenarios, and enables effective analysis in the CV component by ensuring that visual data aligns with quantitative design objectives.

By completing these stages, the 'Data Processing' readies all inputs for the next stages of the DIDO framework. This structured approach to data handling enhances the reliability and accuracy of MOO and CV applications, ensuring that the optimization results reflect well-rounded design solutions aligned with performance and user-centered goals.

3.2.2.2 Multi-Objective Optimization (MOO) Method

In the Data-Driven Immersive Design Optimization (DIDO) framework, the Multi-Objective Optimization (MOO) component serves as a pivotal element, responsible for balancing multiple, often conflicting, design objectives such as cost, energy efficiency, and visual appeal. In the 'Architectural Design Process', achieving this equilibrium is essential for creating solutions that meet stringent technical performance metrics while addressing stakeholder preferences. MOO offers a systematic approach to evaluating trade-offs, enabling architects and designers to identify optimized solutions that satisfy a diverse array of criteria. This ensures that the resulting designs are not only functional and efficient but also aligned with aesthetic and experiential goals.

The application of MOO in the DIDO framework is driven by three primary objectives. First, it prioritizes design criteria based on their relevance to project-specific goals, ensuring that critical factors such as sustainability or user experience receive appropriate emphasis. Second, it bridges computational precision with user-centered considerations by integrating quantitative optimization with qualitative feedback. Lastly, MOO facilitates real-time evaluation of design scenarios by linking its outputs directly to the immersive Virtual Reality (VR) environment. This allows stakeholders to interactively engage with optimized designs and explore the impact of various trade-offs. These objectives collectively ensure that MOO enhances technical performance while fostering informed decision-making and active stakeholder engagement.

The implementation of MOO within the DIDO framework involves a robust technical methodology, as discussed in Chapter 2 'Literature Review' (see Section 2.1.2). The approach begins with the 'Scalarization Method' which consolidates multiple objectives into a single objective function, and is complemented by the 'Analytic Hierarchy Process' (AHP) for assigning weights to objectives. These methods ensure a seamless integration of performance-driven and user-centered goals into the architectural design workflow.

The 'Scalarization Method' is selected as the primary MOO approach within DIDO due to its simplicity and effectiveness in consolidating multiple objectives into a single, optimized solution. Unlike Pareto optimization, which generates a set of equally optimal solutions, scalarization converts multiple objectives into a weighted sum, producing a single, prioritized solution. This method is particularly well-suited to architectural design, where decision-makers often prefer clear solutions that balance competing priorities effectively.

The scalarization method combines the multiple objective functions $f_1(x), f_2(x), \ldots, f_n(x)$ into a single objective function $F(x)$ through a weighted sum of each objective [10]. The general formula for scalarization can be expressed as follows:

$$F(x) = w_1 f_1(x) + w_2 f_2(x) + \cdots + w_n f_n(x) \tag{3.1}$$

$$= \sum_{i=1}^{n} w_i f_i(x) \tag{3.2}$$

Where (x) represents the vector of design variables, $f_i(x)$ represents the i^{th} objective function, w_i denotes the weight assigned to $f_i(x)$, reflecting its relative importance. These weights are normalized such that $\sum w_i = 1$. By adjusting the weights w_i, scalarization enables the prioritization of certain objectives based on project-specific needs, ensuring that the optimization process aligns closely with the intended design outcomes [10].

Within the scalarization process, determining accurate weights for each objective is crucial, as these weights directly influence the balance of outcomes in the final design. To establish these weights, DIDO applies the Analytic Hierarchy Process (AHP), a robust Multi-Criteria Decision-Making (MCDM) technique known for incorporating both expert input and quantitative data [21]. AHP operates by decomposing the decision-making problem into a hierarchical structure, enabling detailed evaluation of each objective's importance relative to others.

The MOO component of the DIDO framework is highly adaptable, addressing diverse architectural challenges by prioritizing objectives based on their significance to technical standards, human perception, and aesthetic appeal. For example, in this study, MOO is applied to two primary contexts: 'Site Layout Planning' (SLP) and 'Facade Complexity Analysis', demonstrating its ability to balance performance-driven metrics with user-centered considerations.

- In the context of SLP, as explored in Chapter 4 (Section 4.3.1), MOO is used to evaluate and balance key criteria such as earthwork cost, earthwork efficiency, and deforestation value, which reflect the environmental impact of site development. By structuring these objectives within the MOO framework, the process ensures that the resulting spatial layout meets logistical requirements while addressing sustainability goals and user preferences. This structured approach allows for the optimization of site designs that are both functional and environmentally considerate.
- Similarly, for Facade Complexity Analysis, discussed in Chapter 5 (Section 5.3.1), MOO prioritizes metrics derived from Computer Vision (CV), such as edge density and contour count, to quantify facade complexity. These metrics are weighted and normalized using data from a database of 200 historical buildings, ensuring that the scores reflect both technical performance and human perception. By aligning the optimization process with user preferences and aesthetic appeal, MOO facilitates the creation of a standarized criteria to quantify complexity capable of guiding the design process along functional requirements.

Whether applied to spatial layouts or facade designs, MOO ensures that ensures that the final solution reflects a realistic compromise between quantitative and qualitative goals and that optimization outputs are robust, adaptable, and aligned with the specific demands of each architectural project.

MOO Woorkflow

The application of Multi-Objective Optimization (MOO) in the DIDO framework follows a structured workflow to balance competing objectives and integrate optimization results into the design process. This workflow ensures a comprehensive approach to achieving both performance-driven and user-centered goals (Figure 3.6).

1. *Objective Definition:* The process begins with identifying and defining specific objective functions for each criterion, such as cost minimization, environmental impact reduction, and aesthetic optimization. These objectives are categorized into performance-driven goals (e.g., earthwork efficiency, cost, environmental impact) and user-centered goals (e.g., spatial preferences, facade aesthetics). This step ensures clarity in the scope of the optimization process.
2. *Weight Assignment Using AHP:* AHP is used to decompose objectives into a structured hierarchy for systematic evaluation. Weights are assigned to each objective based on their significance, reflecting project-specific priorities. By incorporating expert input and empirical data, AHP ensures that the prioritization of objectives aligns with both technical and stakeholder goals [21].
3. *Scalarization of Objectives:* The scalarization method consolidates multiple objectives into a single objective function. This is achieved by applying the 'general scalarization formula' (Equation 3.1) that enables the prioritization of specific objectives while producing a streamlined optimization solution.
4. *Optimization Process:* The scalarized objective function is input into an optimization algorithm, where iterative calculations are performed to identify the optimal design solution. This step balances competing objectives while adhering to constraints, ensuring that the final

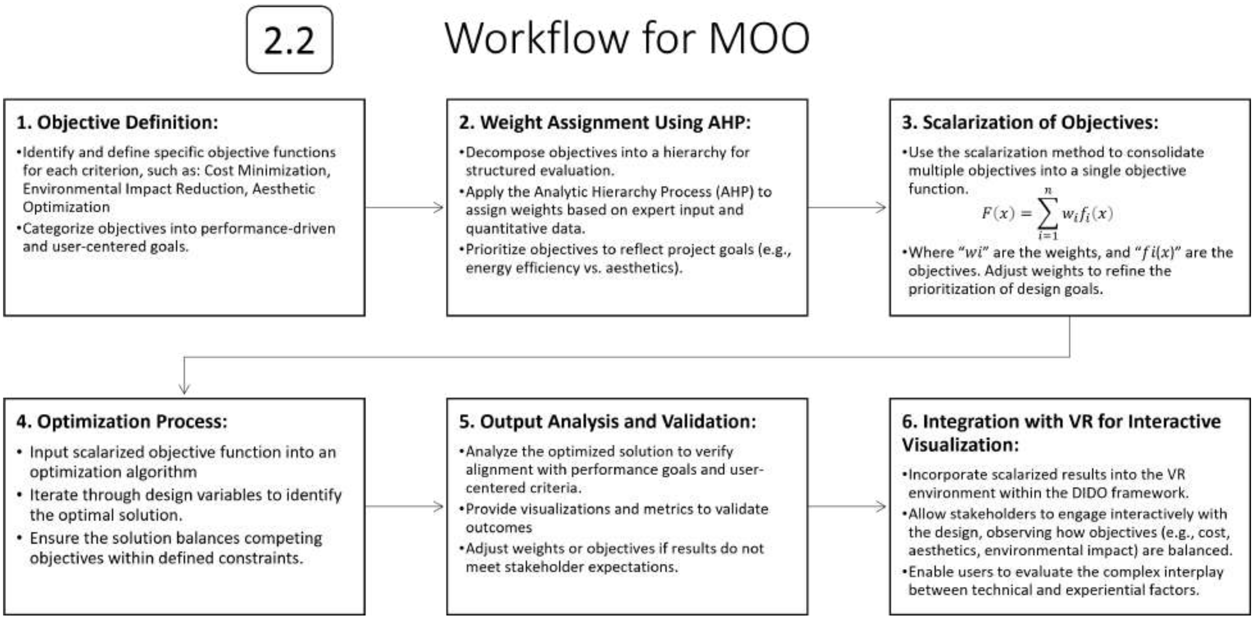


FIGURE 3.6: Multi-Objective Optimization (MOO) within the Data-Driven Immersive Design Optimization (DIDO) framework. The flowchart outlines the sequential stages for balancing multiple design objectives and integrating results into the design process.

solution reflects a realistic compromise between technical performance and user-centered considerations.

5. *Output Analysis and Validation:* After the optimization process, the results are thoroughly analyzed to ensure they align with project goals and user expectations. This phase involves evaluating the accuracy of the optimized solution, verifying that it satisfies both performance metrics and user-centered objectives. Clear visualizations and metrics are provided to stakeholders, fostering transparency and a comprehensive understanding of the optimization outcomes. If the results do not meet stakeholder expectations, adjustments are made by revising weights or refining objectives, ensuring that the optimization process continues to align closely with project requirements.

6. *Integration with VR for Interactive Visualization:* The scalarized results are seamlessly incorporated into the VR environment within the DIDO framework, allowing stakeholders to interactively engage with the optimized design. This integration enables users to visualize how key objectives(e.g. energy efficiency, cost, environmental impact) have been balanced. Stakeholders can explore the immediate impact of design changes on real-time metrics, fostering an iterative and responsive evaluation process.

This approach to MOO in the DIDO framework demonstrates how scalarization, guided by AHP-based weighting, creates a cohesive optimization process that integrates computational precision with stakeholder engagement.

3.2.2.3 Computer Vision (CV) Integration

The Computer Vision (CV) Integration within the DIDO framework supports a data-driven analysis of architectural elements by quantifying typically subjective factors, such as facade complexity, symmetry, and other visual attributes. Through image recognition and feature extraction, CV enables architects to evaluate design elements systematically, bridging subjective assessments with quantifiable metrics that can be used in optimization and analysis.

As part of the DIDO framework, CV offers versatility and can be applied across various stages of design and analysis. Its core strength lies in its ability to process visual inputs—such as facade images, drone-captured site visuals, or material textures—and transform them into actionable data. This makes CV a cornerstone of DIDO's mission to unite computational precision with human-centered insights, enhancing design outcomes that are both optimized and intuitively satisfying.

Computer Vision (CV) provides several critical functionalities that enhance architectural workflows, as previously discussed in the 'Literature Review' (Chapter 2, Section 2.3). These capabilities allow architects to leverage advanced visual analysis techniques to improve both design and decision-making processes.

One of its primary strengths is 'visual feature detection', which allows architects to identify patterns, edges, textures, and other visual attributes crucial for design analysis. For instance, CV can evaluate the symmetry of a building facade or detect intricate textures, providing critical insights into both aesthetic and functional design aspects. These capabilities are especially valuable for quantifying visual features that influence design choices, enabling more informed evaluations.

Another significant capability of CV is the 'Quantification of Subjective Attributes'. Traditionally, aspects such as aesthetic appeal or visual complexity were assessed subjectively, relying on personal judgment or consensus. CV transforms these qualitative evaluations into measurable metrics, such as edge density or contour count, making them accessible for data-driven optimization. This ability to quantify the subjective bridges the gap between computational analysis and intuitive design elements, creating opportunities for more balanced and well-informed decisions.

The 'Flexibility in Data Sources' of CV further enhances its utility in architectural design. It can handle a range of inputs, from high-resolution images and 3D renders to drone-captured site visuals or thermal imagery. This adaptability ensures that CV remains relevant across various architectural scenarios, whether evaluating urban facades, analyzing interior layouts, or assessing construction sites for compliance and safety.

Finally, the seamless 'Integration of CV with Data Analysis and MOO' workflows. The metrics generated by CV serve as valuable inputs to optimization models, aligning visual analysis with performance-based criteria. By feeding these insights into MOO processes, CV complements the other components of the DIDO framework, such as VR and Data-Driven Building Design (DBD). This integration fosters a comprehensive approach to design optimization, ensuring that aesthetic, functional, and user-centered considerations are addressed simultaneously.

CV Integration Workflow

The integration of CV into architectural design workflows involves several key steps (Figure 3.7):

1. *Input Data Preparation:* Relevant visual data is acquired and pre-processed for analysis. This step may include capturing high-resolution facade images, generating 3D renders, or collecting drone footage of a site. Pre-processing techniques, such as noise reduction or image segmentation, ensure the data is optimized for subsequent analysis.

2. *Feature Extraction* Using image processing algorithms, CV identifies critical features such as edges, textures, or patterns. For example, in facade analysis, edge detection algorithms can highlight structural elements, while contour mapping reveals complexity levels.

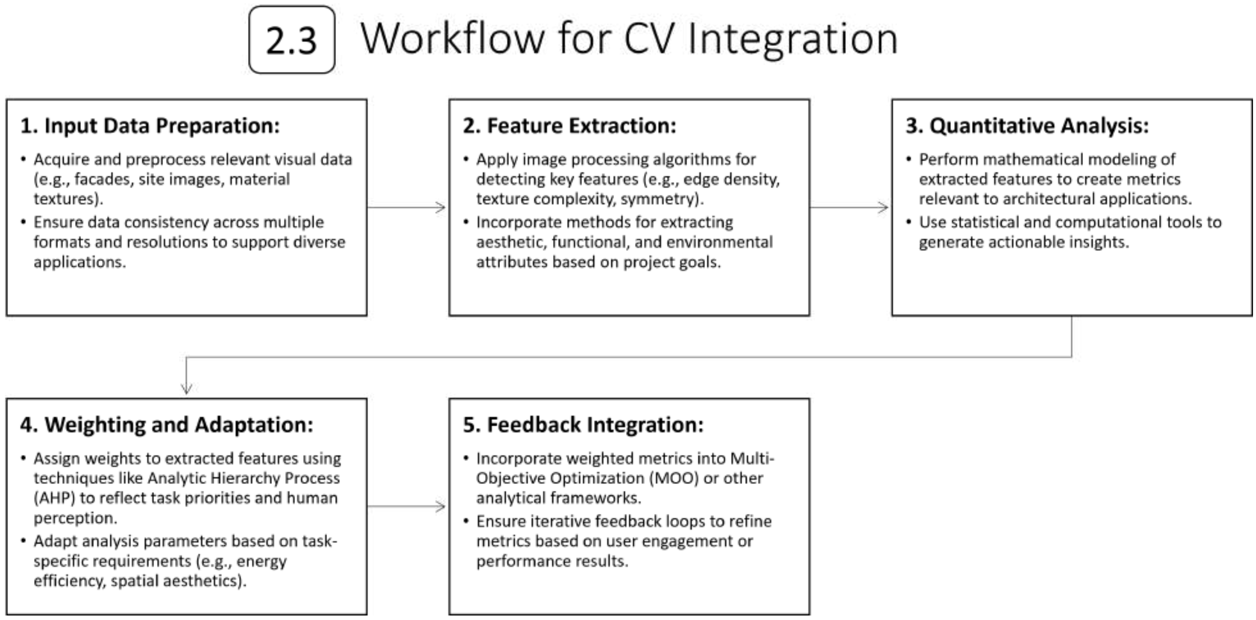


FIGURE 3.7: Workflow for Computer Vision (CV) Integration within the Data-Driven Immersive Design Optimization (DIDO) framework. The flowchart outlines the sequential stages enabling CV to enhance architectural design processes across various tasks.

3. *Quantitative Analysis* The extracted features are modeled into quantitative metrics relevant to the architectural task. These metrics, such as edge density or visual symmetry scores, provide measurable insights that inform design decisions.

4. *Application-Specific Adaptation* The CV analysis is tailored to the specific requirements of the application. For instance, in facade complexity analysis, the focus may be on symmetry and texture, while in sustainability assessments, shading patterns or material reflectivity could be prioritized.

5. *Feedback Integration* The output metrics are integrated into broader data analysis and optimization workflows, such as MOO. This iterative process ensures that CV insights are dynamically applied to refine designs based on evolving requirements and stakeholder feedback.

The integration process applies the Analytic Hierarchy Process (AHP) to assign weights to the extracted features based on both expert input and empirical data, as outlined in Taherdoost (2023) [21]. AHP provides a robust framework for prioritizing visual and functional attributes according to their significance in the design context. By ensuring alignment with human perception and project objectives, this weighting process refines the contribution of CV-generated metrics to the overall optimization model. These weighted metrics are seamlessly incorporated into the scalarization method, supporting balanced optimization across aesthetic, functional, and sustainability objectives. This approach enhances the DIDO framework's ability to adapt to diverse applications while maintaining a user-centered focus.

3.2.3 Virtual Reality (VR) Integration Module

The Virtual Reality (VR) Integration Module is a cornerstone of the DIDO framework, designed to bridge the gap between data-driven architectural optimization and human-centric decision-making. As explored in the 'Literature Review' (Chapter 2, Section 2.2), by leveraging VR's immersive and interactive capabilities, this module is capable of transforming complex data outputs into accessible, experiential environments where stakeholders can directly engage with design elements.

VR plays a dual role within the DIDO framework. On one hand, it visualizes optimized designs at a human scale, enabling stakeholders to explore and assess spatial layouts and facade aesthetics intuitively. On the other hand, it serves as an interactive feedback platform, facilitating real-time design adjustments and fostering collaboration between architects, engineers, and clients. This combination of immersive visualization and interactivity makes VR an indispensable tool in aligning quantitative performance metrics with qualitative user experiences.

Drawing on the insights of Lao et al. [32], we developed the 'VR integration' component using Unity to address the complexities of data-driven optimization outputs. Unity was chosen for its comprehensive VR support, including pre-built templates and seamless integration with Python and C#, enhancing our simulation's interactivity and data handling capabilities cooperativily merging 3D architectural models with sophisticated optimization outcomes (see Figure 3.9).

The core objectives of the VR Integration Module emphasize its potential to improve architectural workflows and enhance stakeholder participation (Figure 3.8). These include immersive visualization, interactive feedback mechanisms, and real-time data connectivity, which collectively ensure that design solutions are both technically sound and aligned with stakeholder expectations.

- *Immersive Visualization:* VR provides a unique opportunity to visualize designs in an environment that mimics real-world conditions. Unlike static 3D models or 2D blueprints, VR allows stakeholders to experience architectural spaces at a human scale. For example, users can walk through a proposed site layout or evaluate facade designs in their intended spatial and environmental contexts. This immersive perspective enhances the clarity of design concepts, particularly for non-technical stakeholders, making complex architectural elements more understandable.

- *Interface and Feedback Mechanism:* Interactivity is a defining feature of the VR Integration Module. Stakeholders can dynamically engage with design components, such as adjusting the placement of structures in a site layout or modifying facade materials and patterns in real time. Additionally, annotation tools enable users to document feedback directly within the VR environment, fostering a collaborative decision-making process. This mechanism not only streamlines communication between stakeholders but also ensures that user preferences are seamlessly integrated into the design process.

- *Real-Time Data Connectivity:* A key strength of the VR module lies in its ability to connect with the data-driven components of the DIDO framework, including MOO and CV. Optimized outputs from these modules are dynamically reflected in the VR environment, allowing stakeholders to see the immediate impact of design changes on performance metrics, such as energy efficiency or aesthetic complexity. This real-time connectivity ensures that the VR module supports both experiential engagement and data-informed decision-making, creating a holistic design evaluation platform.

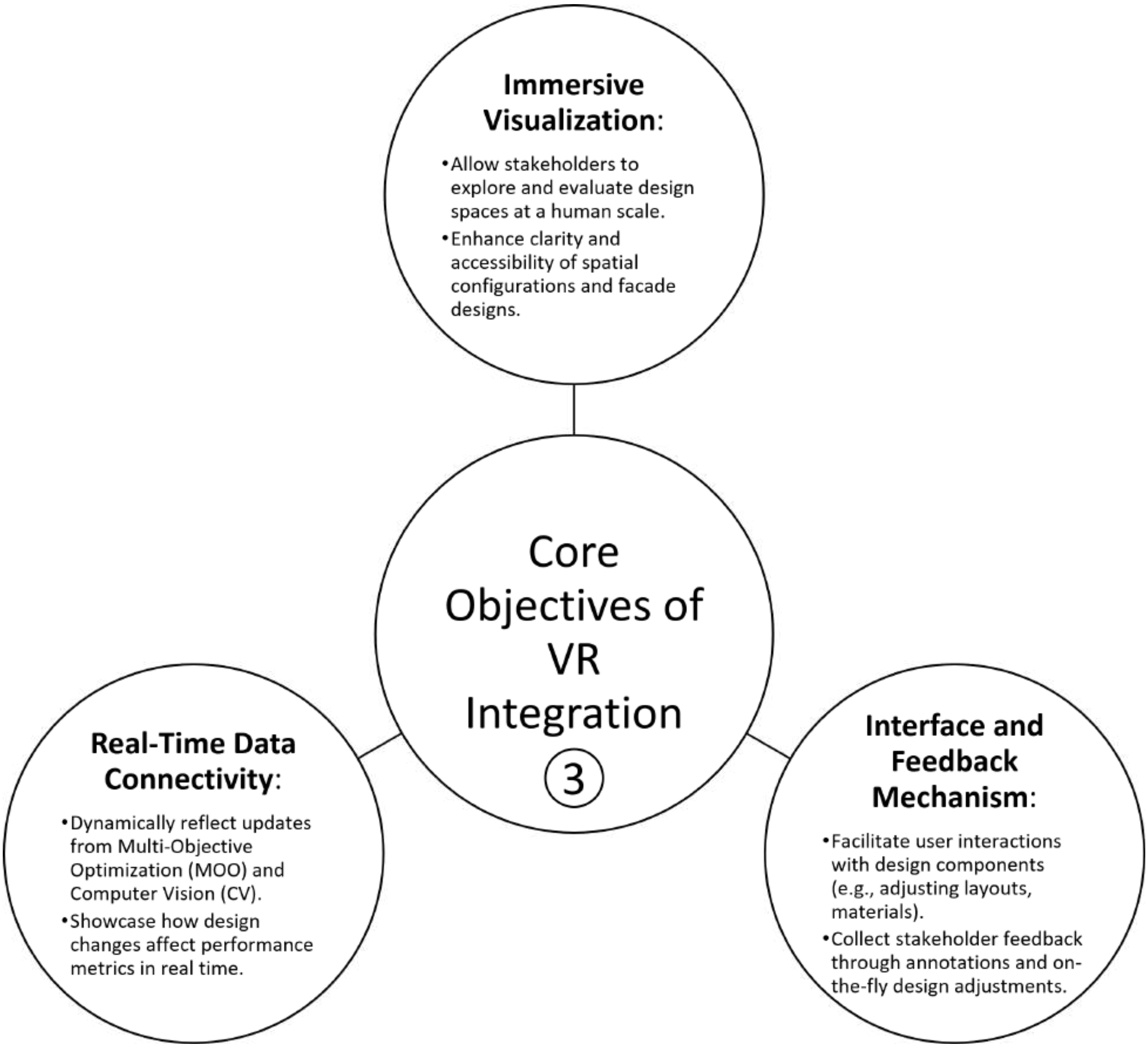


FIGURE 3.8: Core Objectives of the Virtual Reality (VR) module within the Data-Driven Immersive Design Optimization (DIDO) framework.

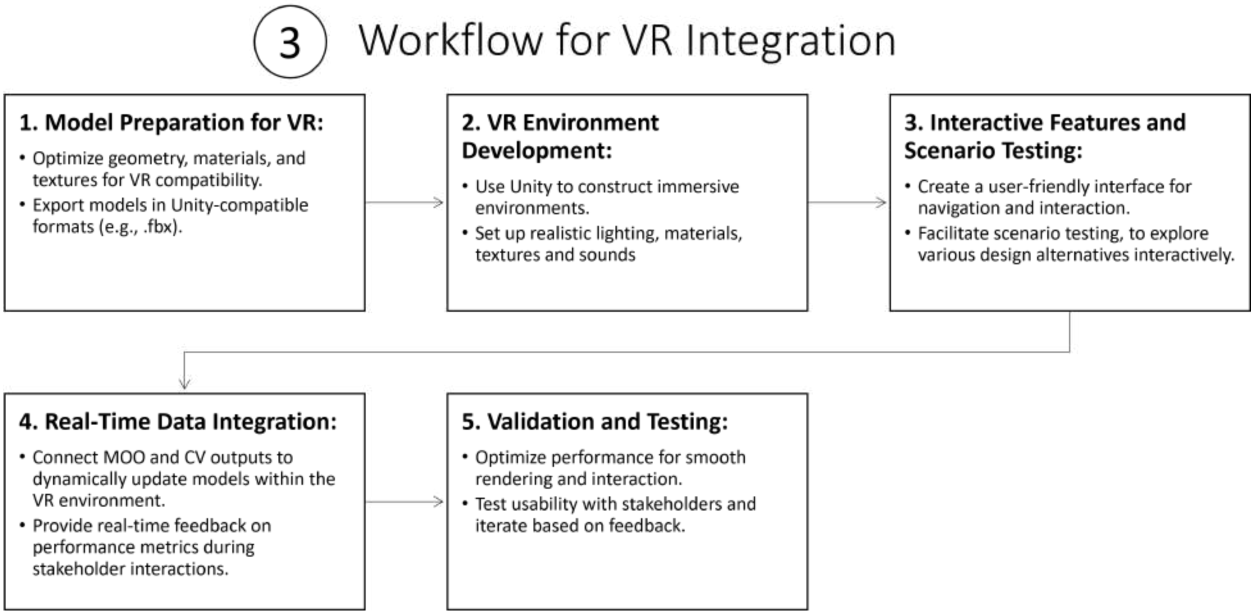


FIGURE 3.9: Virtual Reality (VR) within the Data-Driven Immersive Design Optimization (DIDO) framework. The flowchart outlines the sequential steps for generating the immersive experience into the design process.

Workflow for VR Integration

The VR Integration Module operates through a structured workflow that ensures seamless integration of 3D models, immersive environments, and real-time data (Figure 3.9). This workflow is designed to enable intuitive user interaction, dynamic updates, and robust performance optimization. The following key stages outline the VR integration process:

1. *Model Preparation for VR:* This initial step focuses on optimizing 3D models to ensure compatibility with VR environments. Key actions include reducing polygon counts and balancing texture resolution to maintain computational efficiency while preserving critical design features. Models are then converted into VR-compatible formats, such as *.fbx*, and their level of detail (LOD) is carefully adjusted to align with the specific requirements of the design phase. These preparations ensure that the models render seamlessly within the VR environment.

2. *VR Environment Development:* Using Unity as the development platform, this stage involves constructing immersive environments tailored to the project's architectural goals. Scene elements such as lighting, materials, and textures are configured to achieve realistic and contextually accurate representations. Additional spatial components, such as natural landscapes or urban settings, are integrated to provide meaningful context for the designs. Navigation tools, including teleportation and free movement, are implemented to enable stakeholders to explore the environment effortlessly.

3. *Interactive Features and Scenario Testing:* This phase enhances the VR environment with interactive tools that allow stakeholders to engage with and manipulate designs in real time. These capabilities include modifying spatial configurations or material properties to explore alternative solutions. Scenario-based evaluations are supported, enabling users to assess design impacts under various conditions, such as facade design alternatives or site layout adjustments. Annotation tools facilitate collaborative feedback and record design iterations, while real-time interactivity ensures that stakeholders can immediately observe the effects of their modifications. This immersive approach significantly enhances decision-making.

4. *Real-Time Data Integration:* This critical stage dynamically connects outputs from the MOO and CV modules to the immersive VR environment. Optimized designs generated through MOO are visualized in VR, providing users with insights into how these solutions align with project priorities. Quantitative metrics derived from CV, such as facade complexity scores, are displayed interactively to enhance stakeholder understanding. Real-time updates of key metrics, such as cost, environmental impact, and user comfort, allow stakeholders to iteratively evaluate design changes and their implications.

5. *Validation and Testing:* The final phase ensures the VR module delivers optimal performance and usability. Performance optimization techniques, such as minimizing lag and balancing computational loads, are employed to maintain smooth interactions. Stakeholder usability testing gathers feedback on navigation, interface design, and interactive features, leading to iterative improvements of the VR environment. These refinements ensure the VR module meets user needs while providing an intuitive and impactful design evaluation experience.

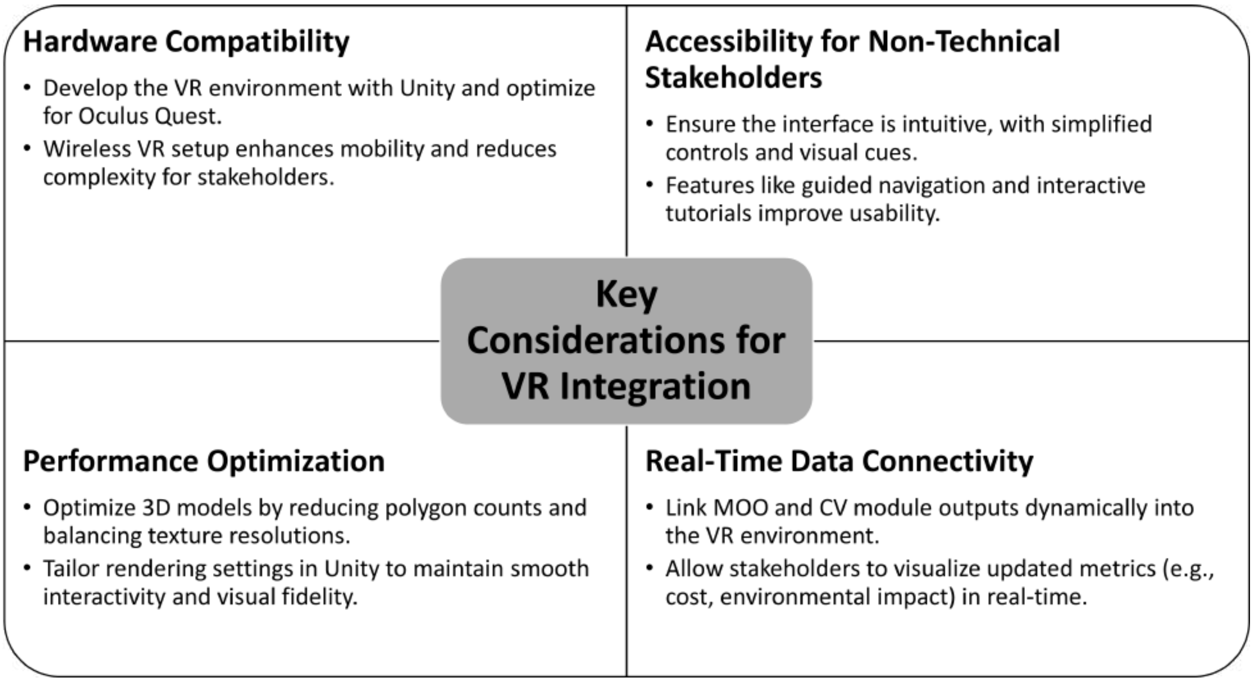


FIGURE 3.10: Key considerations for Virtual Reality (VR) module within the Data-Driven Immersive Design Optimization (DIDO) framework.

Key Considerations for VR Integration

Successful implementation of the VR module within the DIDO framework requires careful attention to several critical factors to ensure usability, accessibility, and performance. They include *'Hardware Compatibility', 'Accessibility for Non-Technical Stakeholders', 'Performance Optimization', and 'Real-Time Data Connectivity'*. These considerations (Figure 3.10) are essential for creating an effective and collaborative platform for architectural design optimization.

'Hardware Compatibility' is a vital factor, and the VR environment in this framework was specifically developed using Unity and optimized for the Oculus Quest headset. The Oculus Quest provides an accessible, standalone VR solution with sufficient performance capabilities for architectural applications. Its wireless setup enhances mobility and reduces the complexity of deployment during stakeholder interactions. By focusing on this hardware, the system ensures compatibility with widely used devices, leveraging Unity's robust development tools to create seamless and tailored VR experiences.

Equally important is *'Accessibility for Non-Technical Stakeholders'*, as the interface must be intuitive and user-friendly to engage participants with limited technical expertise. Features such as guided navigation, interactive tutorials, and simplified controls are incorporated to enhance the usability of the VR environment. Clear visual cues and straightforward interaction tools ensure that a wide range of participants can effectively engage with the platform, fostering meaningful collaboration.

'Performance Optimization' plays a crucial role in maintaining smooth interactions, particularly when rendering complex architectural models. This involves optimizing 3D models for the Oculus Quest by reducing polygon counts and balancing texture resolutions to meet hardware limitations. Additionally, ensuring low-latency connectivity between data updates and the VR environment allows for seamless scenario manipulation and real-time feedback. Unity's rendering settings are fine-tuned to ensure efficient resource use while preserving visual fidelity and interactive responsiveness, ensuring that stakeholders experience a smooth and immersive design process.

'*Real-Time Data Connectivity*' further enhances the VR module by dynamically integrating outputs from the MOO and CV modules. This ensures that stakeholders can visualize updated metrics, such as energy efficiency or visual complexity, as they interact with the design. By aligning the VR environment with the most current optimization results, the system bridges computational precision with immersive stakeholder engagement, fostering a holistic approach to design validation.

By addressing these considerations, the VR module ensures a cohesive integration into the DIDO framework, enhancing its role as a bridge between computational precision and experiential design validation.

In conclusion, the VR integration module plays a pivotal role in enhancing collaboration and decision-making within the DIDO framework. By transforming complex, data-driven designs into accessible, immersive experiences, VR enables stakeholders to engage directly with and evaluate architectural solutions. This fosters a deeper understanding of design trade-offs and allows for more informed decisions that align with both technical metrics and user preferences.

Moreover, VR excels at uniting quantitative metrics with experiential understanding. Stakeholders can simultaneously evaluate technical aspects, such as energy efficiency and structural performance, alongside aesthetic or spatial considerations, such as visual appeal and layout organization. This dual engagement ensures that designs are optimized for performance while remaining aligned with user needs and expectations, reinforcing the DIDO framework's commitment to holistic, user-centered design innovation.

By combining advanced visualization capabilities, real-time feedback, and scenario manipulation, VR integration ensures that stakeholder input is seamlessly incorporated into the design process. This reinforces the framework's goal of fostering collaboration and aligning architectural solutions with both computational rigor and human intuition.

3.2.4 Data Analysis and Evaluation

The 'Data Analysis' module, in the Data-Driven Immersive Design Optimization (DIDO) framework, serves as the bridge between computational precision and stakeholder intuition. By merging qualitative feedback from users with quantitative outputs from Computer Vision (CV) and Multi-Objective Optimization (MOO), the analysis process ensures that architectural designs are both technically robust and aligned with user preferences.

This module involves assessing the accuracy of computational models, evaluating user engagement within the immersive Virtual Reality (VR) environment, and verifying the system's overall applicability to architectural workflows. This integrated approach allows for a comprehensive validation of design solutions, ensuring that they meet both performance metrics and perceptual expectations.

This phase is adaptable to a wide range of architectural applications, as it will be demonstrated in Chapter 4 for Site Layout Planning (SLP) and Chapter 5 for Facade Complexity Analysis.

- In the context of SLP (Chapter 4, Section 4.3.3), 'Data Analysis' evaluates how VR enhances spatial planning by comparing system-generated optimal solutions with user decisions, supported by participant feedback on usability and decision-making precision.
- For Facade Complexity Analysis (Chapter 5, Section 5.3.3), the focus shifts to validating CV metrics, such as CICA scores, against user perceptions of complexity, providing a structured approach to quantify aesthetic preferences and predict emerging trends in facade design.

Through a combination of quantitative assessments and qualitative surveys, the 'Data Analysis' phase synthesizes computational results with stakeholder insights. This approach confirms the effectiveness of the DIDO framework in addressing diverse architectural scenarios while ensuring that optimization outputs reflect well-rounded design considerations.

Additionally, the iterative nature of 'Data Analysis' supports continuous refinement of the DIDO system. By evaluating technical outputs and user feedback, the framework identifies actionable insights to enhance design outcomes, making it an essential step in achieving well-rounded, sustainable, and user-centered architectural solutions.

Workflow of Data Analysis and Evaluation

The 'Data Analysis' module in the DIDO framework is a structured process that consists of five critical steps (Figure 3.11): 'Data Collection', 'Data integration', 'Analysis and Validation', 'Iterative Refinement, Reporting and Recommendations'.

1. *Data Collection:* Information is gathered from computational outputs, such as complexity scores and optimization results, as well as qualitative data from user interactions within the VR environment. This phase relies on robust logging tools to capture user navigation patterns, scenario adjustments, and survey responses. The goal is to create a comprehensive dataset that includes both measurable performance metrics and subjective user feedback.
2. *Data Integration:* It merges these diverse data types into a unified, standardized dataset. Computational metrics from CV and MOO are normalized to align with user feedback data, ensuring consistency and comparability. Organizing the integrated data into structured formats, such as matrices or relational databases, enables efficient analysis and ensures compatibility across the DIDO framework's analytical processes.
3. *Analysis and Validation:* The integrated dataset is examined to assess both system accuracy and user engagement. Quantitative accuracy analysis compares system-generated solutions to user decisions, using statistical methods to evaluate alignment. Meanwhile, qualitative

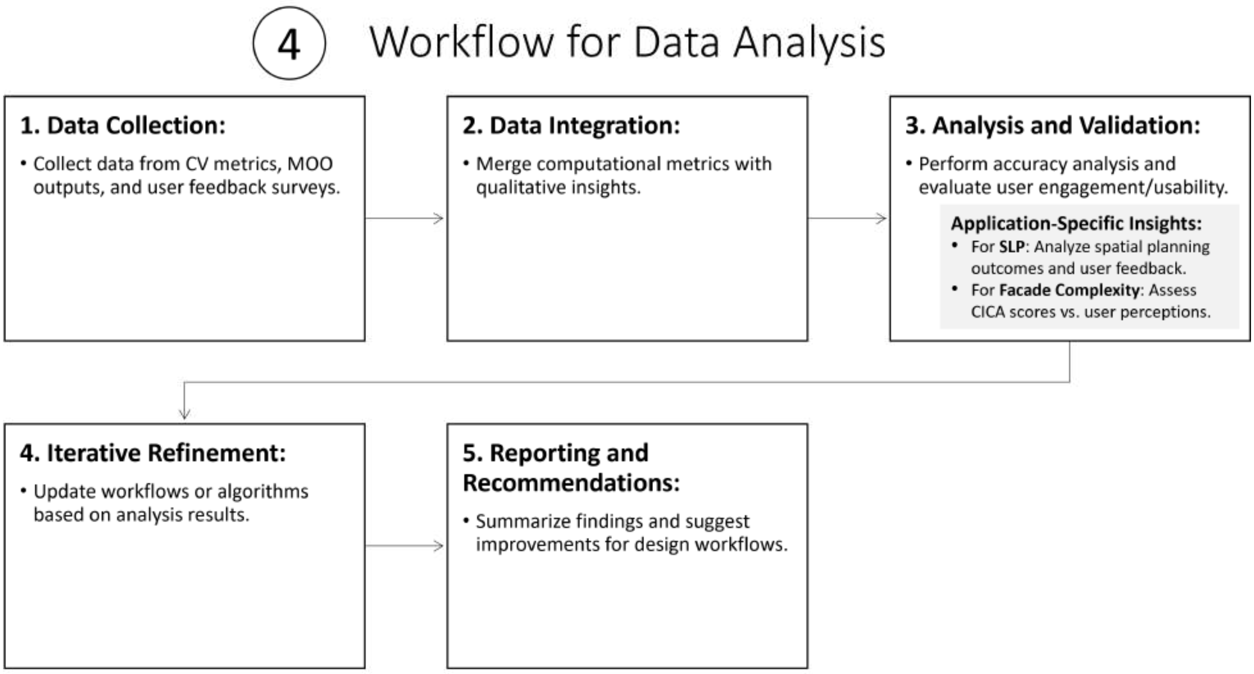


FIGURE 3.11: Workflow of the 'Data Analysis' component within the Data-Driven Immersive Design Optimization (DIDO) framework.

evaluations focus on user feedback, assessing the usability and intuitive nature of the VR environment. This dual analysis ensures that both technical precision and experiential aspects of the system are thoroughly validated.

4. *Iterative Refinement:* The insights gained from analysis inform this stage, where adjustments are made to enhance the system's performance and usability. This includes updating computational models, refining CV algorithms, and modifying VR interaction features to better align with user needs. Feedback from stakeholders plays a critical role in shaping these refinements, ensuring that the system evolves in response to real-world challenges and preferences.

5. *Reporting and Recommendations:* This step synthesizes the findings into actionable insights. It provides a clear summary of results, highlighting areas of success and identifying opportunities for improvement. Recommendations are formulated to guide future iterations of the system, ensuring that the DIDO framework continues to deliver optimized, user-centered architectural solutions. Additionally, these findings contribute to the broader discourse on integrating computational precision and immersive design in architectural workflows.

The 'Data Analysis' component serves as a cornerstone of the DIDO framework, bridging the gap between qualitative user insights and quantitative computational outputs. By merging these perspectives, the module ensures that design solutions are not only technically optimized but also aligned with stakeholder preferences and expectations. Through its structured workflow (see Figure 3.11) the 'Data Analysis' module validates the effectiveness of the DIDO framework in achieving user-centered and data-driven design.

This iterative process strengthens the DIDO framework's capacity to adapt to diverse architectural challenges, ensuring that the solutions it generates are both functional and user-centered, reinforcing its commitment to advancing sustainable, innovative, and inclusive architectural practices.

3.2.5 Optimization and Refinement

The ’Optimization and Refinement’ module within the DIDO framework symbolizes the final stage where computational accuracy is coupled with real-world application. This stage builds on the results from previous components, by using the outputs from Multi-Objective Optimization (MOO), Data Analysis, and insights gained from stakeholder engagements through Virtual Reality (VR), to achieve an optimal balance between algorithmic findings and human intuition.

In contrast to the preceding phases, which are concerned with generating and testing initial solutions, the ’Optimization and Refinement’ phase is dedicated to resolving disparities, refining designs to fit contextual requirements, and ensuring actionable solutions that have been approved by stakeholders. This phase is very important in transforming theoretical optimization into workable, applicable designs that align with both technical requirements and user preferences.

Its role is different from the previous components of the DIDO model. The ‘Data Processing’ and ‘Multi-Objective Optimization (MOO)’ stage (Component 2, Section 3.2.2) generates mathematically optimal solutions based on pre-defined metrics and weights, therefore producing technically robust but abstract outputs. Meanwhile, the ’Data Analysis’ phase (Component 4, Section 3.2.4) focuses on the combination of qualitative and quantitative data to identify convergence or divergence between computational results and stakeholder perspectives. Building on these results, the Optimization and Refinement component addresses remaining problems, adapts designs based on contextual and experiential factors, and optimizes solutions for a balance between computational accuracy and stakeholder-driven priorities. This distinction brings out its unique role as the final gatekeeper in the DIDO framework, in which the focus shifts from validation and evaluation to concrete decision-making and implementation. This step ensures a refined, contextually adaptable, and stakeholder-approved architectural design.

The DIDO framework’s ‘Optimization and Refinement‘ component offers great flexibility to tackle a range of architectural difficulties in a variety of settings and scales. For example:

- In the context of Site Layout Planning (SLP) (Chapter 4), it may be essential to modify an algorithmically optimal layout in response to unexpected logistical limitations or preferences revealed during stakeholder discussions. For instance, alterations to circulation pathways or spatial arrangements could be required to achieve a better balance between functional efficiency and stakeholder satisfaction.
- In the context of ‘Facade Complexity Analysis‘ (Chapter 5), if MOO results recommend a facade design with high edge density to increase aesthetic appeal, VR feedback from stakeholders might identify perceptions of overwhelming complexity. The optimization process, in this case, tunes the complexity metric algorithm based on subjective user view to reach a balance between aesthetic appeal and comfortableness, hence streamlining the design based on both user preferences and performance goals.

The core objectives of the ’Optimization and Refinement’ clearly put forward this role, which helps switch from computational results to real-life, feasible solutions (Figure 3.12). They include the following:

- *Reconciling Conflicts Between Computational and Experiential Insights:* Resolve existing conflicts between mathematically optimized solutions and stakeholder preferences to ensure the final design incorporates both technical performance criteria and heuristic insights.
- *Adapting to Contextual and Real-World Constraints:* The ‘Optimization and refinement‘ component incorporates considerations that are unique to specific sites or projects, including environmental influences, financial constraints, and user interactions, which may not have been thoroughly examined in earlier phases.

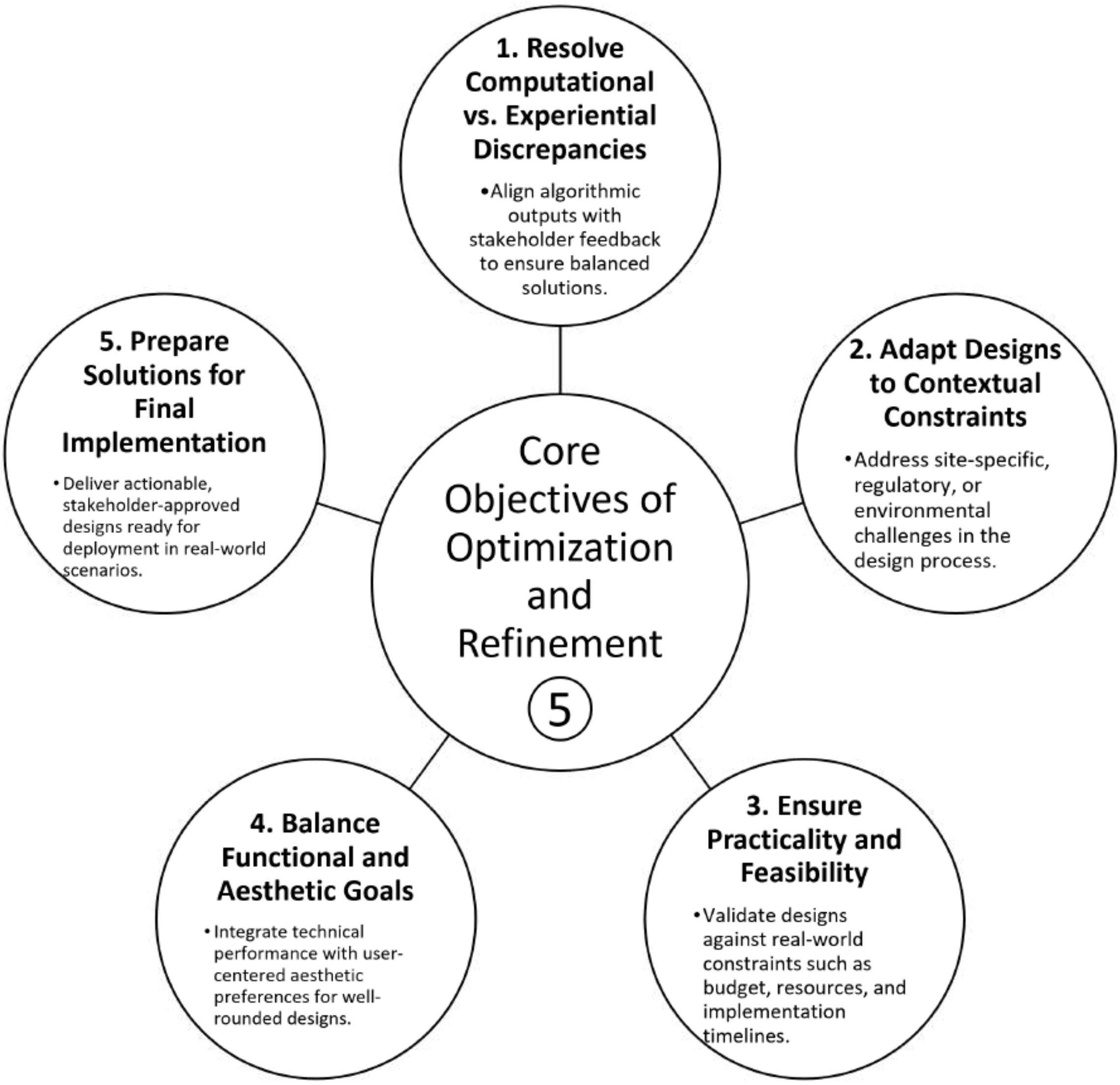


FIGURE 3.12: Core Objectives of the 'Optimization and Refinement' module within the Data-Driven Immersive Design Optimization (DIDO) framework.

- *Enhancing Practicality and Feasibility:* Convert theoretical design solutions into implementable results by ensuring alignment with technical specifications, logistical limitations, and input from stakeholders.
- *Fine-Tuning for Functional and Aesthetic Balance:* Reconsider design parameters in order to ensure that the final outcome reaches an optimal balance between performance criteria, such as spatial efficiency or cost-effectiveness, and qualitative characteristics like visual appeal and user-comfort.
- *Preparing Solutions for Final Implementation:* The polished outputs are organized to facilitate smooth execution, guaranteeing their feasibility within the parameters of construction, logistics, and usability, all while maintaining peak performance. Additionally, these solutions have received approval from stakeholders and are prepared for incorporation into architectural workflows or construction operations.

These objectives establish the 'Optimization and Refinement' module as the final phase of the DIDO framework, effectively connecting computational accuracy with practical application, while simultaneously emphasizing a design approach that prioritizes user needs.

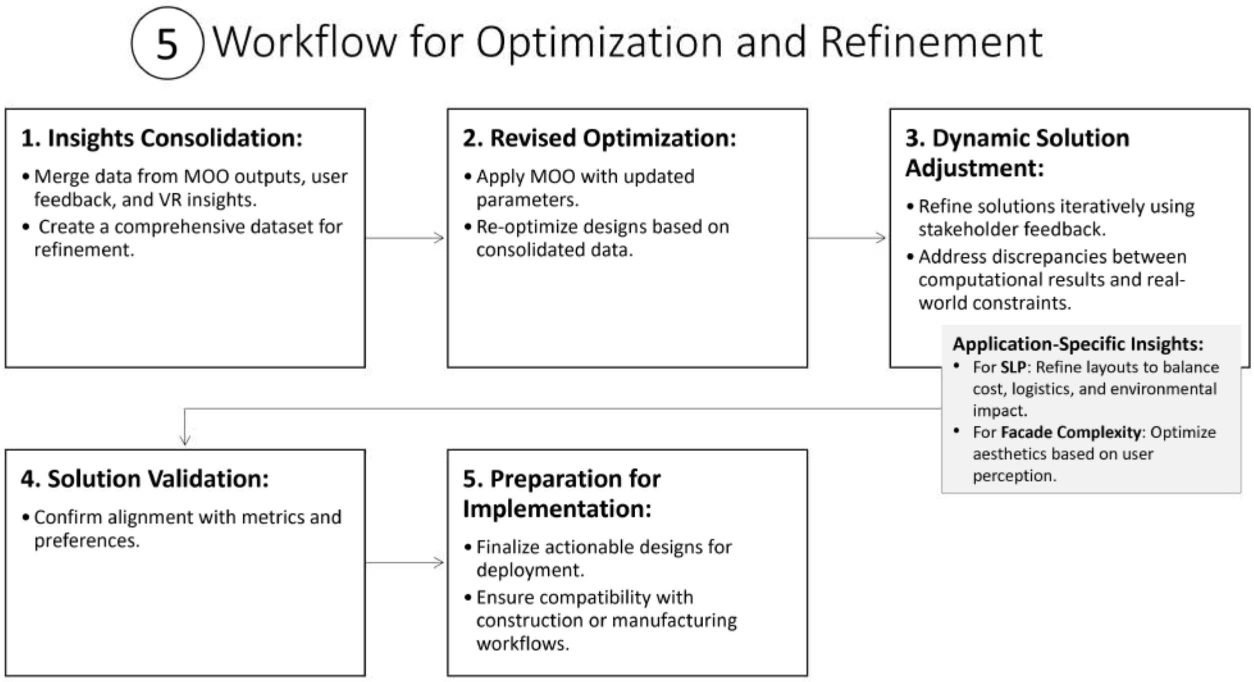


FIGURE 3.13: Workflow of the 'Optimization and Refinement' component within the Data-Driven Immersive Design Optimization (DIDO) framework.

Workflow of Optimization and Refinement

The 'Optimization and Refinement' workflow describes the last step in the DIDO framework, in which computational outputs, stakeholder insights, and contextual considerations are combined in order to create actionable high-quality designs. In contrast with previous components focused on solution generation or solution analysis, this process is actually all about adaptation, validation, and finalization of designs for their implementation in reality. The workflow's main steps are as follows (Figure 3.13):

1. *Insights Consolidation:* Integrate the processed insights obtained in the Data Analysis phase into a single dataset, which includes computational outputs, input from stakeholders, and data on virtual reality interactions. This process lays the foundation for recalibrating design objectives.

2. *Revised Optimization:* Conduct Multi-Objective Optimization (MOO) again with revised parameters or weights based on the combined data set. This step adapts solutions developed previously to new constraints or knowledge gained from the feedback.

3. *Dynamic Solution Adjustment:* Iteratively adjust the design variables with regard to real-time feedback mechanisms and validation results. This ensures that improved solutions align with the project objectives and also address relevant real-world contextual considerations.

4. *Solution Validation:* Validate the improved solutions to ensure they meet both the technical performance objectives and the stakeholder requirements by using a combination of quantitative and qualitative validation methods. Quantitative validation involves checking important parameters relevant to the project goal (e.g cost, energy efficiency, environmental impact) to ensure that the proposed solutions conform to set performance standards. On the

other hand, qualitative validation emphasizes the need for alignment of designs with user-centric preferences through inputs from immersive virtual reality sessions and interviews to ensure that solutions would indeed address stakeholder needs and experiential factors.

5. *Preparation for Implementation:* Finalize actionable design outputs by synthesizing validated solutions into deployment-ready formats. This may include preparing the documentation, ensuring the compatibility of the construction processes, and presenting stakeholders with an implementable design.

In conclusion, the 'Optimization and Refinement' element represents the last stage in the five core components of the DIDO framework. This is where all the collected data converges to create the final solution ready for implementation. This component will ensure that computational accuracy is in line with stakeholder perceptions and contextual needs, resolving any remaining inconsistencies and further iterating designs for technical and experiential coherence. It transforms theoretical optimization into real-world, stakeholder-approved outcomes through iterative validation and improvement. The final stage of the DIDO framework, 'Optimization and Refinement,' has been developed to express the versatility of the framework by integrating data-driven techniques with immersive technologies in an effort to provide holistic architectural solutions that are both practical and innovative.

3.3 Data Collection and Processing

Having presented the main components of the DIDO framework in previous sections (Section 3.2), it becomes necessary to explain how 'Data Collection and Processing' supports these components and enables their seamless integration. 'Data Collection and Processing' happens actively within the DIDO framework, linking its different components, and is key to laying a foundation for a robust and integrated data-driven architectural workflow. By collecting various datasets and organizing them for use by the different components, this step ensures that the system strikes a balance between technical precision and the viewpoints of stakeholders, thus guaranteeing informed and improved design decisions.

This methodological approach is clearly distinct from architectural practices that largely depend on heuristic techniques and manual data handling. In contrast to those previous methods focused on experiential knowledge and linear workflows, the DIDO framework shifts attention toward the structured collection of data and their integration; hence, providing mechanisms for feedback and dynamic analysis that adapt to user interaction and contextual needs. This kind of transformation helps bridge the divide between intuition-based practices and quantitative, data-informed methodologies by enhancing accuracy and adaptability in design outcomes.

This phase entails the systematic processing and structuring of raw data from a variety of sources. It can be from stakeholder feedback, or insights from VR observations, or outputs from CV and MOO. Structuring may include cleaning, normalization, and feature extraction in such a way that the data becomes applicable to the different requirements of the DIDO components. More important is that the processed data will support optimization, but also cross-component compatibility and iterative improvement.

This section details methods for data acquisition and preprocessing under good data management practices to enable the combination of different datasets within the same workflow in the DIDO framework, leading to consistent design solutions that meet the given technical objectives and user preferences.

3.3.1 Data Collection Methods

Effective data collection is a core aspect of the DIDO framework, ensuring that the diverse inputs required for optimization and stakeholder engagement are well captured and systematically organized. In this section, we go over methods used in gathering data needed to inform the different components of the framework. These methods represent a combination of both quantitative and qualitative approaches, all specially designed to accommodate Multi-Objective Optimization (MOO), Computer Vision (CV) analysis, and immersive interactions in Virtual Reality (VR) (see Figure 3.14).

- *Surveys and Stakeholder Feedback:* Surveys and structured feedback mechanisms are employed to gather user preferences and perceptions (examples in Appendix A.1). These inputs are particularly valuable in understanding aesthetic preferences, usability concerns, and subjective evaluations of design scenarios. By including stakeholders from diverse backgrounds, this method ensures that the collected data reflects a comprehensive range of user needs and priorities. Survey data is later quantified and normalized for integration into the optimization framework, aligning subjective preferences with measurable metrics through the Analytical Hierarchy Process (AHP) (see Section 3.2.2).

- *Observational Data from VR Sessions:* VR interactions provide a unique opportunity to observe how stakeholders engage with design scenarios in real time. Data such as interaction frequencies, and scenario-specific feedback are captured during VR sessions. This observational data offers rich insights into stakeholder preferences, highlighting potential adjustments or refinements to align with user needs. Additionally, real-time inputs collected via

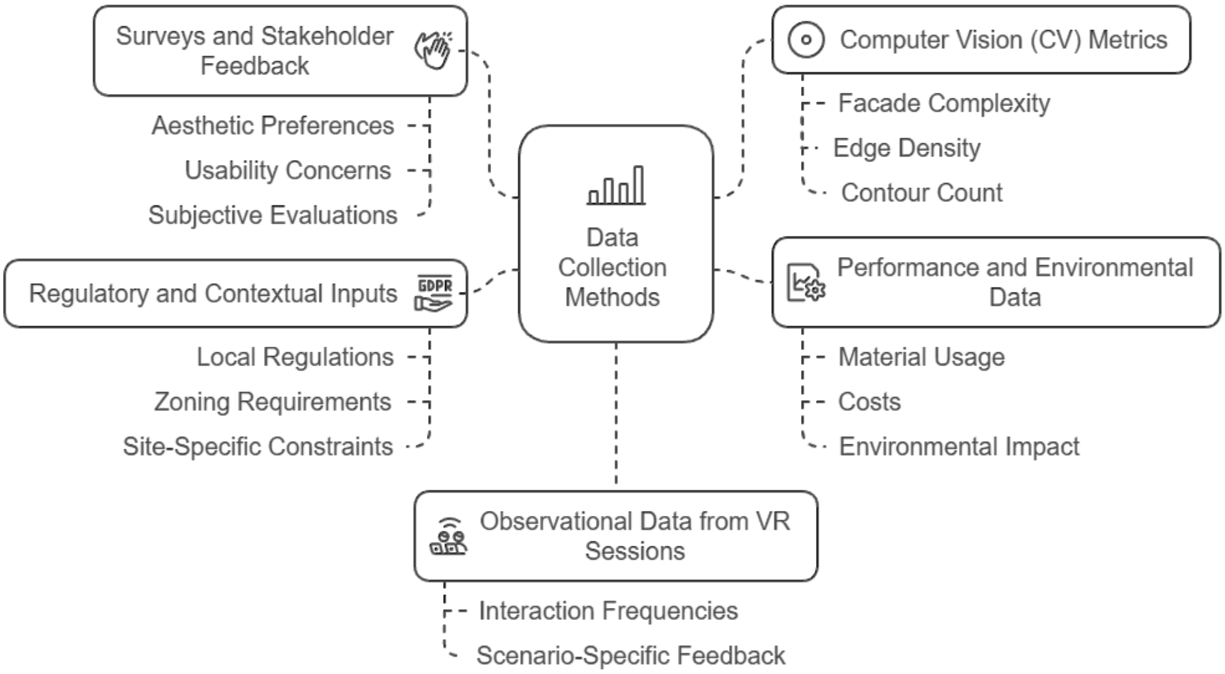


FIGURE 3.14: Flowchart of Data Collection Methods used on the 'Data Collection and Processing' phase for the Data-Driven Immersive Design Optimization (DIDO) framework.

VR interfaces help enrich the iterative feedback loops, enabling a more dynamic design process.

- *Computer Vision (CV) Metrics:* CV methods are utilized to extract quantitative metrics related to visual and aesthetic characteristics. For instance, facade complexity (detailed in Chapter 5) is assessed through edge density and contour count derived from image processing algorithms. These metrics provide a structured approach to analyzing visual elements, transforming subjective design qualities into actionable data points for optimization and refinement.

- *Performance and Environmental Data:* Building performance and environmental metrics are collected to evaluate aspects such as material usage, costs and environmental impact. These datasets are sourced from energy analysis simulations, regulatory guidelines, and material databases. For instance for Site Layout Planning (detailed in Chapter 5), layout optimization was measured from databases of earthwork costs and aerial imagery reporting topography for earthwork calculations and tree density for forestation value. This information forms the technical backbone of the optimization process, ensuring that the solutions meet sustainability and efficiency goals.

- *Regulatory and Contextual Inputs:* Data related to local regulations, zoning requirements, and contextual factors such as topography and site-specific constraints is gathered to ensure compliance and feasibility. These inputs are particularly critical in SLP (detailed in Chapter 5), where logistical and environmental considerations play a significant role in shaping the final design.

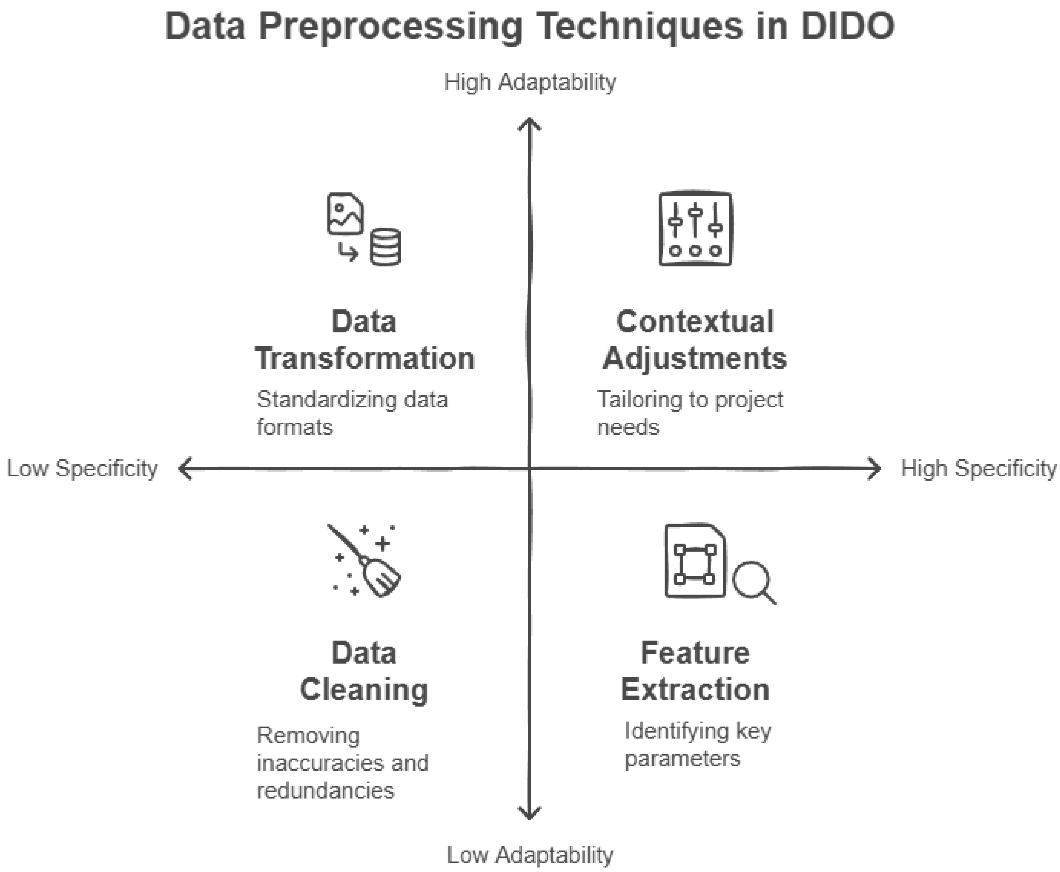


FIGURE 3.15: Flowchart of Data Preprocessing Techniques used on the 'Data Collection and Processing' phase for the Data-Driven Immersive Design Optimization (DIDO) framework.

3.3.2 Preprocessing Techniques

Preprocessing ensures raw data is organized, accurate, and ready for integration into optimization and analysis components. The techniques employed include cleaning, transforming, and personalizing data to meet the specific requirements of Multi-Objective Optimization (MOO), Computer Vision (CV), and Virtual Reality (VR) within the DIDO framework. These processes are essential for aligning diverse datasets into a cohesive and actionable structure (see Figure 3.15).

1. *Data Cleaning:* This step ensures that the datasets are accurate and consistent, allowing the removal of incomplete or contradictory data points. It removes any redundancy issues and addresses mismatches—such as conflicts in user preferences or overlapping metrics—in a structured manner to create a coherent and dependable dataset. For instance, in facade complexity analysis (Chapter 5), the database of building images collected to optimize the complexity analysis algorithm was filtered to remove any image which did not depict a well-documented or well-known building from architectural literature.

2. *Data Transformation:* This step makes the raw data compatible with the DIDO framework. Metric normalization helps to transform different scales, like cost and energy consumption, into a unified scale, and format conversion ensures that the data is compatible with MOO and CV algorithms for accurate analysis. For example, for the SLP application in Chapter 4, the earthwork costs and deforestation metrics were normalized on a 0–1 scale to incorporate seamlessly into the scalarization equation (Equation 3.1).

3. *Feature Extraction:* Identifies and orders the important design parameters, including energy efficiency and material costs, but also aesthetic complexity measures such as edge density. Stakeholder preferences from VR sessions become summarized in metrics that are measurable and easy to integrate into the design process. For instance, in facade complexity analysis (Chapter 5), where CV algorithms operated on the database of building images to get values for edge detection and contour count, which were quantified and used by the complexity analysis algorithm.

4. *Contextual Adjustments:* Tailors data to better fit the project's needs by incorporating local rules, environmental constraints, as well as stakeholder feedback. This ensures compliance with codes, improvement specific to site conditions, and consistency with unique project demands. For example, in the SLP application (Chapter 4), zoning laws defined the allowed site extent, thus ensuring that the optimization algorithm only worked within compliant areas.

Data preprocessing in the DIDO framework is done considering specificity and adaptability. On the one hand, 'Data Cleaning' and 'Data Transformation' are techniques that have high adaptability because they assure accuracy and standardization among a large class of datasets and project types. In contrast, 'Feature Extraction' and 'Contextual Adjustments' were centered on the project-specific needs and targeted the key design parameters or constraints to align data with unique architectural or optimization goals (see Figure 3.15).

When adapting DIDO to different applications—like when applied in this study to SLP or facade complexity analysis—it is important to understand this balance. Consistency across components is ensured by adaptable methods, while specific techniques tailor data to meet the precise project requirements. This interplay supports building robust yet flexible data strategies that will allow DIDO to handle effectively very diverse design challenges.

The 'Data Collection and Processing' are, therefore, the basic modules in the DIDO framework for supplying accurate, consistent, and relevant information to every component of the system. Combining technical accuracy with human interpretation, DIDO maintains a coherent methodology of design optimization through aligning numerous and diverse data sources—from computational metrics to stakeholder views. This mixture of agile and specific methodologies underscores the adaptability of this framework to applications, such as SLP, ranging to the investigation of facade complexity. The transition from conventional workflows to a data-centric model brings out the transformative capabilities of DIDO. In this way, the framework supports data-informed decision-making and solution-driven approaches through performance metrics, answering the changing demands in architectural design.

3.4 Tools and Technologies Used

The 'Data-Driven Immersive Design Optimization' framework is supported by a host of advanced software and hardware tools, which enable data-driven approaches, immersive technologies, and optimization techniques to be incorporated in a seamless manner into the DIDO framework. These tools combine to support the the framework's core components, aiding in tasks that range from data preprocessing to real-time visualization and stakeholder engagement.

As discussed in Chapter 2 (Section 2.1), traditionally, architectural education and practice have placed a strong emphasis on creative and heuristic problem-solving, often with an emphasis on artistic expression and technical drawing abilities. However, data-driven methodologies like DIDO redefine the design process in architecture, and demand new skills in collaboration and technical competencies. Architects are increasingly required to collaborate with data scientists and engineers within even more interdisciplinary frameworks and leave their isolated workflows behind. This shift brings into play tools and technologies that often lie beyond the scope of conventional architectural training, including programming languages and virtual reality platforms.

This section gives an overview of software and hardware technologies that fill in these gaps in the DIDO framework, underlying their importance in migrating traditional workflows into data-driven processes, ensuring interoperability between components, and paving the way to reach integrated and optimized design solutions.

Software Tools

Software solutions form the backbone of the DIDO framework, facilitating seamless integration across its core components. These tools enable tasks such as data preprocessing, optimization, immersive visualization, and stakeholder interaction. By leveraging advanced capabilities in 3D modeling, VR development, and data analysis, the software ecosystem supports the iterative and interdisciplinary demands of modern architectural design workflows.

Each tool was carefully selected for its compatibility with the framework's objectives, ability to integrate with other technologies, and its adaptability to diverse architectural applications (see Figure 3.16). The following software platforms played critical roles in realizing the functionality of the DIDO framework:

Unity:

The primary application for building VR environments within the DIDO framework was Unity (v. 2022.2.21f1). It was chosen for its robust support for VR platforms, because it has pre-built templates that are easy to use, and, most importantly, it its seamless integration with Python and C#. These features offered dynamic interaction with data from both the Multi-Objective Optimization (MOO) and Computer Vision (CV) modules. While most 3D modeling was done in Blender and Revit, Unity was very instrumental in preparing the immersive environments and interaction interfaces for the VR experiences.

Advanced real-time rendering abilities of Unity enabled the creation of communicative, high-fidelity visualizations tailored to the architectural project. In addition, integration with VR equipment, such as the Oculus Quest 2, guaranteed seamless implementation and usability by the stakeholders. Unity thus, in combination with the ability to give instantaneous feedback mechanisms and interactive modeling, served to bridge the computational results and user-centric design exploration.

Blender:

Blender (v. 3.6) was another of the critical tools used to build and refine the detailed architectural models within the DIDO framework. Its choice was informed by its advanced rendering

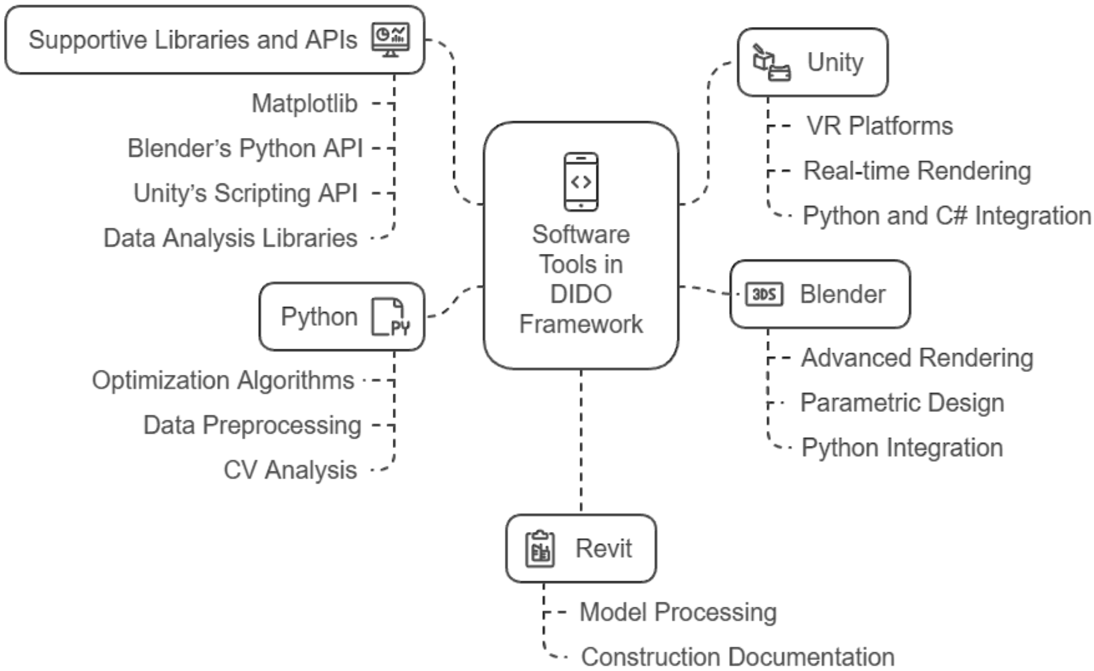


FIGURE 3.16: Software tools employed within the 'Data-Driven Immersive Design Optimization' (DIDO) framework to support the interoperability across its core components.

capabilities, support for parametric and generative design principles, and easy integration with Python. This made Blender a pivotal tool in connecting three-dimensional modeling with CV libraries and virtual reality aspects developed in Unity. This open-source software was primarily used to render and detail architectural elements, ensuring models met aesthetic and technical requirements for immersive simulations. While Revit was employed for processing construction blueprints and building layouts, Blender was used to detail and optimize 3D models for VR compatibility. Its ability to export models in formats such as .fbx, ensured ease of integration with DIDO framework's VR and optimization components. Blender's flexibility and powerful rendering features made it indispensable for creating visually compelling and data-rich models tailored to architectural workflows.

Python:

Python (v. 3.11) forms the backbone of the DIDO framework, which is used for optimization algorithms, data preprocessing, and CV analysis. The vast number of libraries available in Python ensure seamless integration with other tools and technologies that are incorporated into the framework.

- *Optimization Algorithms for MOO*: Python scripts were developed for 'multi-objective optimization' (MOO) scripts balancing earthwork volume, cost, and environmental impact in SLP (Chapter 4). Numerical computation libraries like NumPy and Pandas simplified the handling of data and computation; while the scalarization method translated as a python script ensured efficient and precise optimization.

- *Integration with VR:* Using Python, MOO outputs could be integrated into the VR environment developed in Unity in real time, so that stakeholders could see and interact with design solutions that were updated dynamically throughout a VR session.

- *Computer Vision with OpenCV:* The 'Computational Image Complexity Analysis' system, CICA (5), was aided with Python's OpenCV library that allowed assessing facade complexity via several metrics including edge density and contour count.

The popularity of Python ensures extensive resources and support, but in addition, its flexibility and integration capabilities make it indispensable in unifying the DIDO framework's diverse components. This keeps the framework efficient and responsive by leveraging Python's computational strengths to balance technical precision with user-centered design workflows.

Revit:

Revit (v. 2023) plays a supporting, background role in the DIDO framework, mainly preparing construction documentation and providing support for final implementation after the validation process of the framework has been completed. Chosen based on wide adoption in the AEC industry, Revit provides strong interoperability with Blender, ensuring seamless import and export of models and fluent transitions between design and construction phases.

While most of the data processing, optimization, and immersive experience design are done in Blender, Python, and Unity, two of the most critical workflow steps are performed with Revit. First, it is applied in processing the construction models and layouts of buildings; therefore, it forms a basic framework for further detailing and optimization in Blender. Second, following completion of the iterative analysis and refinement stages, the DIDO framework utilizes Revit to re-import the optimized model or layout solution and develop construction-ready documentation. This supportive yet essential role guarantees that the innovative outputs of the DIDO framework are grounded in practical, industry-standard BIM practices that facilitate their translation into real-world architectural implementations.

Supportive Libraries and APIs:

The integration, visualization, and analysis steps of the DIDO framework were considerably aided by 'Supportive libraries and APIs'. These helped in managing the data and communication more effectively, bridging the gaps between computational methods and stakeholder involvement. Libraries such as Matplotlib, along with a number of APIs, played an important role in enhancing clarity and precision.

- *Matplotlib for Visualization:* The use of Matplotlib was essential in the creation of graphs and visualization that led to actionable insights during the framework implementation. For example, under the Facade Complexity Analysis chapter (Chapter 5), Matplotlib was used to visualize patterns of complexity across different architectural styles from a historical building database. It was also employed to compare the accuracy of the CICA system (Chapter 5) with user-selected preferences, and the SLP optimization algorithm (Chapter 4) demonstrating the model's ability to predict stakeholder choices effectively.

- *Blender's Python API:* The Blender Python API aided in retrieving the geolocation information and automation in 3D modeling processes, supporting the preparation of precise site and design models. It made integration with Blender, Python, and the VR components developed in Unity easier.

- *Unity's Scripting API:* It made it possible for Python-based optimization algorithms and VR simulations to interact easily. This ensured that real-time changes in VR reflected optimized outputs, making the immersive environment even more interactive and responsive.

- *Data Analysis Libraries:* It helped to preprocess the data, standardize and modify the datasets used in both the MOO and the CV part with libraries like NumPy and Pandas. Through the OpenCV API, research regarding the complexity of facade was improved by advanced image analyses, especially through the extraction and quantification of visual metrics such as edge density and contour count.

Together, these supportive libraries and APIs ensured effective integration, accurate analysis, and clear visualization across the framework, instilling confidence and understanding among the design team and stakeholders. They bridged the gap between technical processes with accessible outputs, making the DIDO framework adaptable and more accessible in nature for a wide range of architectural applications.

Hardware Tools

The DIDO framework relies on specialized hardware to execute the computationally intensive tasks and to provide immersive experiences for the stakeholders. This combination of VR devices, high-performance computing system, and input tools ensure seamless operation through all the core components of the DIDO framework.

- *VR Devices:* The Oculus Quest 2, 3, and Pro headsets provided an immersive experience for the different stakeholders. These devices show the flexibility and scalability of the DIDO framework on all types of virtual reality platforms. Their independent functionality, added with intuitive controllers and high rendering quality, eases users to move through virtual environments with simplicity to provide interactive feedback. Moreover, the wireless setup increases accessibility and mobility, making them even more suitable for collaborative design sessions.
- *High-Performance Computing Systems:* The framework's success relies on workstations with dedicated GPUs. These systems enable the rendering of complex VR environments in real time, ensuring smooth visualization and interaction. They also provide support for computationally intensive tasks, such as running optimization algorithms and processing visual data for Computer Vision applications. By using advanced hardware, the DIDO framework reaches the computational efficiency needed for iterative design workflows.
- *Input Devices:* Interactive tools, whether in the form of VR controllers, motion sensors, keyboards, or headsets, are important to solicit user responses and improve design solutions. These tools allow navigation through VR environments and CAD applications, aiding in the manipulation of design elements and providing experiential feedback. Such tools ensure that a very interactive and user-centered approach is followed for design verification and improvement.

The DIDO framework achieves a harmonious balance between computational power and user experience by using advance hardware. Furthermore, It shows how immersive technologies, specifically VR headsets, are fast becoming indispensable tools in the architecture design workflow. This emphasis on immersion not only adds to but also gives collaborative meaning to data-driven optimization and experiential intuition by showing that VR is playing an increasingly important role in defining the architectural workflow of the future.

Role of Technology in the DIDO Framework

The DIDO framework is based on the seamless integration of state-of-the-art software and hardware technologies to align computational accuracy with experiential insight. Combined, these tools increase the flexibility, effectiveness, and immersion the framework provides across all stages of the design process (see Figure 3.17).

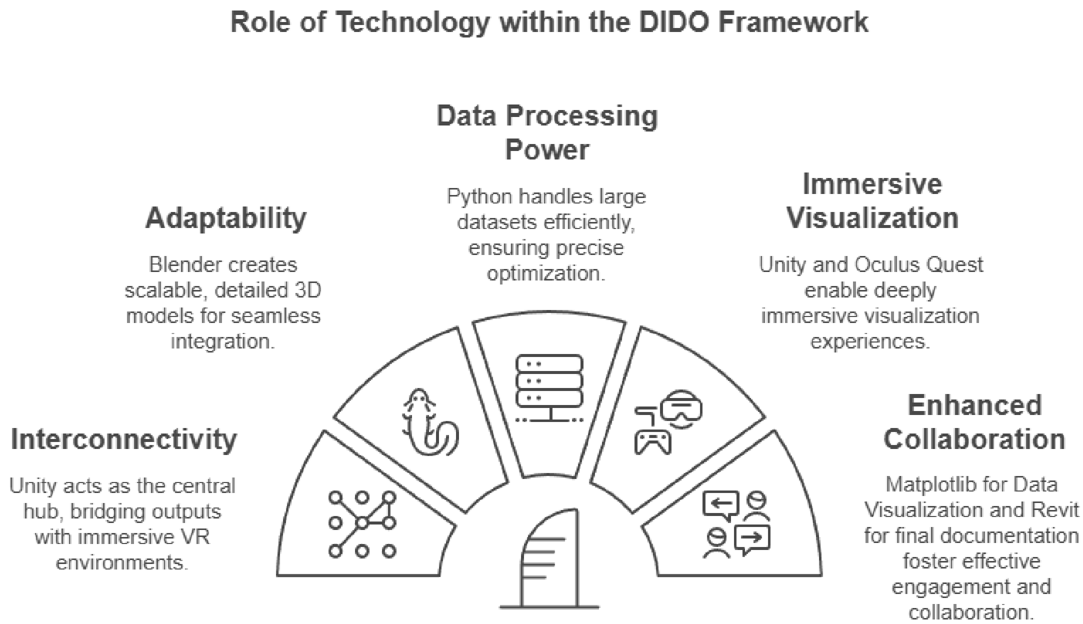


FIGURE 3.17: Roles of Software and Hardware tools employed within the 'Data-Driven Immersive Design Optimization' (DIDO) framework.

- *Interconnectivity:* Unity (v2022.2.21f1) provides the primary interface that integrates results from Python-based Multi-Objective Optimization (MOO) algorithms and Computer Vision (CV) analyses within the immersive virtual reality environment. This setup allows stakeholders to interact with real-time changes and to test design scenarios in a dynamic way.

- *Adaptability:* Blender (v3.6) is instrumental in the development of scalable and intricate 3D models, which can be exported in file formats compatible with virtual reality. It ensures VR platform compliance so that design elements can easily be integrated into DIDO components for optimization and improvement.

- *Data Processing Power:* Python (v3.11) leverages high-performance computing hardware to easily process large datasets. It has supportive libraries and APIs, including NumPy, Pandas, and OpenCV, which provide accurate optimization and feature extraction for actionable insights to refine architecture.

- *Immersive Visualization:* Unity is integrated with Oculus Quest headsets, to give the most immersive experience possible. Users may use intuitive controls to move around in virtual environments in real-time interaction with design elements, closing the gap between abstract data and tangible knowledge.

- *Enhanced Collaboration:* With facilitative tools like Matplotlib, which serves to create data visualization, and Revit, used for final documentation, the framework practically allows members of any discipline to communicate effectively. This allows for a truly collaborative environment where both technical and experiential input is valued.

Taken together, these technologies form a cohesive ecosystem that allows the DIDO framework to offer innovative architectural solutions in performance-driven approaches. Combining computational accuracy with immersive tools, the framework not only increases efficiency but also shows how state-of-the-art technology is changing the design process to keep stakeholders engaged and well-informed at each step.

3.5 Evaluation Metrics and Validation Techniques

The effectiveness of the Data-Driven Immersive Design Optimization (DIDO) framework hinges on its ability to deliver accurate, efficient, and actionable design solutions. This requires not only robust computational methodologies but also reliable evaluation metrics and validation techniques to ensure that outputs align with both technical standards and stakeholder expectations.

In architectural workflows, where diverse parameters such as cost, energy efficiency, and user satisfaction intersect, defining appropriate metrics and implementing rigorous validation processes are critical. Evaluation metrics provide quantifiable benchmarks for assessing the performance of design solutions, while validation techniques incorporate qualitative insights to refine these solutions. Together, these elements bridge the gap between computational precision and real-world applicability, ensuring that DIDO outputs are technically optimized and practically relevant.

This section delves into the key aspects of evaluation and validation within the DIDO framework, exploring the metrics used to assess technical performance, the methods employed to integrate stakeholder feedback, and the comparative analyses that reconcile computational outputs with user perceptions. By establishing a cohesive system of measurement and review, the DIDO framework ensures that its solutions are both innovative and responsive to the dynamic demands of architectural design.

Performance Metrics

The DIDO framework employs a comprehensive set of performance metrics to evaluate and optimize architectural design solutions. These metrics ensure that design outputs are measurable, comparable, and aligned with project objectives, bridging the gap between computational optimization and real-world needs. By addressing both quantitative and qualitative dimensions, the metrics establish benchmarks for efficiency, sustainability, aesthetics, and user satisfaction.

1. Technical Performance Metrics: These metrics focus on the functional and structural aspects of design, emphasizing measurable outcomes.

2. Aesthetic Metrics: Metrics in this category assess the visual and experiential qualities of architectural designs.

3. User-Centered Metrics: To align with stakeholder preferences, DIDO integrates metrics that reflect user experience and satisfaction

The flexibility of DIDO's performance metrics enables their application to a wide range of architectural challenges across various settings and scales. For example:

- In Site Layout Planning (SLP): Technical Performance Metrics evaluate logistical efficiency (e.g., cost and environmental impact of earthwork), while User-Centered Metrics incorporate stakeholder feedback to refine layouts for usability and contextual alignment (Chapter 4).

- In Facade Complexity Analysis: Aesthetic Metrics (e.g., facade complexity scores) quantify visual intricacy, while User-Centered Metrics integrate user perceptions gathered through VR experiments to balance complexity with stakeholder preferences (Chapter 5).

Performance metrics guide the optimization and refinement stages by providing clear benchmarks for success. They also inform iterative validation processes, ensuring that outputs meet predefined standards while incorporating real-time feedback. By quantifying diverse aspects of design, these metrics enable DIDO to address both technical objectives and user expectations cohesively.

Stakeholder Validation

Stakeholder validation is a cornerstone of the DIDO framework, ensuring that computationally optimized designs resonate with real-world requirements and user expectations. While the core components of DIDO focus on technical performance and aesthetic precision, stakeholder validation bridges the gap between algorithmic outputs and human perspectives. By incorporating feedback from those who will ultimately use or interact with the designs, this process enhances both the practicality and acceptability of proposed solutions.

Through immersive VR environments, structured surveys, and iterative feedback loops, stakeholder validation transforms abstract metrics into actionable insights. This approach ensures that DIDO not only meets predefined benchmarks but also adapts to the nuanced preferences and priorities of diverse stakeholders, from design professionals to end-users. By fostering a dynamic exchange between computational precision and experiential input, stakeholder validation plays a pivotal role in achieving cohesive, context-sensitive architectural solutions.

The stakeholder validation process in the DIDO framework comprises several structured components, each designed to align computational outputs with human feedback:

1. Immersive VR Interactions: Immersive VR environments are a key tool for enabling stakeholders to engage with design solutions dynamically. By visualizing and interacting with proposed designs, users can experience the spatial, functional, and aesthetic aspects of a project in a simulated real-world context.

    - For instance, during Site Layout Planning (SLP) (Chapter 4), stakeholders used VR interfaces to evaluate the usability and efficiency of optimized layouts, providing feedback on earthwork and site accessibility.

2. Structured Surveys and Interviews: Surveys and interviews complement VR interactions by gathering quantitative and qualitative feedback on user preferences and priorities. These tools help translate subjective responses into actionable insights for refining designs.

    - For example, on the implementation of DIDO for Facade Complexity Analysis (Chapter 5), surveys measured user perceptions of facade complexity and aesthetics, balancing computational metrics with stakeholder satisfaction.

3. Iterative Feedback Loops: Iterative feedback loops ensure that validation is not a one-time process but a continuous dialogue between stakeholders and the design team. Feedback from VR sessions and surveys is integrated into the optimization workflow to refine design outputs iteratively.

    - For context, Adjustments made to facade complexity metrics based on user preferences during the validation process resulted in designs that aligned better with stakeholder expectations while maintaining aesthetic and functional standards (Chapter 5).

4. Cross-Disciplinary Collaboration: Stakeholder validation facilitates collaboration between architects, engineers, and data scientists, ensuring that feedback addresses both technical and experiential dimensions.

    - For instance, in the implementation of DIDO in SLP (Chapter 4), collaboration between experiment participants and the design team helped prioritize objectives like balancing earthwork costs with view optimization maximizing operational efficiency and comfort.

This multi-faceted approach ensures that stakeholder input is comprehensively captured and effectively integrated, bridging the gap between computational precision and real-world applicability.

Comparative Analysis

Comparative analysis within the DIDO framework evaluates the effectiveness of its outputs by benchmarking them against established standards, traditional methodologies, and stakeholder expectations. This process highlights the advantages of DIDO's data-driven and immersive techniques while identifying areas for refinement, fostering continuous improvement.

The primary goal of comparative analysis is to ensure alignment between computational outputs and stakeholder feedback, demonstrating how DIDO adds value over traditional heuristic approaches. By systematically evaluating quantitative metrics, qualitative feedback, and deviations, this component reinforces the framework's adaptability and practical relevance.

1. Quantitative Comparisons: Quantitative outputs such as cost reductions, efficiency scores, and aesthetic metrics are plotted and statistically analyzed to measure improvements. Outputs from Multi-Objective Optimization (MOO) and Computer Vision (CV) systems are compared directly with stakeholder selections to validate computational results.

    - For example, on the implementation of DIDO for Facade Complexity Analysis (Chapter 5), differences between CICA complexity scores and participant preferences were evaluated to validate the accuracy of the Computational Image Complexity Analysis (CICA) system.

2. Qualitative Comparisons from User Feedback: Stakeholder feedback from VR sessions is compared to feedback gathered through traditional methods and surveys, assessing how immersive interactions enhance engagement and decision-making.

    - For instance, for SLP (Chapter 4), user preferences for site layouts obtained during VR sessions were compared to non-immersive feedback, highlighting how VR influenced decision-making and improved stakeholder satisfaction.

3. Identifying Deviations and Reconciling Them: Deviations between computational outputs and stakeholder feedback are systematically analyzed to identify gaps or patterns. These insights are integrated into the Optimization and Refinement process (Section 3.2.5), ensuring improved alignment with project goals through adjustments to metrics, weights, or parameters of the optimization algorithm.

    - For instance, for SLP (Chapter 4), feedback on the relative importance of metrics (e.g., cost and environmental impact of earthwork), obtained during post-experiment surveys, led to recalibration of weights in the optimization algorithm, enhancing its responsiveness to user priorities.

4. Case Study Analysis: Context-specific evaluations are performed to highlight the framework's flexibility and scalability across different architectural challenges.

    - For context, SLP optimizations (Chapter 4) were assessed across varied site conditions (e.g., mountainous vs. flat terrain), demonstrating DIDO's ability to adapt to diverse environmental constraints.

Addressing deviations between computational results and stakeholder input enhances transparency, trust, and reliability, encouraging stakeholder adoption of DIDO-generated solutions. By aligning technical precision with real-world considerations, comparative analysis ensures that outputs are not only optimized but also actionable and relevant.

Furthermore, insights from comparative analysis drive iterative improvements, enabling DIDO to refine its methodologies and expand its applicability to evolving design contexts. By benchmarking its outputs across diverse metrics and case studies, the framework establishes itself as a robust, adaptable, and forward-thinking tool for architectural design. It not only validates its strengths but also positions itself for continuous evolution, meeting the dynamic needs of modern architectural practice.

Role of Evaluation Metrics and Validation Techniques

The DIDO framework has incorporated 'Evaluation Metrics and Validation Techniques' that would serve to bridge computational accuracy with user engagement. Only through the strict application of performance metrics, qualitative feedback mechanism, and comparative analyses is it ensured that the design results are not only technically sound but also aligned with the expectations of stakeholders.

This section establishes a proper basis for evaluating and optimizing DIDO applications regarding diverse architectural problems. The framework ensures reliable, feasible, and context-concrete design solutions by including measurable criteria and iterative validation steps. These approaches increase not only the confidence in the results from the framework but also raise its flexibility to guarantee it remains very much relevant to answering modern architectural workflows' dynamic needs.

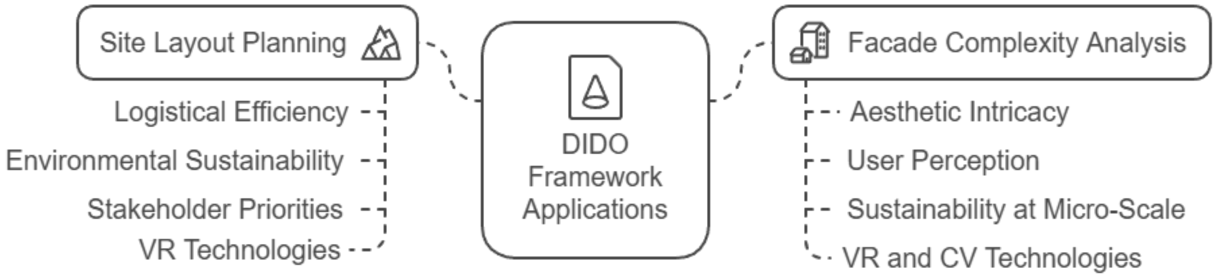


FIGURE 3.18: Flowchart illustrating the two practical application of the DIDO framework in architectural design: VR-Based Site Layout Planing and VR and CV-based 'Facade Complexity Analysis'.

3.6 DIDO-Based Applications in Architectural Design

The Data-Driven Immersive Design Optimization (DIDO) framework is developed to address various architectural issues by combining computational accuracy with experiential insights. Its adaptability can be seen in its ability to respond to a wide range of design contexts, from large-scale logistical planning to intricate aesthetic considerations. The future applications of DIDO span across all fields of sustainable site planning, optimization of interior layouts, analysis of urban streetscapes, and performance-based façade designs, hence it is a comprehensive framework that fits well within modern architectural practices. This section highlights the practical application of the DIDO framework in two distinct areas of architectural design : Site Layout Planning (SLP) (Chapter 4) and 'Facade Complexity Analysis' (Chapter 5), illustrating its scalability and adaptability (see Figure 3.18). This applications are explored in detail in the following chapters of this thesis.

The choice to concentrate on SLP and 'Facade Complexity Analysis' arises from their interrelated characteristics and their capacity to illustrate various aspects of DIDO's competencies. SLP serves as a fundamental component within construction processes, highlighting the importance of logistical efficiency and environmental sustainability while balancing stakeholder priorities. On the other hand, facade complexity analysis addresses aesthetic intricacy, user perception, and sustainability at the micro-scale, offering a distinct yet equally critical perspective on architectural design. Collectively, these applications encompass a broad range of design challenges, facilitating a comprehensive assessment of DIDO's potential.

SLP and 'Facade Complexity Analysis' also represent very significant areas in which the use of innovative technologies like Virtual Reality (VR) and Computer Vision (CV) have a great potential to enhance traditional workflows./ SLP uses immersive environments to optimize spatial configurations based on active stakeholder involvement, while 'Facade Complexity Analysis' studies visual intricacy and relates it to user preferences. These case studies prove DIDO's ability to show interdisciplinary adaptability and incorporation of technology and thus set a strong base for its broader applicability within contemporary architectural practice.

We hypothesize that by demonstrating DIDO's capacity to address both macro-level planning and micro-level aesthetic considerations, this applications will illustrate how the framework can seamlessly adapt to evolving design challenges. In that respect, by such applications, DIDO not only has the potential of improving decision processes but also to redefine the link between computational optimization and human experience in architecture workflows.

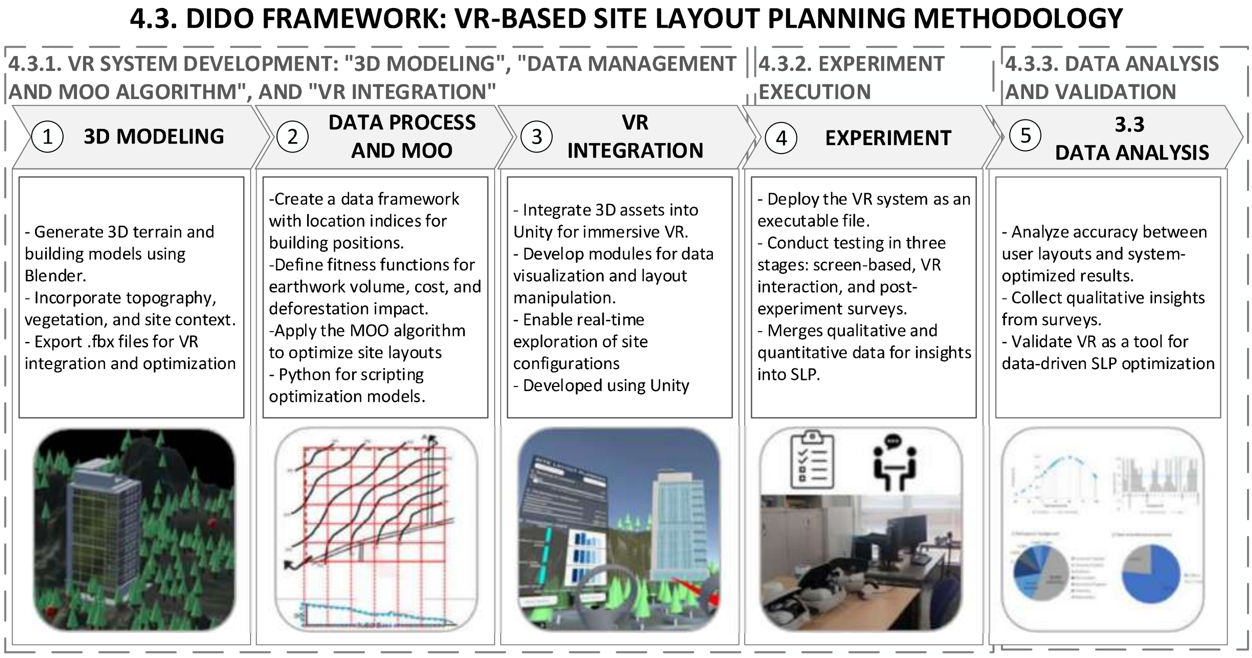


FIGURE 3.19: Methodology Flowchart illustrating the sequential steps of the implementation of the VR-Based Site Layout Planing (SLP) for Building Design based on the 'Data-Driven Immersive Design Optimization' (DIDO) framework. (See detailed methodology in Figure 4.2).

3.6.1 DIDO for Site Layout Planning (SLP)

Site Layout Planning (SLP) is a critical process in the Architecture, Engineering, and Construction (AEC) industry, encompassing the organization of resources, site accessibility, and operational efficiency. The DIDO framework leverages the power of Multi-Objective Optimization (MOO) and Virtual Reality (VR) to bridge traditional heuristic methods with data-driven approaches. This integration allows stakeholders to evaluate, refine, and optimize site layouts dynamically, creating solutions that balance technical precision with user-centered considerations. A detailed exploration of this application is provided in *Implementation of Virtual Reality-Based Site Layout Planning for Building Design* (Chapter 4).

The methodology for implementing DIDO in SLP revolves around three key components: VR System Development, Experiment Execution, and Data Analysis and Validation (see Figure 3.19). VR scenarios enable stakeholders to interact with proposed site layouts in real-time, fostering a deeper understanding of spatial relationships and design trade-offs. MOO ensures a systematic evaluation of competing priorities, such as cost efficiency, environmental impact, and operational functionality, while iterative feedback loops refine solutions based on stakeholder preferences.

By applying DIDO to SLP, this case study demonstrates the framework's capability to streamline site planning workflows, enhance stakeholder engagement, and deliver actionable design solutions. The findings, including a 48.3% reduction in deviations between computational predictions and stakeholder decisions, validate DIDO's effectiveness in addressing complex, multifaceted challenges in architectural design. This application underscores the framework's scalability and flexibility, setting the stage for further exploration in Facade Complexity Analysis (Chapter 5).

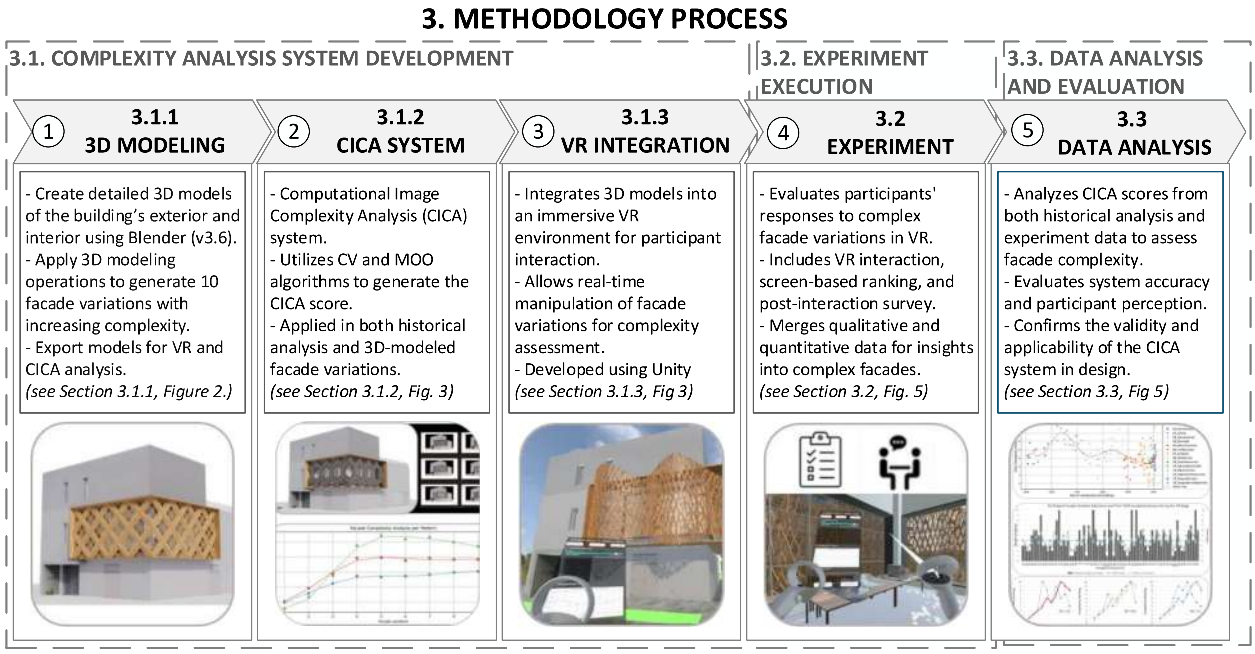


FIGURE 3.20: Methodology Flowchart illustrating the sequential steps of the implementation of the VR and Computer Vision-Based Facade Complexity Analysis for Building Design based on the 'Data-Driven Immersive Design Optimization' (DIDO) framework. (see Detailed version of this process in Figure 5.5).

3.6.2 DIDO for 'Facade Complexity Analysis'

Building upon the conclusions drawn from the literature, the methodology of this study is structured around three core components: the development of the 'Complexity Analysis System' using Virtual Reality (VR) and the Computational Image Complexity Analysis (CICA) system, supported by Computer Vision (CV) algorithms, both specifically designed for this research; the 'Experiment Execution,' aimed at assessing user perceptions of facade complexity; and a rigorous 'Data Analysis' phase to validate the system's effectiveness (see Figure 3.20).

The DIDO framework's application to facade complexity analysis demonstrates its adaptability in addressing challenges at the intersection of aesthetics, sustainability, and user engagement. Facades, as the most visible element of a building, play a critical role in defining architectural character and urban identity. However, the balance between aesthetic complexity and sustainability poses a significant challenge, especially in modern contexts where intricate designs must also align with user preferences and environmental considerations. A detailed exploration of this application is provided in *Implementation of VR and Computer Vision-Based Facade Complexity Analysis* (Chapter 5).

The methodology for implementing DIDO in facade complexity analysis focuses on three key components: the development of the 'Complexity Analysis System' using VR and the 'Computational Image Complexity Analysis' (CICA) system, created for this study, 'Experiment Execution' to assess user responses to varying complexity levels, and 'Data Analysis' to validate the system's effectiveness (see Figure 3.20). By integrating VR and Computer Vision (CV), this application enables stakeholders to interact with and evaluate facade designs dynamically, providing both quantitative complexity metrics and qualitative feedback on aesthetic preferences.

Through this case study, the DIDO framework demonstrates its ability to quantify facade complexity, identify trends across architectural styles, and align modern user preferences with historical patterns. The findings not only validate the framework's scalability but also highlight its potential to inform sustainable design practices, balancing complexity with long-term adaptability. This application further underscores DIDO's versatility, transitioning seamlessly from site planning to facade analysis while maintaining its core principles of computational precision and stakeholder-centered design.

Conclusion

The applications of the DIDO framework in Site Layout Planning (SLP) and Facade Complexity Analysis highlight its versatility in addressing architectural challenges across scales and contexts. By integrating computational optimization, immersive visualization, and stakeholder engagement, DIDO bridges the gap between technical precision and user-centered design. In subsequent chapters, these application will validate DIDO's potential as a transformative tool for modern architectural workflows, advancing decision-making processes and fostering a dynamic interplay between technology, creativity, and human experience.

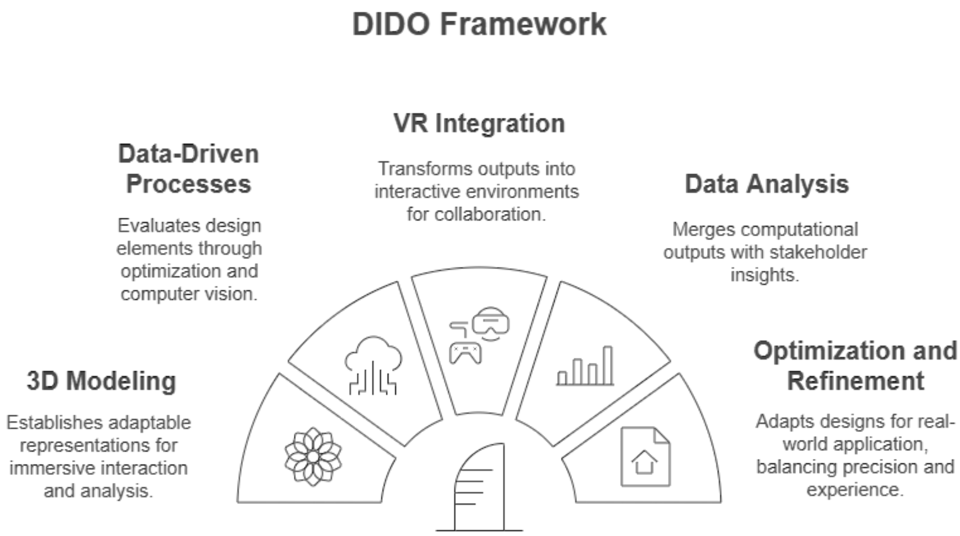


FIGURE 3.21: Summary of the 'Five Core Components' in the 'Data-Driven Immersive Design Optimization' (DIDO) Framework.

3.7 Summary

Chapter 3 introduces the Data-Driven Immersive Design Optimization (DIDO) framework, an innovative solution designed to address the intricate demands of modern architectural design. By integrating Data-Driven Building Design (DBD), Virtual Reality (VR), and Computer Vision (CV), DIDO bridges the gap between computational precision and human-centric experiential insights. Its overarching goal is to empower architects and designers to create sustainable, efficient, and adaptable solutions that balance technical performance metrics with stakeholder engagement, addressing the evolving challenges of the Architecture, Engineering, and Construction (AEC) industry.

The DIDO framework integrates a structured methodology encompassing five core components —*3D Modeling, Data-Driven Processes (including Data Processing, Multi-Objective Optimization (MOO), and Computer Vision (CV) Integration), Virtual Reality (VR) Integration, Data Analysis, and Optimization and Refinement* (see Section 3.2). *3D Modeling* forms the foundation, creating adaptable representations for immersive interaction and performance analysis. *Data-Driven Processes*, including 'Multi-Objective Optimization' (MOO) and 'CV integration', allow for the systematic evaluation and quantification of design elements, balancing competing objectives. *VR Integration* transforms complex outputs into interactive, human-scaled environments, enabling real-time collaboration and feedback. *The Data Analysis and Evaluation* module merges computational outputs with stakeholder insights, ensuring alignment between technical accuracy and user preferences. Finally, *the Optimization and Refinement* phase adapts and validates designs for real-world application, achieving a balance between computational rigor and experiential considerations. Each of these components plays a critical role in ensuring that the framework balances computational precision with human-centric design, delivering solutions that are functional, sustainable, and aligned with stakeholder expectations (see Figure 3.21).

The comprehensive workflows for these components are visually summarized in Figure 3.2, which highlights the sequential processes, decision points, and feedback loops within the DIDO framework. This figure provides a clear depiction of how each component contributes to an integrated system, enabling the alignment of technical performance metrics with immersive user engagement. This figure underscores how each component contributes to an integrated and adaptable system capable of addressing diverse architectural challenges.

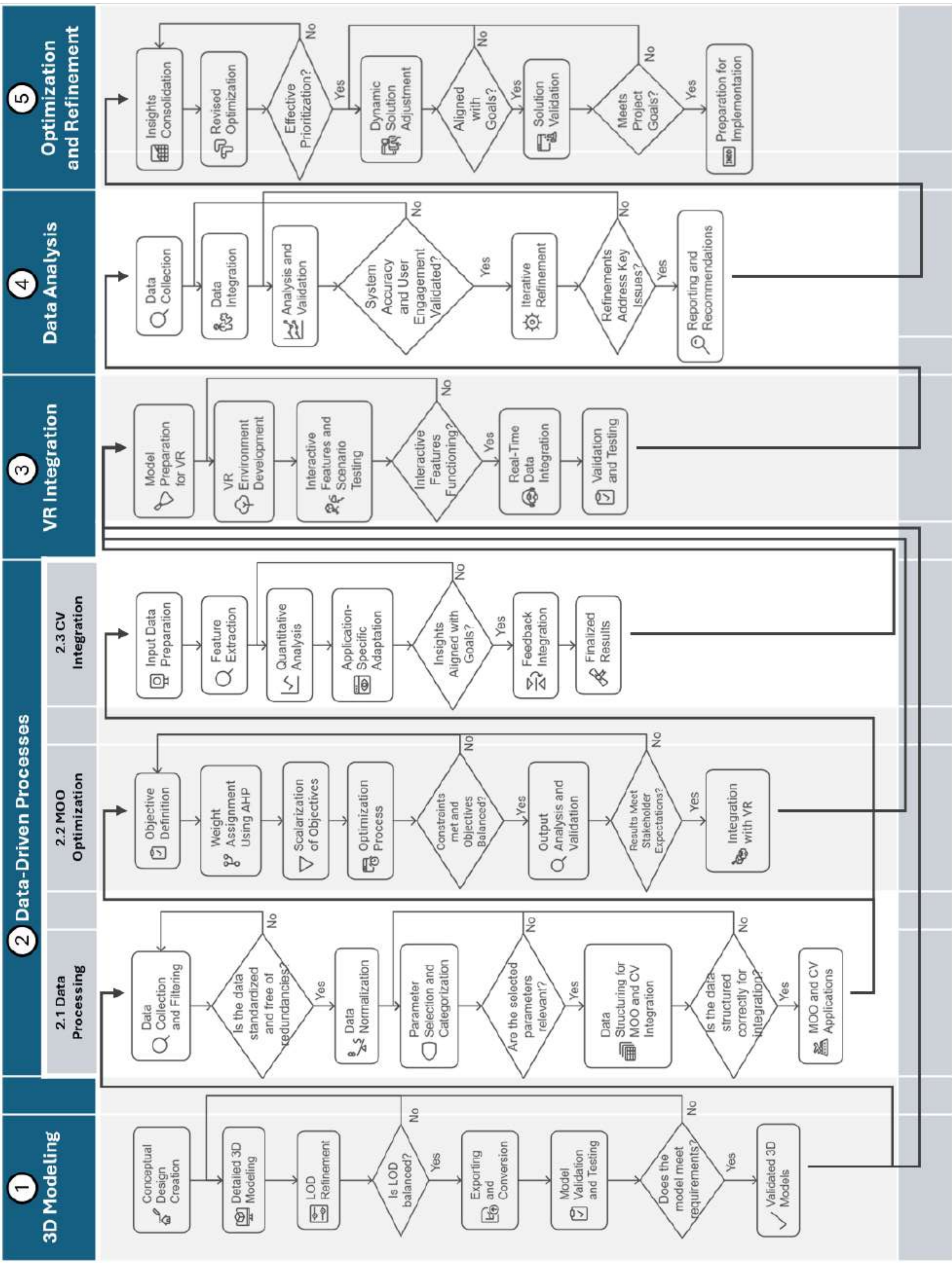


FIGURE 3.22: Flowchart of complete workflow of the 'Five Core Components' in the 'Data-Driven Immersive Design Optimization' (DIDO) Framework.

The ‘Data Collection and Processing‘ phase (Section 3.3) serves as the foundational link connecting the framework’s components by transforming raw inputs from diverse sources into structured, actionable datasets. Through systematic techniques like data cleaning, normalization, feature extraction, and contextual adjustments, this phase ensures cross-component compatibility and accuracy. Data sources include stakeholder feedback, VR observational insights, CV metrics, and building performance datasets. By blending adaptable methodologies with project-specific adjustments—such as regulatory compliance or facade complexity quantification—this phase supports DIDO’s ability to balance technical precision with human-centered design insights.

The ‘Tools and Technologies Used‘ (Section 3.4) form an integrated ecosystem of advanced software and hardware, enabling the seamless operation of the DIDO framework. Software tools like Unity, Blender, and Python power tasks ranging from detailed 3D modeling to immersive VR simulations and optimization algorithms. Python’s libraries, including NumPy, Pandas, and OpenCV, facilitate data preprocessing, MOO, and facade complexity analysis. Unity provides a robust platform for interactive VR experiences, while Blender ensures precision in 3D model preparation. Complementing these software tools, VR headsets like the Oculus Quest and high-performance computing systems enable real-time visualization and stakeholder engagement. Together, these technologies streamline DIDO’s workflows, enhancing adaptability, collaboration, and innovation in architectural design.

The ‘Evaluation Metrics and Validation Techniques‘ in the DIDO framework ensure that its outputs meet both technical standards and stakeholder expectations through a balanced combination of ‘Performance metrics‘, ‘Stakeholder Validation‘, and ‘Comparative Analysis‘ (Section 3.5). ‘Performance metrics‘ address quantitative aspects such as energy efficiency, cost, and facade complexity while integrating qualitative user feedback to align technical precision with aesthetic and experiential qualities. ‘Stakeholder Validation‘ leverages immersive VR interactions, structured surveys, and iterative feedback loops, enabling dynamic collaboration between designers and users to refine design solutions. ‘Comparative Analysis‘ benchmarks DIDO’s outputs against traditional methodologies and stakeholder priorities, identifying deviations and integrating improvements into the optimization process. Together, these evaluation mechanisms create a robust framework for refining architectural solutions, ensuring that outputs are both innovative and practically relevant.

The chapter also introduces two key applications of DIDO: ‘Site Layout Planning‘ (SLP) and ‘Facade Complexity Analysis‘ (Section 3.6). These case studies, explored in detailed in subsequent chapters, highlight DIDO’s scalability, with SLP addressing large-scale logistical challenges and ‘Facade Complexity Analysis‘ exploring intricate aesthetic considerations. Together, they exemplify how DIDO adapts to diverse architectural contexts, seamlessly transitioning between macro-level planning and micro-level design.

In conclusion, Chapter 3 lays the foundation for understanding the DIDO framework as a holistic, adaptable, and innovative approach to architectural design. It emphasizes the framework’s ability to unite data-driven methodologies with immersive technologies, offering solutions that are both technically optimized and aligned with user needs. This chapter sets the stage for detailed explorations of DIDO’s applications in subsequent chapters, showcasing its transformative potential in modern architectural practices.

Chapter 4

Implementation of Virtual Reality-Based Site Layout Planning for Building Design

The implementation of Virtual Reality (VR) into Site Layout Planning (SLP) builds on the foundation of the Data-Driven Immersive Design Optimization (DIDO) framework, which integrates data-driven methodologies, Multi-Objective Optimization (MOO), and immersive technologies to enhance decision-making in architectural workflows (Chapter 3). This chapter investigates a critical question: can immersive technologies influence stakeholder decision-making and facilitate the adoption of optimized design solutions?

By leveraging VR's ability to combine computational precision with stakeholder intuition, the DIDO framework adapts to the specific challenges of SLP, offering a dynamic platform for real-time interaction with data-driven insights. Through VR simulations, participants evaluate key site planning factors such as earthwork volume, cost, and environmental impact, bridging the gap between technical outputs and experiential understanding. Unlike other applications of the DIDO framework that integrate advanced tools such as Computer Vision (CV), this study excludes CV to focus solely on validating the effects of VR on stakeholder decision-making.

Results, as highlighted in this chapter, show a significant 48.3% increase in decision-making accuracy among participants using VR, underscoring its transformative potential. This improvement highlights VR's role in aligning heuristic approaches with modern optimization strategies, enhancing site efficiency, and fostering stakeholder collaboration. These findings provide a compelling case for the broader applicability of the DIDO framework, demonstrating its potential to revolutionize decision-making processes and improve design outcomes across diverse architectural challenges.

4.1 Introduction

In the rapidly evolving field of Architecture, Engineering, and Construction (AEC), Site Layout Planning (SLP) represents a critical juncture where the heuristic approaches to problem-solving traditionally employed,encounter the Data-driven Building Design (DBD) methodologies of modern construction. This intersection poses a significant challenge: how can the experiential wisdom embedded in heuristic approaches be harmoniously integrated with the precision and efficiency of DBD strategies? This paper seeks to address this question, proposing that Virtual Reality (VR) simulations can serve as a bridge between these paradigms, enhancing stakeholder assimilation of performance-based design solutions in SLP.

SLP is foundational to the AEC industry, dictating the efficient allocation of resources and optimizing site operations. Despite its importance, the field has been slow to adopt advancements that seamlessly integrate technology with more traditional methodologies.

Historically, the AEC field has lagged in fully leveraging science and technology. Naboni (2015) [33] identifies this gap and discusses efforts to integrate digital fabrication and Building Performance Simulation (BPS) into mainstream practices. Knippers et al. (2021) [34] further emphasize the benefits of combining digital tools with traditional construction methods, advocating for a holistic and integrative computational approach.

Central to our discussion is the role of DBD and Multi-Objective Optimization (MOO) in navigating the complex trade-offs inherent in building design. DBD, a branch of data-driven design, as highlighted by Cantamessa et al.(2020) [4], focuses on generating a range of design alternatives from established variables, underscoring the critical role of data visualization in the decision-making process. Yet, as Seyed et al.(2022) [31] point out, the effectiveness of these visualizations is often hampered by the limitations of traditional 2D screens, suggesting a potential avenue for VR to improve data-driven design analysis and communication.

The implementation of VR in this study builds on the foundation of the 'Data-Driven Immersive Design Optimization' (DIDO) framework. DIDO integrates immersive technologies like VR with data-driven methodologies and MOO to address complex architectural challenges. In the context of SLP, DIDO enables a dynamic interaction between computational precision and stakeholder intuition, bridging the gap between heuristic knowledge and optimization strategies. While the DIDO framework can incorporate advanced tools like Computer Vision (CV) for enhanced data analysis, CV was not applied in this study to maintain a focused evaluation of VR's effects. This integration aligns with the study's broader objective to modernize design and construction processes through advanced visualization and interaction tools.

Literature on SLP underlines the necessity for performance-oriented methodologies and the critical role of algorithmic design processes in achieving stable solutions [35, 36, 37, 38]. While DBD and BPS are recognized for their decision-making efficacy, their success is predicated on the adaptability of models to incorporate varied stakeholder inputs [33]. This interdisciplinary engagement, though essential, risks deviations from the optimal design paths, emphasizing the need for dynamic data review processes to ensure decision-making precision [39].

Despite the recognized potential of immersive VR simulations and real-time feedback in bridging the gap between heuristic and data-driven processes, limited attention has been paid to their impact within the context of SLP. This study aims to bridge this research gap by examining how VR immersion and instantaneous feedback from a MOO model via a Heads-Up Display (HUD) can align stakeholder decisions more closely with data-driven optimized outcomes.

To achieve our research objectives, we employ a mixed-methods approach that combines quantitative analysis with qualitative insights. The methodology is structured around three primary components (see Figure 4.1):

1. VR System Development: Crafting immersive SLP scenarios to facilitate real-time stakeholder interaction and decision-making.

2. Experiment execution: Deploying the VR system to engage a diverse stakeholder group in VR-based decision-making, complemented by comprehensive data collection through surveys and interviews.

3. Data Analysis and Validation: Assessing the data collected during the experiment to evaluate the effectiveness of the VR system in improving the decision-making and SLP outcomes.

We hypothesized that, regardless of their professional background and prior knowledge of SLP design, participants in a VR experiment would be more likely to favor a DBD recommendation, thereby fostering a stronger connection between their experiential knowledge and the design model, and minimizing the deviation between MOO-predicted outcomes and stakeholder-selected designs.

Therefore, the aims of this study will be as follows:

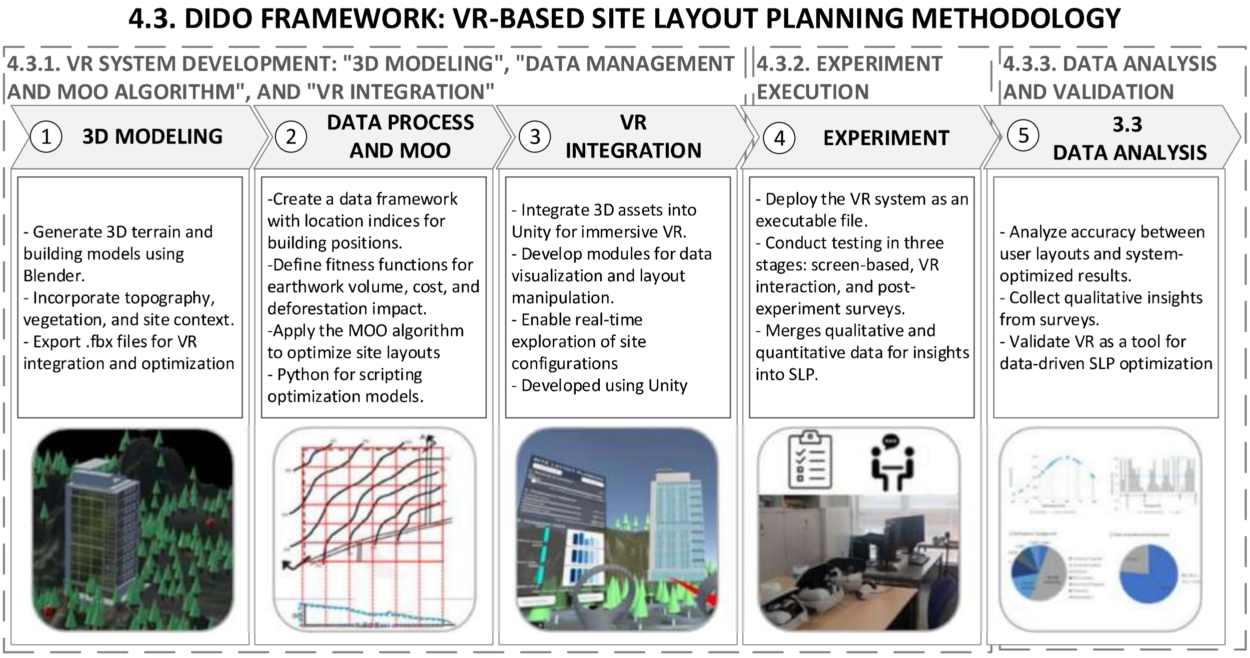


FIGURE 4.1: Methodology Flowchart illustrating the sequential steps of the implementation of the VR-Based Site Layout Planing (SLP) for Building Design. (See detailed methodology in Figure 4.2).

- To investigate the potential of VR simulations in enhancing stakeholder engagement and decision-making in SLP.
- To assess the effectiveness of VR in bridging the gap between heuristic approaches and data-driven optimization methodologies.
- To explore the impact of real-time feedback on reducing deviation errors in SLP design decisions.

By focusing on these aims, our research aspires to contribute to a more cohesive, efficient, and enlightened SLP process within the AEC industry. The integration of VR into SLP workflows demonstrates the applicability of the DIDO framework, showcasing how immersive visualization technologies can revolutionize decision-making, enhance stakeholder collaboration, and modernize design and construction practices.

4.2 Literature Review

The process of constructing our environment is deeply rooted in our aspiration to mimic the natural world. As Baker [40] eloquently articulates, architecture is the manifestation of a human-crafted universe, tailored to human needs and aspirations. While buildings may draw inspiration from nature and strive to harmonize with their surroundings, they exist as distinct entities within the dynamic fabric of the environment, serving as dedicated spaces for human habitation.

Amidst growing environmental concerns, the challenges identified by Knippers et al. [34] bring to the forefront the urgent need for building construction practices that not only address human requirements but also prioritize environmental sustainability. This dual objective calls for innovative solutions that reduce pollutants, conserve resources, and enhance the quality of living spaces.

In the specific context of Site Layout Planning (SLP), DBD Optimization has proven to be a powerful tool. SLP is a critical phase in the construction process that involves the strategic arrangement of elements on a construction site to maximize efficiency, safety, and environmental performance. Traditionally, SLP was dominated by heuristic approaches, which, while practical, often lacked the precision needed for optimizing complex projects.

Central to addressing these challenges is our research focus, which investigates the intersection of three pivotal concepts:

- SLP Design
- DBD Optimization
- Transformative potential of VR technology in the AEC industry

Through an in-depth analysis of each of these facets, we aim to uncover their individual contributions as well as their synergistic effects in revolutionizing the landscape of construction methodologies and decision-making processes.

SLP Design

Amidst the challenges outlined by Knippers et al. [34] regarding the future of construction, SLP design emerges as a pivotal and universally recognized stage in the construction process across the AEC field. As described by Ning [41], SLP involves a decision-making process encompassing problem identification, recognizing opportunities, developing solutions, selecting the best alternatives, and executing them. This critical phase sets the foundation for successful building construction and plays a pivotal role in achieving optimized outcomes that balance various design objectives, economic factors, and environmental considerations.

The importance of SLP extends beyond mere planning; it is a collaborative effort involving a diverse group of stakeholders at various stages of the construction process. These stakeholders include project managers, architects, engineers, contractors, and clients, each bringing unique perspectives and expertise to ensure the project's success [42]. For instance, architects and engineers contribute to the initial design and layout considerations, while contractors and project managers focus on the practical aspects of site utilization and logistics. Clients, on the other hand, are integral in defining the project's objectives and constraints.

Kulabi et al. [43] highlight that SLP problems have traditionally been addressed through heuristic methods and mathematical optimization. Heuristic methods, relying on knowledge-based systems, offer practical albeit not always optimal solutions. These methods have been the backbone of the construction industry, guided by established rules and the experience of planners, despite variations in accuracy and reliability across projects [44]. On the other hand, mathematical optimization aims to enhance reliability and achieve stable outcomes by striving for optimal results. However, the complexity and computational demands of large projects often limit the application of mathematical optimization, making heuristic methods more prevalent in such contexts [43].

Understanding the roles and contributions of each stakeholder in SLP is crucial. Their collaboration ensures that SLP can effectively address the multifaceted challenges of construction projects, from ensuring safety and maximizing space utilization to optimizing resource allocation and minimizing environmental impact. By integrating the insights and expertise of all stakeholders, SLP becomes instrumental in navigating the complexities of construction projects, leading to more sustainable, efficient, and successful outcomes.

In summary, SLP is a cornerstone of construction project planning, requiring the active participation of all stakeholders to leverage both heuristic and mathematical optimization methods effectively. This comprehensive approach enables the construction industry to meet today's challenges and lay the groundwork for future advancements.

DBD Optimization

The continuous research towards mathematical optimization methods proves the allure of the promise for optimal design [44]. The recurrent venture into this method has created a trend in DBD optimization where a solution to a building project is no longer a single static result instead it is seen as a process from which an assort of solutions can be presented with various degrees of optimization, while still given the final choice to the stakeholders [39].

It is understood that traditionally design solutions were driven by prescriptive terms, rather than the expected performance of the solution, with building codes and regulations being the main contributors to prescriptive specifications [42] and as Hemsath argues, data-driven design, such as Performance-based Design, requires a deliberate approach with a focus on front-loading information and reducing the time between critical feedback [39]. Aside from the data which sits at the core of the DBD, an accurate BPS is needed to support the design evolution, not only for reviewing purposes but on the role of a virtual experiment [42].

Yi et al. [44] advance the application of data-driven strategies in SLP by introducing a mathematical model aimed at optimizing the allocation of temporary facilities on construction sites. Their approach, grounded in multi-objective optimization, concurrently addresses safety, health, environmental concerns, and transportation costs—factors critical to the efficiency and sustainability of construction projects. Unlike traditional heuristic methods, their model demonstrates a significant improvement in optimizing SLP, achieving up to 19% enhancement in real-world scenarios. This finding underscores the superiority of data-driven design optimization in managing complex criteria, highlighting its potential to revolutionize SLP by offering more effective, efficient, and environmentally responsible solutions.

The practical advantages of data-driven optimization in SLP are profound, particularly in forecasting and analyzing building behavior. As Hemsath [39] notes, the efficiency and cost-effectiveness of addressing potential issues through predictive analysis rather than post-construction interventions are undeniable. This preemptive approach not only applies to the construction phase but also significantly benefits SLP by facilitating more informed and strategic decisions from the outset.

In exploring solutions for SLP, it becomes crucial to consider the building in its environmental context, a concept Baker [40] encapsulates as the interaction between site forces—such as orientation, views, and access—and the internal organizational forces of the building. This holistic view underscores the necessity of integrating performance-based design and simulations with traditional heuristic methods, fostering a dynamic interplay that enhances both the design process and its outcomes.

Incorporating VR technology represents a pioneering step in this integration, offering a vivid, immersive platform for stakeholders to visualize and evaluate the implications of different SLP options. This innovative approach not only enriches the design experience but also serves as a powerful catalyst for the broader acceptance and implementation of DBD principles.

Research has shown that integrating DBD Optimization into SLP can significantly enhance the decision-making process. For instance, multi-objective optimization models enable the simultaneous consideration of multiple criteria, providing stakeholders with a range of optimized solutions to choose from. This approach not only improves the efficiency of SLP but also aligns the final layout with broader project goals, such as minimizing environmental impact and maximizing resource utilization.

4.2.1 VR and its impact on the AEC field

VR has emerged as a transformative technology in the AEC industry. Initially used for visualization purposes, VR has evolved to play a crucial role in design exploration, stakeholder engagement, and decision-making processes.

In the context of architectural design, VR provides an immersive environment where stakeholders can interact with design models at a human scale. This capability is particularly valuable in complex projects, where understanding spatial relationships and the potential impacts of design decisions is critical. VR enhances the ability to present complex data interactively, making it more accessible and understandable to non-experts.

- Hardware and Software: Overview of the key VR hardware (such as headsets and motion sensors) and software platforms (such as Unity, Unreal Engine, and specialized architectural VR tools) used in the industry.
- Adaptation for Architecture: How VR technology has been adapted specifically for architectural applications, including the development of tools that allow for real-time design adjustments and collaboration in a virtual environment.

The Architecture, Engineering, and Construction (AEC) industry is grappling with the dual challenge of rapid technological advancements and persistent issues such as safety hazards, inefficiencies, and labor shortages [45]. Despite efforts to integrate innovations like prefabrication, automation, and robotics, the industry encounters substantial barriers, including a lack of understanding and training. In the UK, for example, the construction sector is currently facing a record high skill shortage [46].

Within the AEC industry, the adoption of Extended Reality (XR) technologies — encompassing Virtual Reality (VR), Augmented Reality (AR), and Mixed Reality (MR) — is reshaping traditional practices. Alizadehsalehi et al.(2020) [47] underscore the relationship between Building Information Modeling (BIM) and XR technologies, revealing their potential to revolutionize design management, safety protocols, and decision-making processes. Similarly, Seichter's exploration of AR's impact on architectural visualization emphasizes XR's role in enhancing communication with clients and stakeholders [48].

Advancements in XR are not without challenges, as the industry grapples with issues of technology adoption and user acclimatization driven by advancements in XR, AI, and 5G technologies, emphasizing the need for updated infrastructure and greater stakeholder acceptance to fully leverage XR's capabilities in enhancing AEC workflows and remote collaboration [47]. However, XR is poised to become a cornerstone in the AEC sector, fundamentally altering how projects are conceived, planned, and executed [49].

To remain competitive and address these challenges, AEC firms are increasingly turning to modern technologies, with VR standing out as a key area of investment [47].

VR is recognized as a transformative technology within the AEC industry, offering novel solutions to longstanding issues of safety, labor, and efficiency. A 2016 survey by ARC Document Solutions found that 65.7% of industry professionals identified VR as the most impactful technological advancement [50].

VR's capacity to blend the real with the virtual revolutionizes our spatial perception, as Schnabel [51] noted, creating immersive experiences that enhance visualization, streamline project completion, reduce labor and material needs, and facilitate interactive design evaluation at a human scale.

4.2.2 VR in Site Layout Planning (SLP)

One of the most promising applications of VR in architecture is site layout planning. In traditional design processes, site planning can be challenging due to the difficulty of visualizing how different elements will interact in a real-world environment. VR addresses this by enabling designers to:

- Simulate Different Configurations: Architects can create multiple site layouts and explore them in VR, gaining insights into how different configurations will affect factors like light, airflow, and spatial relationships.
- Assess Environmental Impact: VR can be used to simulate environmental conditions such as sunlight, wind, and noise, helping architects design layouts that optimize environmental performance.
- Enhance Stakeholder Engagement: Stakeholders can explore proposed site layouts in an immersive environment, providing feedback that can be incorporated into the design process.

VR's application in Site Layout Planning (SLP) offers significant advantages. By allowing stakeholders to experience proposed layouts in a fully immersive environment, VR facilitates a deeper understanding of spatial configurations and their implications. This immersive experience leads to more informed decision-making, as stakeholders can better visualize and assess the potential outcomes of different design options.

The transformative potential of VR in SLP is well-documented. Studies have shown that VR can enhance decision-making accuracy by providing real-time feedback and enabling a more interactive design process. For example, VR can simulate the flow of people and vehicles through a site, helping to optimize layouts for safety, accessibility, and efficiency. Additionally, VR has been shown to improve stakeholder engagement by making it easier for participants to understand and contribute to the design process.

The 'VR smart' tool is a prime example of VR's practical application in engineering design review. This VR-based tool demonstrated its effectiveness by enabling users to identify design errors more readily compared to traditional 2D documentation methods, thereby streamlining the entry into design reviews [5]. Similarly, Muhammad et al.'s research into VR's role in SLP revealed its potential to enhance job site organization understanding, collision detection, and assessment of layout arrangements [52]. While VR accelerated comprehension and improved identification of collision points, it also highlighted the ease of understanding and time efficiency of traditional 2D methods for tasks requiring an overview of the entire site. However, this preference may reflect the participants' unfamiliarity with VR technology.

These studies [5, 52] confirm VR's emerging significance in the AEC field, offering a new lens through which projects are approached. As the industry continues to embrace VR, it moves closer to realizing the full potential of data-driven design optimization, facilitated by VR's ability to present complex data as interactive and responsive environments. This shift not only enhances project comprehension and decision-making but also heralds a new era of innovation in construction methodologies.

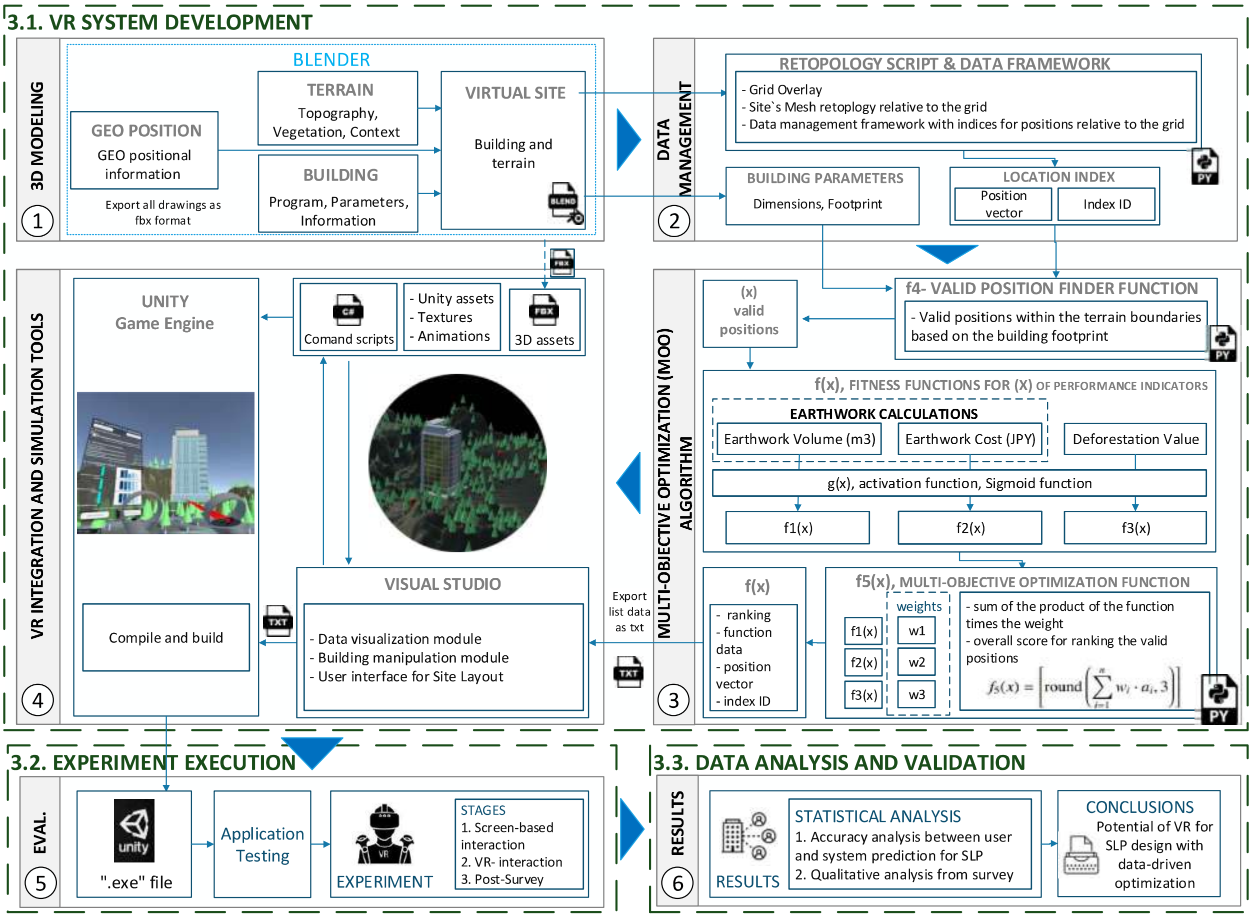


FIGURE 4.2: Methodology Flowchart illustrating the sequential steps of this study's approach to assess the impact of VR simulations on SLP decision-making. Higlighting the transition from 'VR System Development' (4.3.1), 'Experiment Execution' (4.3.2) and 'Data Analysis and Validation' phase.

4.3 Methodology

The methodology of this study, comprises three primary components: 'VR System Development', 'Experiment Execution', and 'Data Analysis and Validation', each designed to build upon the previous, ensuring a cohesive progression from theoretical foundation to practical application (see Elements 3.1 to 3.3 in Figure 4.2 for a visual illustration).

The first component, 'VR System Development', focuses on the technical development of the VR system, which is crucial for simulating realistic SLP scenarios.

The second component, 'Experiment Execution' component, detailed in Section 4.3.2, involves the deployment of the VR system in a controlled experimental setup to evaluate its impact on participant decision-making processes.

The final component, 'Data Analysis and Validation', focuses on analyzing the data collected during the experiments to validate the effectiveness of the VR system in improving SLP outcomes.

With the methodology outlined, we now move forward to a comprehensive breakdown of each component.

4.3.1 VR system development

The advent of VR in the AEC industry marks a shift from traditional methods like physical mock-ups and computer-aided design (CAD) to a more immersive, interactive environment [53]. VR's ability to enhance information and user interaction requires a system surpassing traditional methods in efficiency and effectiveness. To achieve this, the 'VR System Development' component is structured around four key elements (as shown in Figure 4.2, elements labeled 1 to 4):

1. *3D Modeling and Environment Setup:* Using Blender, detailed models of terrain, buildings, and vegetation are created. This setup is foundational for realistic simulations necessary for effective SLP (See Element 1 in Figure 4.2 and detailed description in Section 4.3.1).

2. *Data Management and Retopology Scripts:* Using Python scripts within Blender, to manage data and refine 3D terrain meshes, ensuring precise site representation and simulation accuracy (See Element 2 in Figure 4.2 and detailed description in Section 4.3.1).

3. *MOO algorithm Implementation:* Incorporation of MOO algorithms to assess various SLP metrics, such as cost, environmental impact, and spatial efficiency—to determine optimal site layouts (See Element 3 in Figure 4.2 and detailed description in Section 4.3.1).

4. *VR Integration and Simulation Tools:* using Unity, to create an immersive virtual environment where users can interact with and explore the SLP design in real-time (see Element 4 in Figure 4.2 and detailed description in Section 4.3.1).

The following sections will delve into each of these components in detail to provide insights into the system's innovative approach to SLP.

3D Modeling and Environment Setup

Using Blender (version 3.5), we developed 3D models critical for simulating the SLP process. Blender was selected for its advanced rendering capabilities, support for complex geometries, and seamless Python integration, making it ideal for visualizing architectural and environmental elements accurately. Our focus was on three main components: building structures, terrain topography, and surrounding vegetation (see Figure 4.3). These models were not intended to achieve photo-realism but to clearly represent key features essential for participant understanding and evaluation.

We created three fictional yet realistic site simulations each featuring unique geographical characteristics like varying slopes and natural features to address diverse SLP challenges and inspired by Fukuoka, Japan, due to it being the site of where this research was conducted (detailed in Table 4.2). The central building model was designed for photo-realistic interaction, enhancing user engagement with various positioning strategies within the VR environment (see Figure 4.3). Its parameters (Table 4.1) such as the building's dimensions—specifically, its boundaries— are a critical input to delineate the building footprint that coupled with the MOO algorithms (see Element 3 in Figure 4.2 and detailed description in Section 4.3.1), helped assess the environmental and spatial impacts effectively, underlining the importance of clear visualization for participant comprehension and interaction, thereby improving decision-making in SLP.

By prioritizing readability and user engagement through these modeling choices, our research aims to facilitate a more intuitive and effective exploration of SLP solutions.

TABLE 4.1: Proposed Educational Building Parameters. Information used for evaluating building impact in the optimization process for SLP

Parameters	*Values*
Height	42 m
Width	16 m
Length	16 m
Footprint Area	256 m^2
Number of floors	8
Gross Floor Area	2560 m^2
Program	Educational building

FIGURE 4.3: 3D Model of the Proposed Building and Site in Blender. Preliminary simulation for SLP analysis and optimizing building placement.

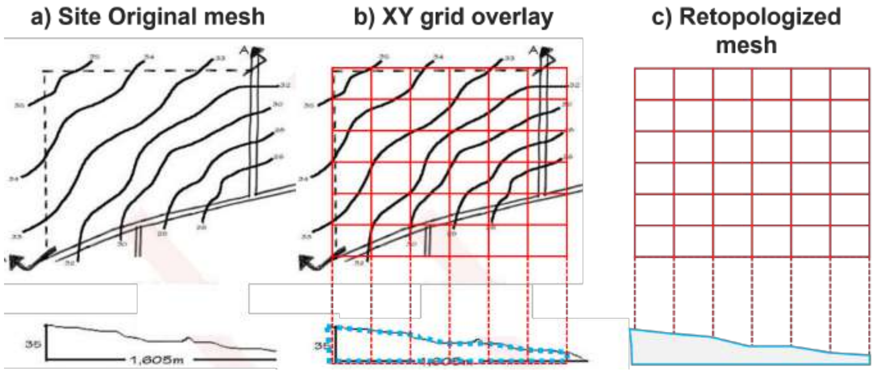


FIGURE 4.4: 'Retopology Script' Workflow, showing site topography from the original mesh (a), through XY grid overlay (b), to the final retopologized mesh (c).

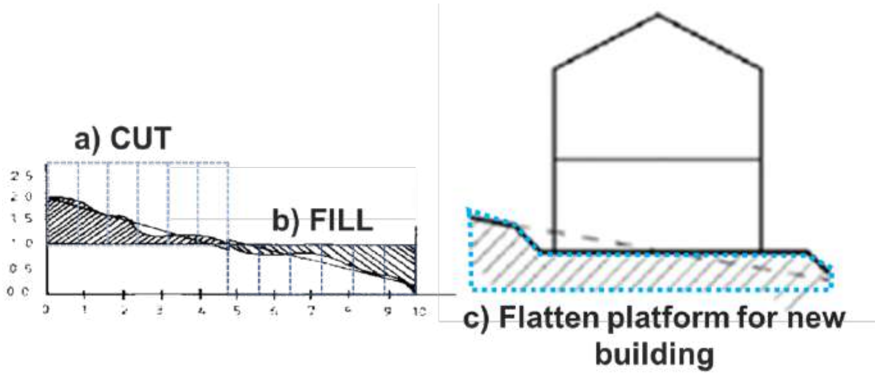


FIGURE 4.5: Earthwork Operation Process, showcasing the transition from initial cut and fill activities (left) to achieving a level building platform (right).

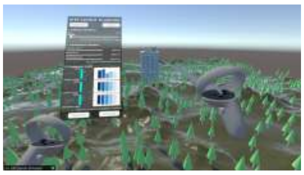
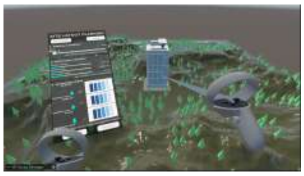
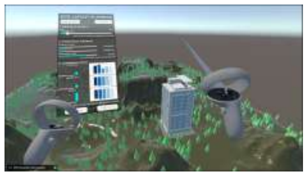
Data Management and Retopology Script

Efficient data management is essential in handling the complexities of terrain meshes for DBD optimization. The 'Retopology Script' developed in Python within the Blender environment, capitalizes on Python's strengths in handling large datasets and its seamless integration with Blender to enhance environmental simulation accuracy. This script is integral for detailed terrain modeling in our 'VR System Development', contributing to the overall simulation process (illustrated in Element 2 of Figure 4.2).

Retopology, as Barsanti et al.(2017) articulate, is the operation that restructures a 3D model's topology by applying a simpler, low-polygon mesh that retains essential geometrical features, favoring quads for their efficiency [54]. This process is implemented on the 'Retopology script' and is essential for transforming complex terrain meshes into organized, manageable 3D models, facilitating their integration into standardized databases critical for efficient data management. The 'Retopology Script' simplifies the terrain mesh by overlaying a grid and using ray intersections to mark terrain points, forming a retopologized mesh (see Figure 4.4). This mesh supports crucial calculations like area and volume estimations and environmental impact assessment by marking tree positions within the grid, aiding in the assessment of deforestation, enhancing the efficiency of SLP optimization. It's pivotal to note that the retopologized mesh, while fundamental to calculations, operates behind the scenes, preserving the original mesh as the primary visual representation of the terrain.

This systematic approach creates an efficient framework for handling and optimizing terrain data. As Hemsath (2012) [39] notes, such computational strategies enhance traditional methods, improving team performance and decision-making in architectural projects.

TABLE 4.2: Site Parameters and simulation preview in Blender and Unity VR

Description	*Site 1*	*Site 2*	*Site 3*
Terrain type	Plains	Canyon	Mountainous region
Width	200m	200m	200
Length	200m	200m	200
Grid area selection	150x100m	150x100m	150x100m
Platform level from 0	1m	2m	2m
Max Height	14m	14m	28.3
Top Rec. Location (x,y,z)	(35, -35, 2)	(-3.0, 20.0, 4)	(-26.0, 40.0, 0.0)
Blender Simulation			
VR Simulation			

MOO Algorithm Implementation

The optimization of SLP harnesses a MOO algorithm, integral to the development of the VR system as ilustrated in Element 3 in Figure 4.2, which showcases the alignment with sophisticated optimization strategies for adaptive system design [55]. The MOO framework is built around two essential components:

a) *Fitness ($f_1(x), f_2(x), f_3(x)$) and Sigmoid Functions*: These tools are employed to assess and normalize scores from performance indicators, ensuring a consistent basis for comparison across varied criteria.

b) *Sorting $f_4(x)$ and Multi-objective $f_5(x)$ Functions*: These functions are pivotal in categorizing performance indicators and amalgamating them into a cohesive evaluation framework, thereby facilitating the prioritization of optimization objectives.

Drawing upon the insights of Tian et al.(2021) on the critical role of comprehensive building performance data [9], our method utilizes a well-structured database created by the 'Data Management and Retopology Script' (Section 4.3.1). This database serves as the repository for the 'performance data' crucial to MOO, emphasizing key metrics such as 'Earthwork volumes', 'Earthwork - cost analysis', and 'Deforestation Value' (refer to Table 4.3).

The quantitative assessment of these indicators via 'Fitness Functions' contributes to a scoring mechanism. When integrated with a Multi-criterion Decision Analysis (MCDA) approach [42], this system underpins the ranking of potential construction sites. Such a process is vital for pinpointing the most suitable site layouts, facilitated by the 'Sorting Position' function (refer to Equation 4.12). This function adeptly manages the inherent trade-offs of MOO, guiding towards the most balanced site selection.

In optimizing SLP, our approach employs a specific Multi-Criteria Decision-Making (MCDM) technique known as the Analytic Hierarchy Process (AHP), integral to the development of our VR system as depicted in our methodology flowchart (Figure 4.2, element 3). AHP was chosen for its robust framework when dealing with complex decision-making processes where multiple, often conflicting criteria must be evaluated. AHP is particularly suited to our MOO algorithm

TABLE 4.3: Performance Indicators (PI) and Weights for MOO in SLP. This table outlines the key criteria used in MOO, detailing each PI's significance and assigned weight in the decision-making process.

Performance criteria	*PI*	*PI name/description*	*Quantitative method*	*Weights*
Earthwork calculations	1	Cut/fill operations to flatten the ground for the building.	Measured the volume m^3 of soil for cut/fill operations.	5
Earthwork costs	2	Cost of the earthworks necessary to flatten the ground for the building.	Measure in JPY based on the volume of soil to be displaced and the unit price $630 JPY$ determined by the RIBC [56]	3
Deforestation value	3	Trees being removed to implant the new building	Measured the number of trees that fall under the projection of the new building.	2
		TOTAL		**10**

because it allows for a hierarchical structuring of decision criteria, enabling a detailed analysis and prioritization based on expert input and quantitative data [21].

As we transition to a detailed examination of the MOO's key components, we focus on: a) the application and normalization of performance indicators through the 'Fitness' and 'Sigmoid' Functions, and b) the strategic organization and synthesis of these indicators using the 'Sorting' $f_4(x)$ and 'Multi-objective' $f_5(x)$ Functions. Delving into the specifics of these components will shed light on their indispensable roles within the MOO algorithm, ensuring that our optimization strategy is both comprehensive and meticulously attuned to the complex requirements of SLP.

a) **Fitness and Sigmoid Functions**

In our optimization framework, we employ 'fitness functions' to quantitatively assess three key performance indicators: Earthwork Volumes, Earthwork Cost, and Deforestation Value. These functions are intricately designed to produce normalized scores within a [0, 1] range, facilitating a unified evaluation of the site's performance against the defined criteria, as follows:

- Earthwork Volumes $f_1(x)$: This function calculates the total volume of earthwork required, providing insight into the extent of site manipulation needed (refer to Equation 4.3).
- Earthwork Cost Analysis $f_2(x)$: It estimates the cost associated with the earthwork volumes, offering a financial perspective to the earth manipulation efforts (see Equation 4.5).
- Deforestation Value $f_3(x)$: This function evaluates the environmental impact, specifically focusing on deforestation, to ensure sustainability is factored into the planning (Equation 4.7).

Each indicator is meticulously measured using tailored methods, as outlined in Table 4.3. The 'fitness functions' incorporate the relevant variables and objectives, enabling a comprehensive integration of scores across all indicators.

To further refine our analysis, we apply a 'Sigmoid Function' to the outputs of these 'fitness functions'. The 'Sigmoid Function' represented mathematically as:

$$f(x) = \frac{1}{1 + e^{-(k(x-t_0))}}, \tag{4.1}$$

where x is the initially normalized result from the fitness function, $k = 10$ represents the severity of the penalization, and $t_0 = 0.5$ is the inflection point, serving as the threshold for penalization versus reward.

Afterward, we re-normalize the sigmoid outputs to ensure comparability and aggregation into a cohesive overall score. The normalized scores are calculated as follows:

$$g(x) = \frac{f(x) - \min(f(x))}{\max(f(x)) - \min(f(x))}, \tag{4.2}$$

This structured approach underscores our commitment to a balanced evaluation of the SLP process, prioritizing efficiency, cost-effectiveness, and environmental sustainability.

Having established the foundational role of 'fitness functions' in our optimization framework and the strategic application of the 'Sigmoid Function' to refine our evaluation, we will now delve into the specifics of each function.

- Earthwork Volumes $f_1(x)$

The Earthwork Volumes component is essential for quantifying the ground leveling required for construction, involving both 'cut' and 'fill' operations. These operations adjust soil levels to achieve a desired terrain profile, crucial for the construction's foundation(see Figure 4.5).

The primary goal of the 'Earthwork Volumes fitness function', $f_1(x)$(refer to Equation 4.3), is to identify site locations where the balance between cut and fill activities minimizes the need for external soil transport. This balance is vital for reducing both environmental and financial impacts. The function is represented mathematically as:

$$f_1(x) = \left| \sum_{i=1}^{n} V_i \right| \tag{4.3}$$

$f_1(x)$ calculates the absolute sum of earth volumes where V_i represents the volume of soil moved at each position x on the site.

The ideal result is to have a net volume change of zero m^3, indicating no unnecessary earthwork and optimal resource utilization.

To compare results uniformly across different sites, the outcomes of $f_1(x)$ are normalized to a [0, 1] range:

$$g_1(x) = \frac{f_1(x) - \max(f_1(x))}{0 - \max(f_1(x))}, \tag{4.4}$$

with a score of 1 indicating no additional soil modification needed and 0 representing the maximum deviation from this ideal.

We further apply the 'Sigmoid Function' (Equation4.1) to the normalized scores from $g_1(x)$ to enhance the differentiation of performance near the critical threshold, and improve decision-making clarity.

This strategic application ensures that the 'fitness scores' not only reflect the quantitative balance of earthwork but also emphasize scenarios that approach an optimal environmental and logistical efficiency.

- Earthwork Cost Analysis $f_2(x)$

The Earthwork Cost Analysis aims to quantify the financial implications of site leveling activities required for building construction. This analysis is integral to the optimization process, ensuring economic feasibility alongside environmental and logistical considerations.

The fitness function $f_2(x)$ (see Equation 4.5) assesses the economic cost of 'cut' and 'fill' operations needed to prepare the building's site. The function is represented mathematically as:

$$f_2(x) = \sum_{i=1}^{n} |V_i| \cdot M, \tag{4.5}$$

where $|V_i|$ is the absolute volume of soil moved (either cut or filled) at each position x on the site, and M represents the unit cost for earthwork, set for excavation work up to 2.5m priced at

$630 JPY/m^3$ based on 2023 rates from the Research Institute on Building Cost (RIBC) for Fukuoka, Japan [56].

$f_2(x)$ aims to minimize the financial cost of earthwork operations. The optimal scenario, represented by a cost of $0 JPY$, indicates no additional earthwork is required beyond the original site conditions.

Results from $f_2(x)$ are normalized within a [0, 1] range to standardize comparison across various scenarios:

$$g_2(x) = \frac{f_2(x) - \max(f_2(x))}{0 - \max(f_2(x))}, \tag{4.6}$$

where a score of 1 indicates no incurred cost (optimal), and a score of 0 corresponds to the maximum financial impact observed.

To refine our evaluation, we apply the 'Sigmoid Function' to the normalized scores from $g_2(x)$, enhancing the differentiation between scores, particularly near the critical threshold. This methodological approach emphasizes cost-effective configurations, aiding in the identification and prioritization of the most economically viable scenarios.

- Deforestation Value $f_3(x)$

The 'Deforestation Value fitness function', $f_3(x)$ (referenced in Equation 4.7), quantifies the environmental impact by evaluating the number of trees affected by construction activities within the building's footprint at each site location (x). The function is represented mathematically as:

$$f_3(x) = \sum_{i=1}^{n} T_i, \tag{4.7}$$

where T_i represents the number of trees affected per area under consideration at position x on the site.

The primary goal of $f_3(x)$ is to minimize the environmental footprint, ideally finding a location that requires no tree removal. This focus helps in maintaining ecological balance and adhering to sustainability goals.

The results are normalized within a [0, 1] range to ensure effective comparison:

$$g_3(x) = \frac{f_3(x) - \max(f_3(x))}{0 - \max(f_3(x))}, \tag{4.8}$$

where a score of 1 indicates no trees are affected (optimal), and a score of 0 indicates the maximum deforestation impact observed. Crucially, the normalization process excludes the total tree count across the entire site to prevent skewed assessments. This approach ensures that the evaluation focuses solely on the direct impact within the building's footprint area, rather than comparing it to the site's total vegetation. By adopting this method, we accurately reflect the relative deforestation impact of each potential building location.

To further refine the analysis, a 'Sigmoid Function' (refer to Equation 4.1) is applied to the normalized scores from $g_3(x)$. This adjustment emphasizes configurations that exceed environmental conservation thresholds, aiding in the identification of site locations that best meet our criteria for minimal environmental impact.

These measures ensure that the 'Deforestation Value function' not only assesses but also aids in significantly reducing the environmental impacts of construction projects by prioritizing sites with minimal ecological disruption that fulfill or exceed our environmental conservation criteria.

b) **Sorting $f_4(x)$ and 'Multi-objective' $f_5(x)$ functions**

A structured approach is employed to sift through and pinpoint the most suitable solutions across the site, leveraging the insights derived from the three performance indicators. The cumulative data from the 'fitness functions' for each potential site location are collected into a comprehensive database for subsequent analysis.

- Sorting Position ($f_4(j)$):

Initially, the optimization process incorporates a 'Sorting Position function', $f_4(j)$ (see Equation 4.12). This function is designed to identify permissible building locations on a site by evaluating terrain constraints. It operates by considering the dimensions of both the site and the building footprint. Specifically, the function examines the length (d_x) and width (d_y) of the site alongside the length (b_x) and width (b_y) of the building footprint.

The function systematically processes each row on the grid of the site to ensure all potential building positions fall within the allowable bounds. For each row i, ranging from 0 to $(d_y - b_y + 1)$, the function calculates the permissible range for the column index j. This range is determined by the formula:

$$j \in [j_{\text{min}}, j_{\text{max}} + 1] \tag{4.9}$$

where,

$$j_{\text{min}} = \left(b_y \cdot \frac{d_x}{2}\right) + b_x + \left(d_x + \frac{b_x}{2}\right) \cdot i, \tag{4.10}$$

$$j_{\text{max}} = j_{\text{min}} + d_x - b_x. \tag{4.11}$$

The valid positions are then extracted from the grid vertex list (vtx_{list}), checking each index j within the specified range. If the grid position meets the criteria, it is marked as valid:

$$f_4(j) = vtx_{\text{list}}[j] = x, \tag{4.12}$$

where x represents a 'valid position' within the site boundaries that accommodates the building footprint without violating any site constraints. This meticulous approach ensures that only feasible locations are considered in the subsequent phases of SLP.

- Multi-objective Evaluation function ($f_5(x)$):

This function, $f_5(x)$(Equation 4.13), plays a crucial role in the final ranking and selection of optimal SLP for construction projects by integrating various performance indicators.

It operates by calculating an overall score for each valid position on the site, identified by the 'Sorting Position function', $f_4(j)$(Equation 4.12). It does so by summing the weighted scores of each performance indicator, which are normalized to ensure comparability and reflect the strategic priorities of the project. The mathematical representation of this process is as follows:

$$f_5(x) = \left[\text{round}\left(\sum_{i=1}^{n} w_i \cdot a_i, 3\right)\right] = \text{overall\_score} \tag{4.13}$$

where n represents the number of performance indicators included in the assessment. Each indicator, denoted by w_i, is assigned a weight reflecting its importance relative to other factors in the project. The normalized score for each indicator a_i, ensures that contributions to the overall score are balanced, allowing each indicator to influence the outcome proportionately to its assigned weight.

The overall score generated by $f_5(x)$ serves as the basis for ranking the potential site locations. Locations are sorted in descending order of their scores, with higher scores indicating better alignment with the project's objectives. This sorting facilitates an efficient decision-making process by highlighting the locations that best meet the comprehensive criteria set out in the project's planning phase.

By applying $f_5(x)$ to the list of 'valid positions', the optimization framework effectively prioritizes the most suitable locations for construction, taking into account a balanced consideration of the trade-offs and the weights attributed to earthwork cost, volume and environmental impact. This ensures that the selected site offers the most advantageous combination of attributes, aligning with the project's strategic goals and sustainability considerations.

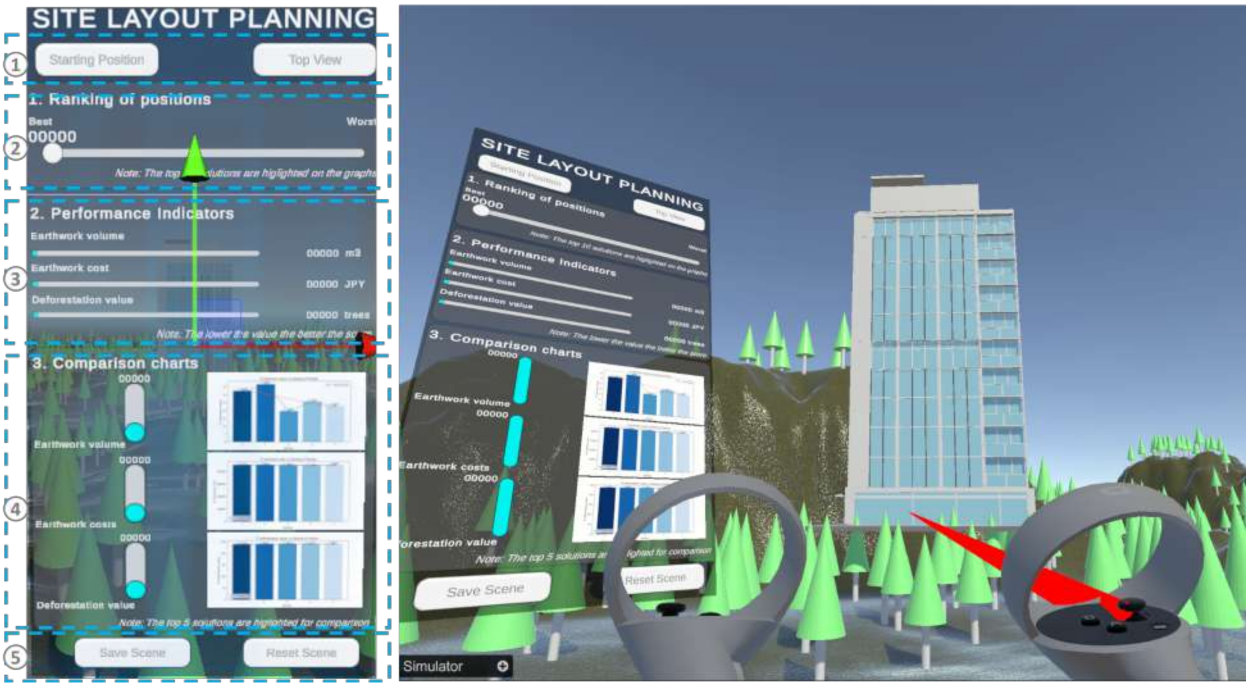


FIGURE 4.6: VR interface for DBD optimization in SLP. Viewpoint Navigation(1), Location Slider(2), Performance Indicator (PI) Visualization(3), CComparative Analysis Charts(4), Utility Functions(5)

VR Integration and Simulation Tools

Drawing on the insights of Lao et al. [32], we developed the 'VR integration and simulation tools' component using Unity to address the complexities of data-driven optimization outputs. Unity was chosen for its comprehensive VR support, including pre-built templates and seamless integration with Python and C#, enhancing our simulation's interactivity and data handling capabilities cooperativily merging 3D terrain and architectural models with sophisticated optimization outcomes (see Figure 4.2, element 4).

The 'VR data visualization interface', detailed in Figure 4.6, comprises five modules designed to enhance the accessibility and interpretability of optimization data:

1. *Viewpoint Navigation:* Facilitates site exploration from various perspectives, improving spatial understanding (labeled 1 in Figure 4.6).

2. *Location Slider:* Allows easy navigation through top building locations, simplifying design adjustments (labeled 2 in Figure 4.6).

3. *Performance Indicator Visualization:* Displays crucial metrics through cluster bar charts, providing instant insights into performance impacts (labeled 3 in Figure 4.6).

4. *Comparative Analysis Charts:* Offers column charts for comparative performance analysis, aiding in informed decision -making (labeled 4 in Figure 4.6).

5. *Utility Functions:* Includes essential tools for resetting the analysis and saving design choices, supporting iterative design processes (labeled 5 in Figure 4.6).

These tools transform complex optimization results into an intuitive format, significantly enhancing the design process and decision-making in SLP.

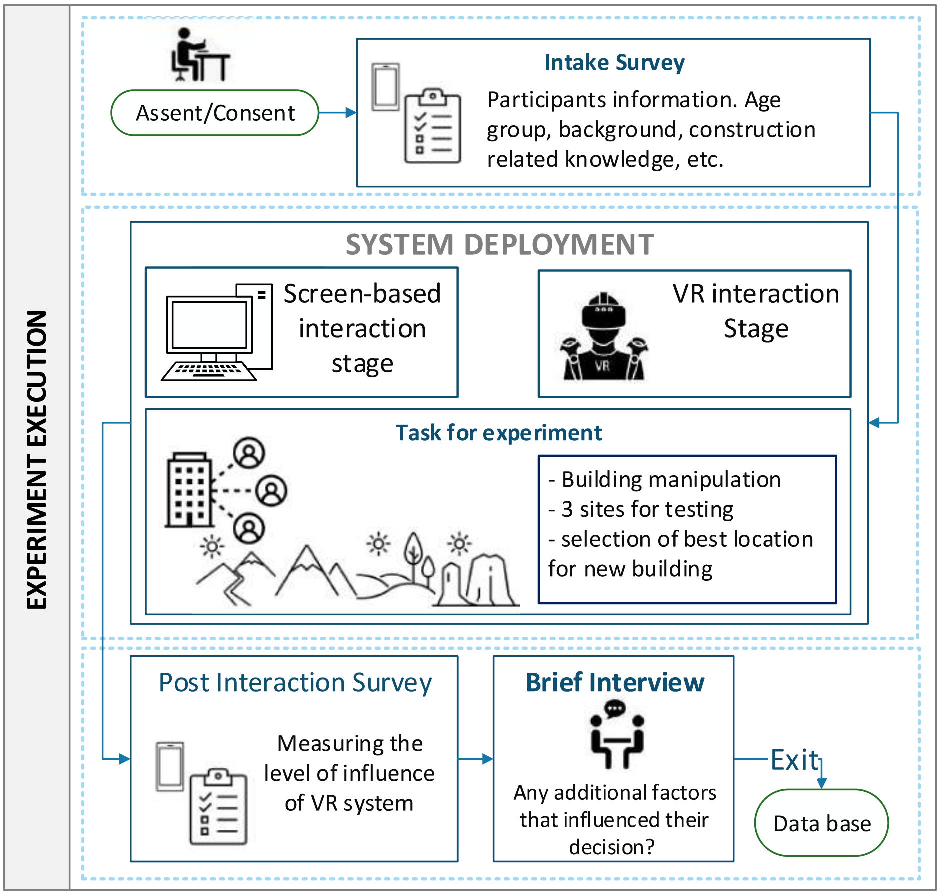


FIGURE 4.7: Experiment Execution Evaluation Flowchart, depicting the three stages—screen-based interaction, VR interaction, and post-interaction survey.

4.3.2 Experiment Execution

The experiment evaluated the impact of VR immersion on decision-making in SLP, using a HUD in a controlled VR simulation (see Figure 4.7).

Participants engaged with VR environments to explore and assess SLP against three key performance indicators: 'Earthwork Volume', 'Earthwork Cost', and 'Deforestation Value', as listed in Table 4.3. This evaluation was conducted across three different sites presented in random order to ensure an unbiased assessment (illustrated in Table 4.2).

The experiment consisted of three main stages:

1. *'Screen-based Interaction' stage:* Participants used a multi-monitor setup with Blender to review terrain and building models, guided by visual cues indicating optimal locations (see Figure 4.8).

2. *'VR Interaction' stage:* Using an Oculus Quest 2 headset, participants experienced a deeper immersion, interacting directly with the site and receiving real-time feedback on performance indicators (Figure 4.9).

3. *Post-interaction Survey:* After interactions, participants completed a detailed survey to collect feedback on their experience and the VR impact on their decision-making. This survey included questions about their background (see Figure 4.10 4.11), the usability of the VR interface (see Figure 4.17), and their perceptions of VR influence on their choices (see Figure 4.18). Both the 'usability' and 'perception' sections of the survey are posed on a 7-point Likert scale, which ranges from 'Strongly Disagree' (1) to 'Strongly Agree' (7). This scale is

chosen for its ability to capture nuanced responses regarding intuitiveness, ease of use, and overall satisfaction.

This structured approach aims to systematically evaluate how VR technology influences SLP decision-making by combining quantitative accuracy analysis with qualitative participant feedback. The goal is to ascertain whether VR can enhance decision-making precision and user engagement compared to traditional methods, addressing both empirical and perceptual dimensions of technology adoption in SLP.

FIGURE 4.8: 'Screen-Based interaction' stage. Detail of Monitor setup (left) and Blender simulation (right).

FIGURE 4.9: 'VR Interaction' stage. Detail of HUD Oculus Quest 2 (left) and Unity simulation (right).

4.3.3 Data Analysis and validation

The final phase of our methodology involves a detailed analysis of the data collected during the experiments, crucial for validating the effectiveness of the VR system in enhancing SLP outcomes. It is structured as follows:

1. *Data Processing and Analysis:* Advanced statistical tools are used to analyze user feedback and interaction data, helping to identify patterns and insights that elucidate user interactions with the VR system and their responses to the simulated SLP scenarios.

2. *Performance Evaluation:* We assess the VR system's impact on user decision-making by examining:

    - *Accuracy Analysis:* Evaluates how participant choices align with system-generated optimal solutions, quantifying the improvement in decision-making precision through VR (See Figure 4.12).
    - *Participant Perception Survey:* Gathers subjective assessments on the VR system's usability and its influence on decision-making, providing qualitative insights into its effectiveness (see Figure 4.17 4.18).

    These metrics are critical for comparing empirical and perceptual decision-making improvements provided by VR against traditional methods.

3. *Results Interpretation and Reporting:* Data synthesis draws conclusions on the VR system's performance and identifies improvement areas. This analysis confirms the system's role in enhancing heuristic and data-driven SLP approaches and explores the broader implications of VR technologies in architectural and urban planning.

This streamlined analysis approach ensures a comprehensive evaluation of the VR system's impact, setting the stage for the Results section to discuss detailed outcomes. The methodology thus ensures a thorough exploration of VR's potential to revolutionize decision-making processes in architectural design and planning, directly addressing our research objectives.

4.4 Results

This study was carried out at Kyushu University, Fukuoka, Japan. Over 15 days, from June 10 to 25, 2023, 17 participants, including university students and faculty members with diverse professional backgrounds, engaged in the study. The distribution of participants' backgrounds and their experience in SLP is graphically represented in Figures 4.10 and 4.11, respectively. With over 50% being students from various faculties, approximately 20% having a construction background, and 23.5% reporting previous experience in SLP.

The study's quantitative findings on the effectiveness of VR in SLP are complemented by insights drawn from participant feedback in the areas of usability and perception, gathered through a detailed survey and the post-survey interviews and presented as follows.

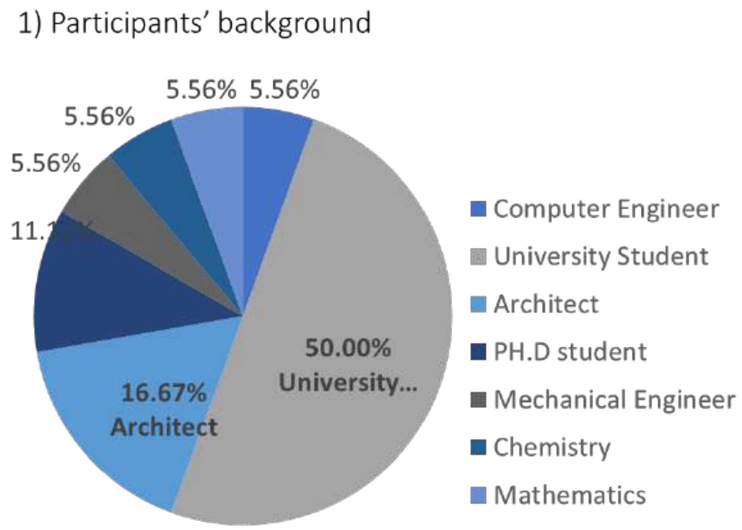


FIGURE 4.10: Professional Background of participants in the experiment for VR in SLP

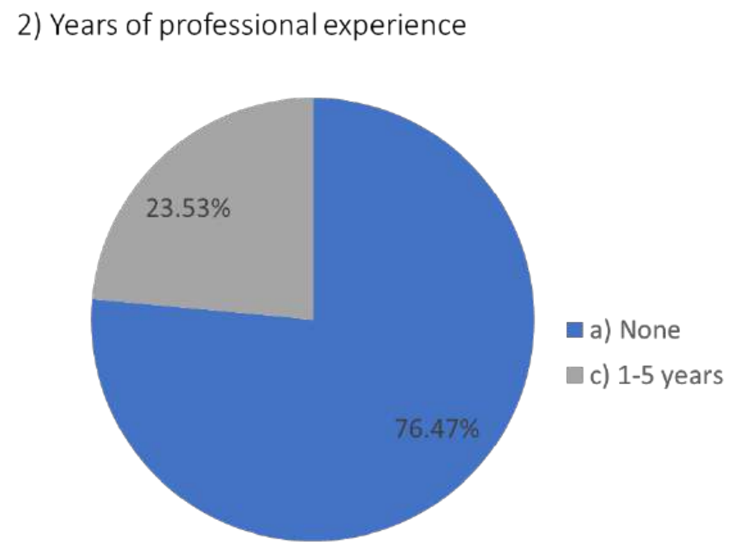


FIGURE 4.11: Years of experience in SLP of participants in the experiment for VR in SLP

a) Accuracy Analysis and Participant Decisions:

Participants were tasked with selecting optimal locations for a new educational building across three different sites, resulting in 39 distinct sessions. Their selections were compared in two stages: 'screen-based interaction' and 'VR interaction,' with the accuracy of their choices visualized in 'accuracy analysis graphs' (Figure 4.12). These graphs plot participants' decisions relative to the system's top recommendations, providing a spatial and directional analysis of each choice.

In the 'accuracy analysis graphs' (Figure 4.12), the center serves as a reference point, representing the top recommendation provided by the optimization system for each specific site. The coordinates of this center point vary for each site, reflecting the distinct optimal locations suggested by the system. On the other hand, the participants' chosen locations are plotted on the graph, precisely indicating the positions they deemed most suitable for the new educational building within the boundaries of the site.

By analyzing the 'accuracy analysis graphs' (Figure 4.12), the contribution of the VR system was determined by examining the vector resultant from the center point (top recommendation) to the participant's chosen location. A reduction in the vector magnitude in the 'VR answer' compared to the 'screen-based answer' indicated an improvement percentage in alignment with the suggested answer given by the system, while an increase represented a decline. This analysis allowed us to quantify the impact of VR immersion on participants' decision-making accuracy in SLP design.

This comparison, that aimed to measure deviation errors between the MOO model's recommendations and participants' selections in both interaction stages, illustrated in the 'Accuracy improvement' bar chart (Figure 4.13), revealed an average improvement of 48.3% in accuracy through VR, despite a broad variability among participants, as highlighted by the standard deviation of 44.1% and depicted in the probability bell graph (Figure 4.14), with evidence of only 4, out of 39 cases, showing a decline as seen in the 'Accuracy improvement' bar chart in Figure 4.13.

b) Complexity and Topographical Impact:

An examination of accuracy improvements across different sites (Figure 4.15) show an improvement of 42.1% for site 1, 57.2% for site 2 and 49% for site 3, hinting a correlation between the topographical complexity of a site and the level of improvement observe.

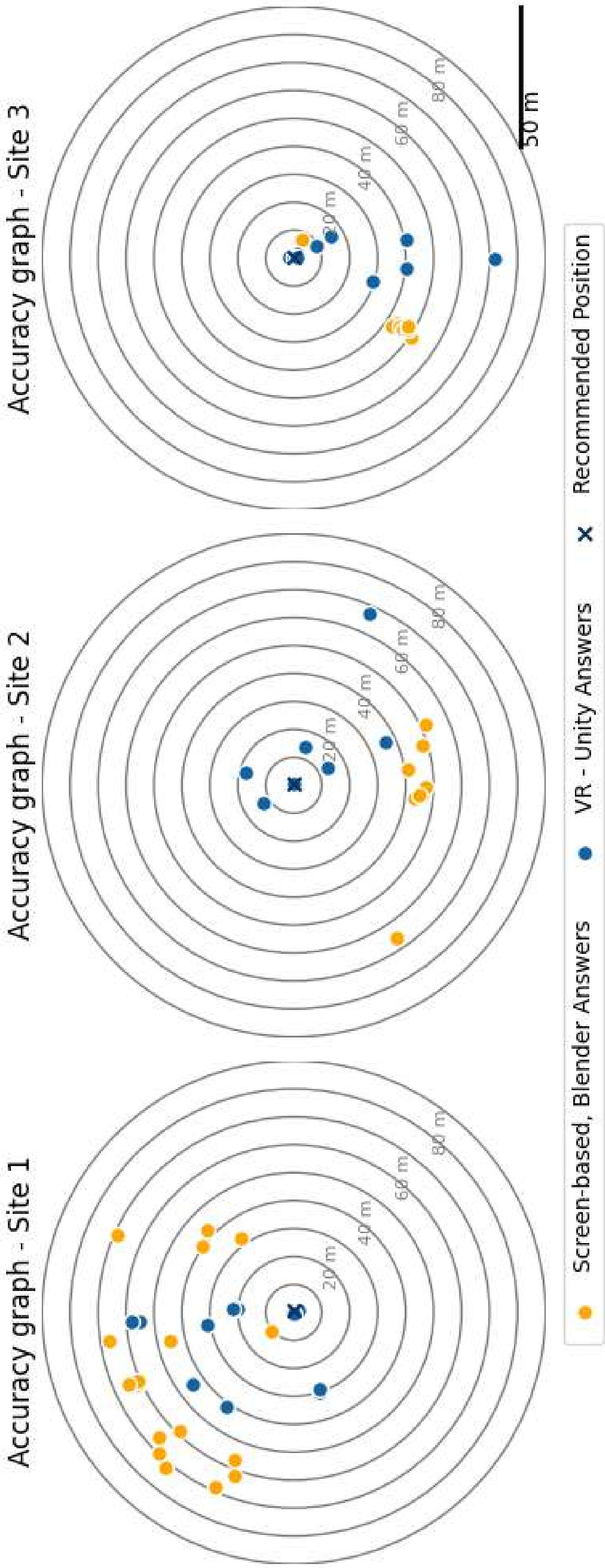


FIGURE 4.12: Accuracy scatter graph per site. Illustration of the deviation and improvement of accuracy between the screen-based stage and the VR stage.

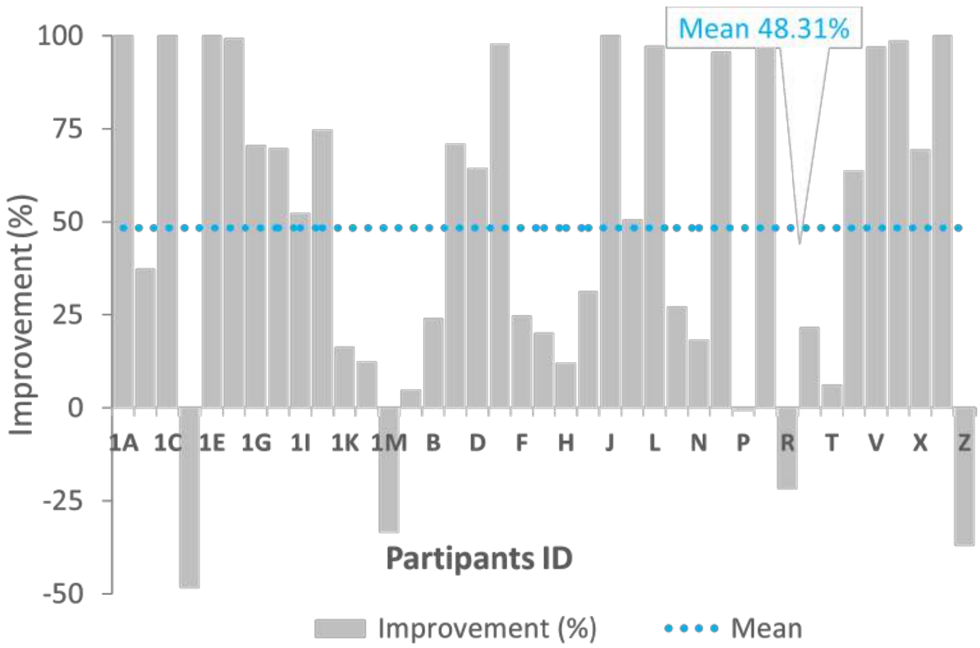


FIGURE 4.13: Improvement in accuracy among participants with the use of VR simulation compared to the screen-based simulation (Mean = 48.3%, SD =44.1%)

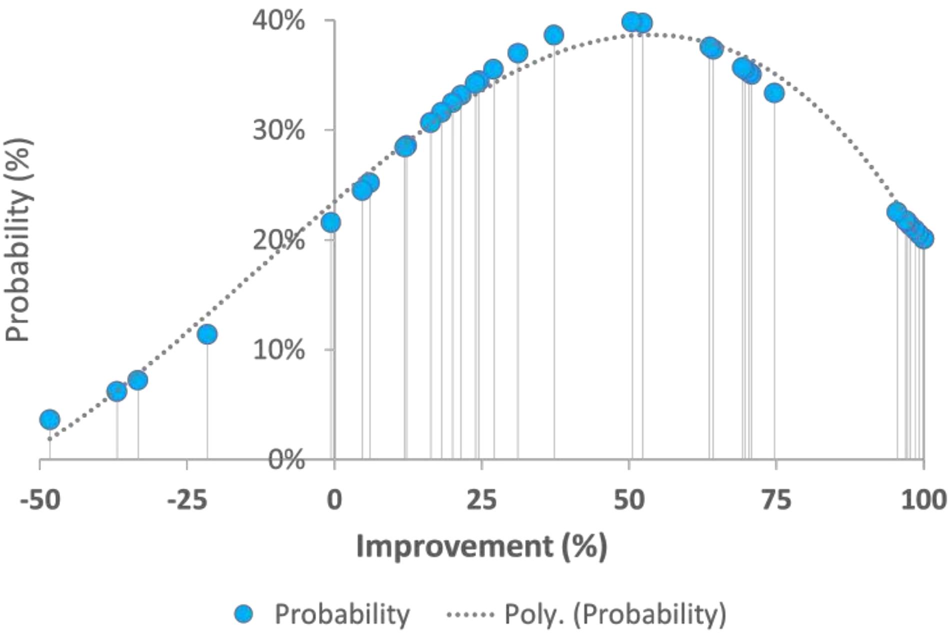


FIGURE 4.14: Probability of accuracy improvement with the use of VR simulation (Mean = 48.3%, SD =44.1%)

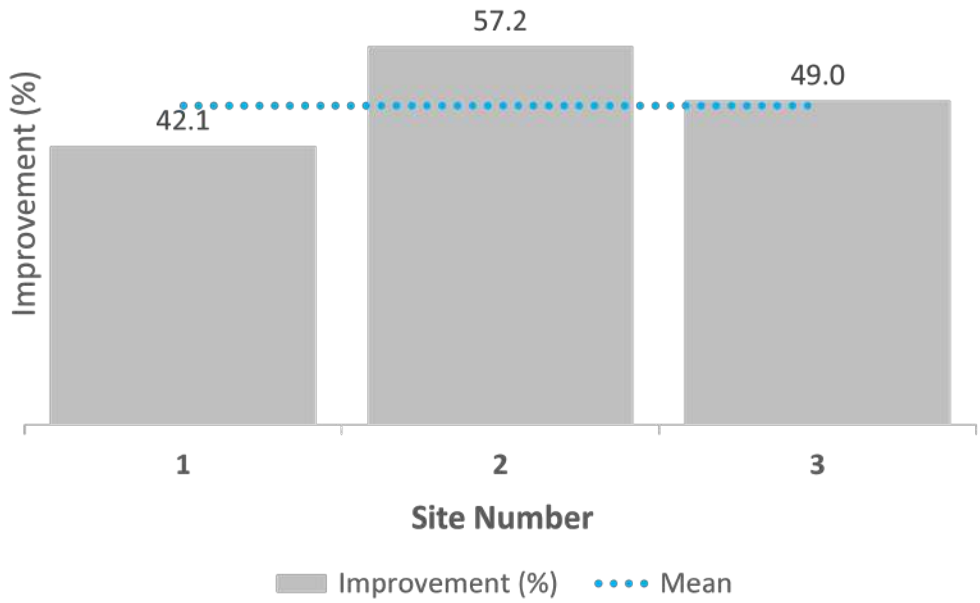


FIGURE 4.15: Average of Improvement in accuracy per Site with the use of VR simulation compared to the screen-based simulation, with detail of the overall average of the experiment (Mean = 48.3%, SD =44.1%)

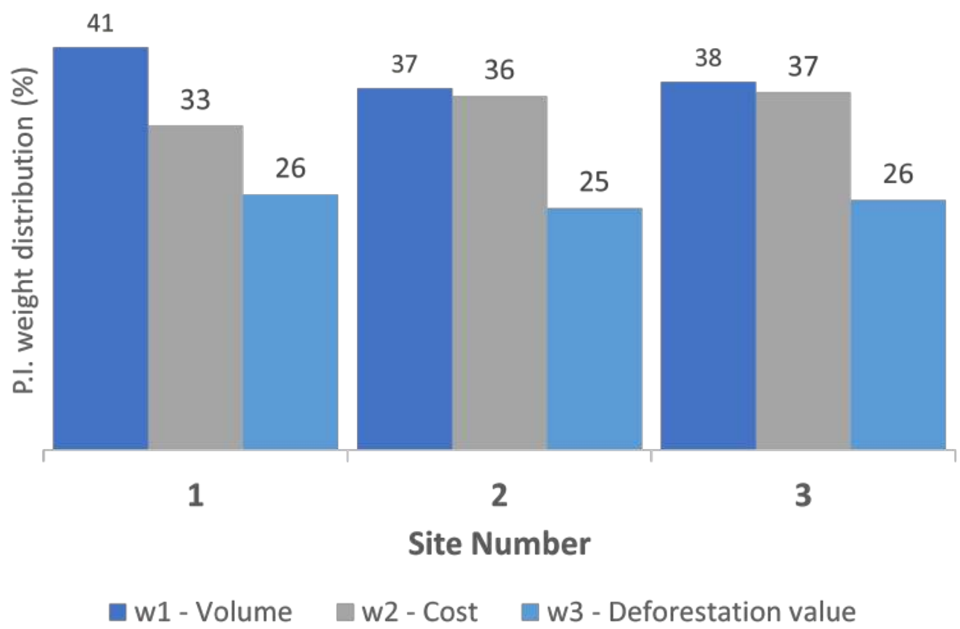


FIGURE 4.16: Average of weight distribution when ranking the importance of the performance indicators, defined by the participants, per site.

c) Survey Insights on Usability of VR Simulation:

Survey responses pertaining to the usability of the VR simulation for SLP design yielded an average score of 5.1, indicating a positive user experience (Questions 6–10 in Figure 4.17). Participants found the VR simulation relatively easy to use, with a mean score of 5.4 (Q8 in Figure 4.17), and they felt it allowed for a satisfactory exploration of different design options, scoring 4.7(Q7 in Figure 4.17). However, the scores suggest that the VR simulation's ability to enhance visualization of the SLP (4.9, in Q7 in Figure 4.17) and aid in identifying potential design flaws (5.1, in Q10 in Figure 4.17) fell short of participant expectations. These insights (Figure 4.17) point to specific areas within the VR interface that may benefit from targeted improvements to meet user needs more effectively.

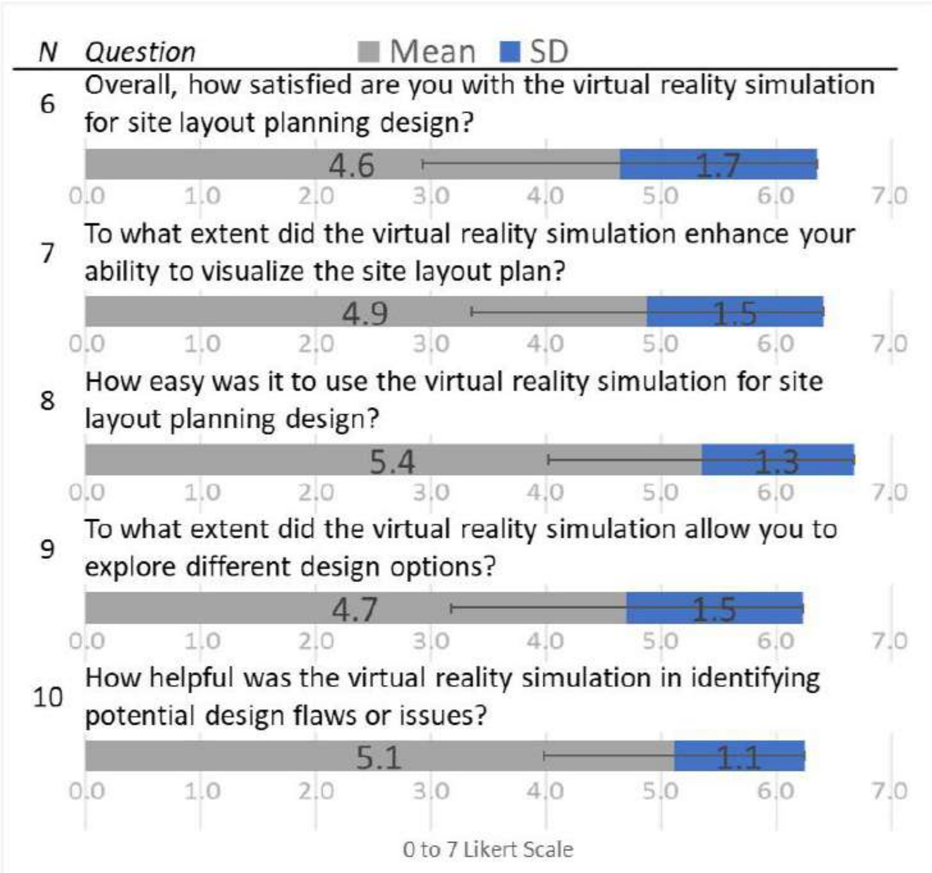


FIGURE 4.17: "User Satisfaction section questions from User Survey of SLP System. (n = 17), 1 - strongly disagree, 7 - strongly agree

d) Survey Insights on Perception of VR's Influence:

The survey also delved into participants' perceptions of how the VR simulation influenced their decision-making process in SLP (Questions 11–15 in Figure 4.18). The suggested solutions presented through VR were deemed valuable, with an average score of 5.6(Q11 in Figure 4.18), indicating that the system's recommendations had a meaningful impact on participants' decisions (5.6, Q11 in Figure 4.18. The likelihood of participants implementing these VR-suggested solutions in their final SLP also received a strong positive response, with an average score of 5.6(Q13 in Figure 4.18). Equally, the propensity to use VR for future SLP tasks was affirmed, scoring 5.6(Q14 in Figure 4.18). Overall, participants rated the effectiveness of the VR simulation in SLP at 5.4(Q15 in Figure 4.18), reinforcing the technology's potential as a decision-making aid while also signaling areas for enhancement in conveying data-driven recommendations more effectively.

e) Post-survey insights on Optimization Model:

Post-experiment feedback focused on the optimization model's weight distribution among the three performance indicators, initially set at 50%, 30%, and 20% (out of 100%). Despite general agreement on the importance ranking of these indicators, participants suggested slight adjustments to the weight distribution, as visualized in Figure 4.16.

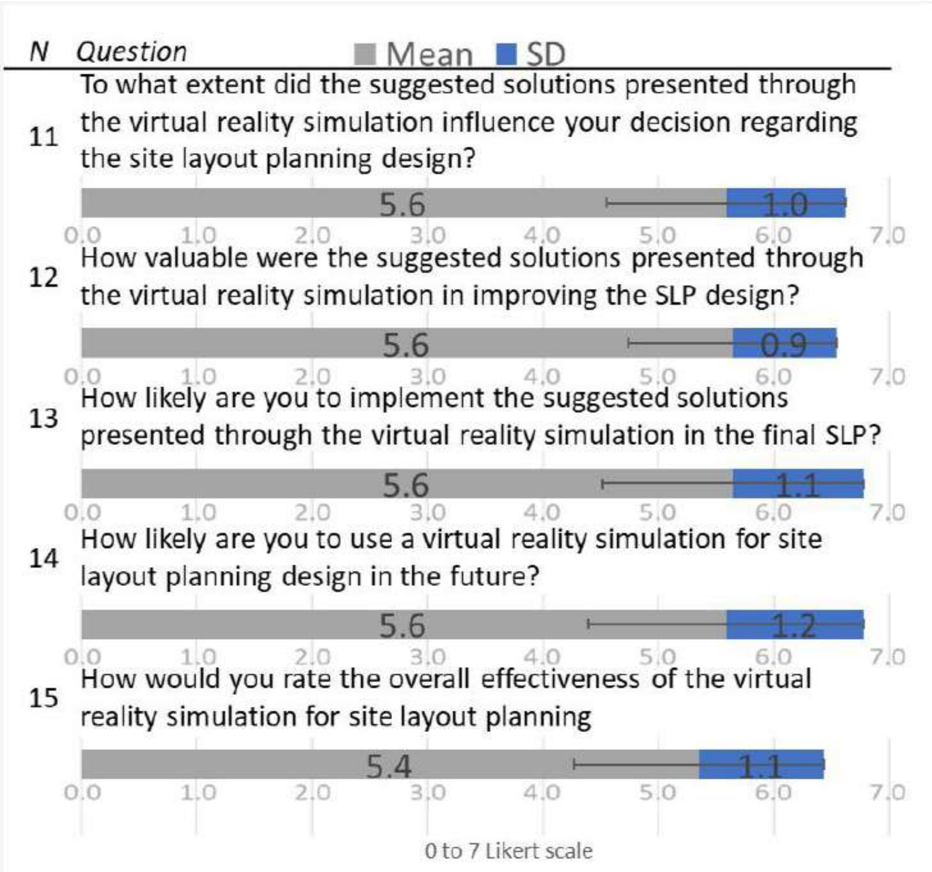


FIGURE 4.18: User-System Influence Perception section" questions. (n = 17), 1 - strongly disagree, 7 - strongly agree

4.5 Discussion

In the ensuing discussion, we meticulously examine our findings in light of the initial aims delineated in the introduction, providing a structured exploration of the transformative potential of VR in SLP.

Enhancing Stakeholder Engagement and Decision - Making through VR

Our investigation into VR's application in SLP underscores its pivotal role in fostering stakeholder engagement and enhancing decision-making efficacy. The transition to VR from traditional screen-based methods has demonstrably narrowed the gap between proposed solutions and stakeholder selections, affirming VR's capacity to intuitively convey complex data-driven insights.

The survey data (Figure 4.17, 4.18) and accuracy analysis (Figure 4.12) from our study reveal that stakeholders showed a pronounced inclination towards adopting VR-recommended solutions, reflecting VR's effectiveness in engaging users and guiding them towards optimal decisions.

This evidence highlights VR's capacity to integrate user input with data analytics, facilitating a more inclusive and informed decision-making framework in SLP. Moreover, similar studies, such as Astaneh et al.(2022)[24], which compared screen-based approaches with VR in resolving building system conflicts, also reported a greater comprehension of technical issues in immersive VR compared to screen-based approaches. And while previous research has focused on small details[35], these results demonstrate that an overview of the whole scale of the project can also be impacted by the integration of VR techniques in a positive matter and perhaps show a larger impact that may tilt the preferential adoption of VR when solving SLP.

Bridging Heuristic and Data-Driven Optimization with VR

Our findings illuminate VR's capacity to render complex datasets into intuitive, spatial experiences, thereby enabling stakeholders to make informed decisions grounded in empirical data without relinquishing the intuitive insights gained from heuristic approaches. This merger not only enhances the decision-making process but also democratizes access to sophisticated data analytics, making them accessible and actionable for all project participants.

Evidence from our study suggests that VR's immersive environment fosters a more collaborative and interactive review process(refer to Figure 4.14). Stakeholders can virtually navigate through site layouts, assess potential impacts, and make adjustments in real-time, significantly reducing the gap between theoretical data models and practical, on-the-ground decision-making(see Figure 4.15). Moreover, this approach has been instrumental in facilitating a more holistic understanding of project complexities, thereby streamlining the integration of multifaceted design and planning considerations.

By leveraging VR, the AEC industry can transcend traditional barriers to data interpretation, empowering professionals to harness the full spectrum of insights available from both heuristic experiences and quantitative analysis.

Impact of Real-Time Feedback on SLP Design Decisions

The introduction of real-time feedback through VR has significantly impacted SLP design decisions. Our results illustrate that this immediate feedback mechanism enhances the accuracy of stakeholder decisions by providing a dynamic and responsive environment for testing and modifying design choices (refer to Figure 4.13). This is quantitatively supported by an observed average improvement of 48.3% in decision-making accuracy when employing VR, despite the presence of variability among participants (as indicated by a standard deviation of 44.1%, Figure 4.14). Such improvement underscores the dynamic nature of VR in providing stakeholders with an interactive platform to evaluate and refine their design choices in real-time, directly impacting the virtual site's layout.

Stakeholders could instantly see the implications of their decisions on the virtual site layout, leading to more informed and confident choices. This process not only reduces the likelihood of errors but also accelerates the decision-making cycle, underpinning the vital role of real-time feedback in optimizing SLP outcomes.

The notable correlation between terrain complexity and the level of decision-making improvement (42.1% for site 1, 57.2% for site 2, and 49% for site 3, Figure 4.15) further highlights the substantial impact of real-time feedback in navigating and assessing complex site conditions. This effectiveness of VR in conveying intricate spatial information rapidly and intuitively presents a compelling case for its broader adoption in SLP practices.

Addressing Variability in User Experience

Notably, our analysis revealed considerable variability in VR interaction outcomes across different users, as indicated by the standard deviation in system improvement metrics (SD = 44.1%, Figure 4.13). This variability underscores the importance of designing VR interfaces that can be customized to meet diverse user preferences and proficiency levels, a need further evidenced by user satisfaction levels (Mean = 4.6, SD = 1.7, Q6 in Figure 4.17). The findings suggest that tailoring VR experiences could significantly mitigate instances of suboptimal interaction, ensuring that VR's full potential in enhancing SLP decisions is accessible to all users, regardless of their prior experience with VR technology.

These individual variations highlight the potential and current limitations of the selected VR system, emphasizing the need for further refinement of the data visualization interface to enhance the understanding of system recommendations.

The Role of Terrain Complexity

Our findings underscored terrain complexity as a critical factor influencing the efficacy of VR in SLP decisions. The accuracy graphs and improvement measurements revealed that users could more easily identify optimal site layouts in complex terrains, suggesting VR's visual and interactive features are particularly beneficial in navigating and assessing diverse topographical challenges (see Figure 4.15). The survey responses corroborate this, with participants noting a heightened ability to navigate and assess varied topographical features within the VR environment. This underlines the necessity for VR systems to be adeptly designed to manage such complexity, thereby improving decision-making accuracy and enhancing the user experience in intricate SLP scenarios. The integration of advanced data visualization techniques, informed by visual cues from VR simulations, could further optimize decision-making processes, even in less complex terrains, by accentuating key differences between potential site layouts.

4.6 Conclusions, Limitations and Future Work

This paper set out to explore the impact of VR simulations on enhancing the adoption of data-driven design solutions in SLP. Our focused investigation, grounded in both quantitative and qualitative analyses with 17 participants, yielded insights into the integration of VR and data visualization techniques within the SLP design process. The empirical evidence points to a 48.3% improvement in decision-making accuracy when employing VR simulations, underscoring the technology's potential to facilitate a deeper engagement with DBD recommendations.

The research substantiates the hypothesis that VR simulations can significantly reduce deviation errors between the optimal SLP design suggested by data-driven models and the choices made by participants. This finding not only highlights the efficacy of VR in promoting data assimilation but also underscores the critical role of intuitive data visualization in guiding stakeholders towards informed decisions.

Our study reveals that the effectiveness of VR in SLP extends beyond immersive experience; it lies in its ability to present data in formats that intuitively align with human cognitive processes. By doing so, VR serves as a pivotal tool in enhancing the comprehensibility and applicability of complex data sets, marking a significant step forward in the realm of DBD and beyond.

This work builds on the foundational principles of the Data-Driven Immersive Design Optimization (DIDO) framework, which integrates data-driven methodologies, Multi-Objective Optimization (MOO), and immersive technologies to enhance decision-making in architectural workflows. The findings presented here exemplify DIDO's adaptability, demonstrating how it bridges the gap between computational precision and stakeholder engagement in the context of SLP. By leveraging VR as a dynamic platform for interaction with data-driven insights, this research validates DIDO's potential to address diverse architectural challenges, reinforcing its value as a transformative tool for modern design practices.

Limitations

While this research offers valuable insights into VR's role in SLP, caution is needed due to limitations. The study's generalizability is constrained by its small, university-affiliated sample size. Additionally, the experimental design's focus on contrasting 'screen-based' and 'VR-based' interactions, without integrating similar data visualization techniques in both stages, might have influenced the accuracy improvement outcomes.

Variances in VR technology familiarity among participants, coupled with the current technological limitations in simulating complex environments and the economic feasibility of broad VR adoption, present challenges. Furthermore, the potential psychological impacts of prolonged VR use, such as motion sickness or cognitive overload, were not explored.

Future Work

This study's findings and identified limitations present valuable opportunities for further investigation. Notably, the insights into user satisfaction and the efficacy of visualization techniques provide a solid foundation for future inquiries and development.

Future studies can delve into an in-depth examination of user interface enhancements within VR systems that explore alternative design paradigms that prioritize usability and intuitive navigation, potentially leveraging advancements in user experience (UX) research to inform these developments. Given the observed variability in user responses, subsequent research could systematically assess how various presentation styles influence user comprehension and decision accuracy.

Future works can expand on the specific impact of VR immersion on data visualization techniques, aiming to understand how VR influences the adoption of data-driven design methods by providing the same interface for both screen-based and VR interactions, facilitating a comprehensive analysis of the effects of VR on data visualization.

Expanding the scope of VR applications in SLP to include more diverse and complex site conditions could also bring additional insights. Investigating sites with varying levels of topographical heterogeneity might offer a richer understanding of how VR can be optimized to accommodate a broader range of design challenges.

Alternatively broadening participant demographics beyond university-affiliated individuals to include seasoned professionals in the field of urban planning and architecture could enhance the generalizability of the findings. Such studies could also benefit from incorporating real-world SLP projects, enhance realism in VR simulations, and evaluate the economic and psychological aspects of VR implementation in SLP to assess the practical applicability of VR-enhanced methodologies.

Lastly, exploring the integration of other forms of Extended reality (ER) like mixed reality (MR) and augmented reality (AR) technologies in the context of SLP could offer novel insights into the future of immersive design practices. These technologies could further bridge the gap between heuristic approaches and data-driven optimization methodologies, offering new dimensions of interaction and visualization.

Conclusion

The integration of VR into SLP represents a promising avenue for advancing data-driven design methodologies. VR's unique ability to transform abstract data into accessible and actionable insights offers new perspectives on design optimization, bridging computational precision with human intuition. By building on the principles of the DIDO framework, this research underscores the potential for immersive visualization technologies to revolutionize the DBD process and enhance human-machine collaboration. Future research will continue to refine these techniques, unlocking VR's transformative power in architecture and urban planning.

Chapter 5

Implementation of VR and Computer Vision-Based Facade Complexity Analysis

To demonstrate the flexibility and adaptability of the 'Data-Driven Immersive Design Optimization' (DIDO) framework, this chapter transitions its application from Site Layout Planning (SLP) to facade design, specifically through facade complexity analysis. By addressing a distinct yet complementary aspect of architectural workflows, this shift underscores the DIDO framework's ability to tackle diverse challenges in design optimization. This chapter introduces the development of a Computational Image Complexity Analysis (CICA) system, which integrates Virtual Reality (VR) and Computer Vision (CV) technologies to quantify facade complexity, by implementing the DIDO framework process. The goal is to create a robust scoring system that guides facade design while aligning with user perceptions. Central to this investigation is the question of whether a VR and CV-based approach can effectively measure facade complexity in a manner that resonates with stakeholder preferences. In controlled experiments, the CICA system revealed an average standard deviation of 9% between its complexity scores and participant preferences, demonstrating both accuracy and reliability in predicting user responses. The findings indicate a notable preference for moderate complexity in facade designs. Expanding this analysis to urban streetscapes across five cities further highlighted patterns of facade complexity influenced by cultural and architectural diversity. These results validate the versatility of the DIDO framework, illustrating how computational precision and immersive visualization tools can bridge the gap between data-driven insights and stakeholder engagement. Moreover, this chapter advances architectural design theory by integrating quantitative CV-based metrics with qualitative user feedback. It highlights how facade complexity, shaped by historical and cultural contexts, can be assessed to inform sustainable and user-centered urban design. Participants' preferences for moderate complexity (mean CICA score of 4.05) suggest emerging trends that favor designs balancing intricacy and simplicity. Contextual factors, such as views and privacy, also play a significant role in shaping perceptions. By synthesizing these insights, the CICA system acts as a case study demonstrating the DIDO framework's validity as an architectural design process. It highlights DIDO's potential as a transformative method, capable of enhancing both the aesthetic and functional dimensions of modern architectural workflows.

5.1 Introduction

Recent advancements in Building Information Modeling (BIM) and digital fabrication are transforming architectural practice. These technologies enable architects to design intricate and complex forms, moving beyond the uniformity of barren walls and fully glazed facades that often dominate contemporary streetscapes. By leveraging these advancements, architects can introduce complexity and detail into their designs, enhancing both the visual and functional aspects of buildings, and creating more engaging and dynamic environments that potentially redefine the relationship between form and function [57].

Understanding facade complexity is crucial, as facades are the most visible part of a building and significantly impact urban aesthetics and user perception. Designs that balance simplicity and complexity can create environments that are visually stimulating, functional, and comfortable for occupants [58]. Additionally, facades contribute to energy efficiency and material optimization, particularly when combined with advanced technologies like digital fabrication and parametric design.

However, the pursuit of complexity in architectural design must be balanced with sustainability and user satisfaction. Overly complex designs, when not thoughtfully integrated, can quickly become obsolete, leading to construction waste, a significant contributor to carbon emissions [59]. By optimizing and controlling facade complexity, architects can create visually engaging designs that are adaptable, long-lasting, and reduce the need for frequent renovations and replacements.

Previous research has explored the mathematical relationships between complexity and aesthetic value [60, 61, 62]. Despite these insights, the architectural field has yet to develop frameworks that leverage these principles for practical design applications, especially considering modern technological advancements such as digital fabrication and parametric design. These technologies not only enable the creation of complex forms but, when paired with Data-driven Building Design (DBD) optimization, support energy efficiency, material reduction, and sustainability.

This study aims to bridge the gap between theory and practice by developing a methodology to measure facade complexity. The goal is to generate data that enhances DBD through a complexity scoring function, helping to find the optimal balance between simplicity and complexity based on historical analysis and user preferences. By integrating these insights with modern technologies, we seek to provide actionable, data-driven recommendations for sustainable architectural practices.

We hypothesize that by analyzing facade complexity across time, architectural styles, and real-world urban contexts through a computational model, discernible patterns could emerge. These trends, derived from the analysis of historical data, can then be compared with real-time user perceptions collected via a VR experiment and further validated through an urban streetscape analysis. By aligning modern user preferences, historical patterns, and urban diversity, we aim to validate the model's effectiveness in predicting and assessing facade complexity, offering a comprehensive framework for informed design decisions.

To support this, a comprehensive literature review was conducted, focusing on foundational theories of complexity and the historical evolution of architectural styles. By identifying key trends in complexity over time, we can connect these findings with user perception studies to explore how people today interact with complex facades. Comparing these trends with modern perceptions helps determine whether current preferences align with or diverge from historical patterns. This review established the theoretical basis for developing our methodology, focusing on the relationship between complexity, aesthetic value, and user satisfaction.

Building upon the conclusions drawn from the literature, the methodology of this study is structured around three core components: the development of the 'Complexity Analysis System' using Virtual Reality (VR) and the Computational Image Complexity Analysis (CICA) system, supported by Computer Vision (CV) algorithms, both specifically designed for this research; the 'Experiment Execution,' aimed at assessing user perceptions of facade complexity; and a rigorous 'Data Analysis' phase to validate the system's effectiveness (see Figure 5.1). Together, these components create a comprehensive framework for understanding the influence of complexity on architectural design and user satisfaction, through historical analysis of an image database, real-time evaluations in virtual environments, and comparative analysis of urban streetscapes.

This study proposes a system to measure and adjust facade complexity, which could be integrated with tools for energy efficiency, material optimization, and environmental comfort. Such an

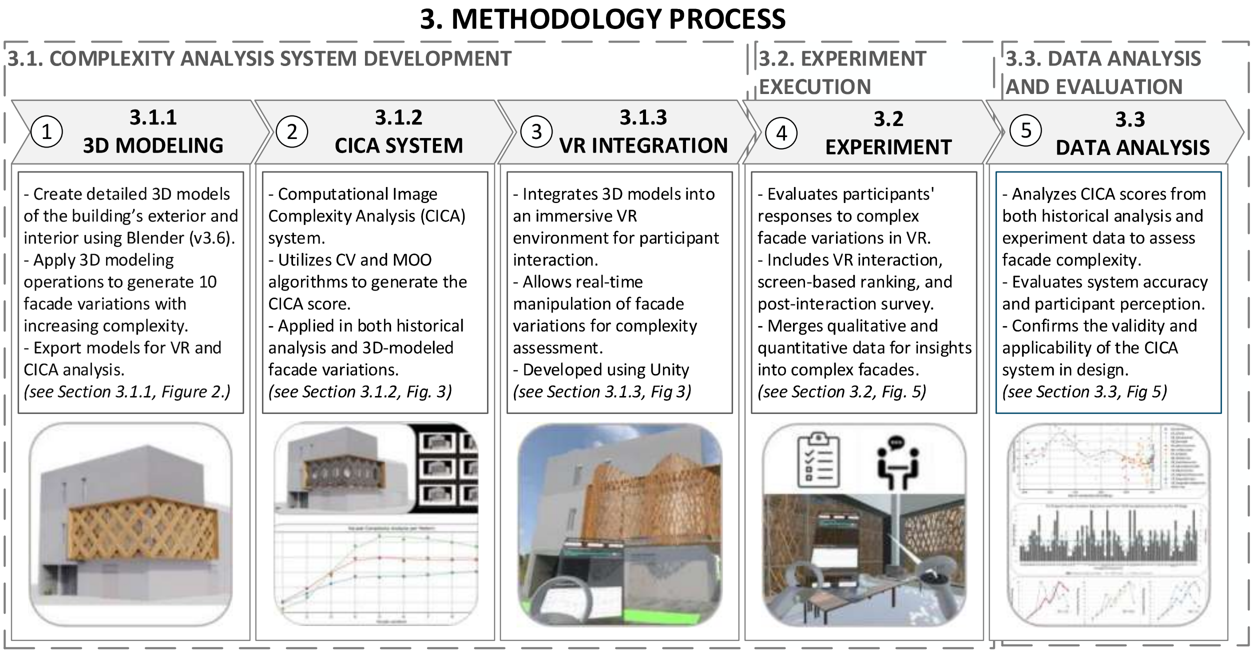


FIGURE 5.1: Methodology Process Flowchart: It highlights the three main components: 'Complexity Analysis System Development' (Section 5.3.1), 'Experiment Execution' (Section 5.3.2), and 'Data Analysis and Validation' (Section 5.3.3). (see Detailed version of this process in Figure 5.5).

approach addresses sustainability challenges while minimizing environmental impact, emphasizing the importance of balancing complexity with long-term adaptability and user satisfaction in modern architectural practices. This comprehensive approach aims to enrich our understanding of facade complexity and its role in the contemporary Architectural, Engineering, and Construction (AEC) industry.

The development of the CICA system and its integration into these analyses are underpinned by the Data-Driven Immersive Design Optimization (DIDO) framework. DIDO's adaptability is demonstrated through its transition from Site Layout Planning (SLP) to facade complexity analysis, showcasing its ability to address distinct architectural challenges while maintaining computational precision and stakeholder engagement.

5.2 Literature review

This section delves into the multifaceted nature of architectural complexity, examining its historical evolution and the theoretical foundations that underpin contemporary architectural practices. It aims to provide a comprehensive understanding of how complexity influences both design practices and user experiences. The literature review is organized into two key themes:

- *Evolution of Architectural Styles:* focusing on the historical transitions between simplicity and complexity in architecture, highlighting significant shifts across different periods.
- *Theoretical Foundations of Architectural Complexity:* exploring foundational theories and previous research surrounding complexity in architecture, offering insights into how these theories inform current design practices.

By linking historical analysis, and complexity theories with user perception studies, this review provides a framework for understanding how past architectural trends in complexity influence modern user preferences, allowing us to explore whether contemporary design trends align

FIGURE 5.2: Early timeline. Sequential representation of architectural styles illustrating the shift between complexity and simplicity. From left to right: Romanesque[a] with its solid and massive structure; Gothic[b] featuring verticality and lightness; Classicism[c] characterized by geometrical clarity and order; Baroque[d] with dynamic shapes and rich decorations; followed by the restrained and symmetrical formality of Neo-classicism[e]. (*Images edited from source*)

with these historical patterns. These insights are crucial for validating the CICA findings by comparing empirical data with theoretical perspectives on architectural evolution, thereby confirming observed patterns of simplicity and complexity.

5.2.1 Evolution of Architectural Styles: Oscillations Between Simplicity and Complexity

Architecture stands as a unique art form, transforming the ordinary into the extraordinary while fulfilling functional purposes [63]. Its evolution is characterized by the integration of technologies and information flows, which shape the complexity and functionality of urban environments, reflecting contemporary societal values and technological advancements [64] From early architectural styles like Romanesque, characterized by robust and simplistic forms, to the Gothic period with its intricate, skyward designs, shifts in architectural complexity have often mirrored technological and cultural advancements(see Figure 5.2). Gothic architecture, for example, was made possible by structural innovations like the pointed arch and flying buttress, allowing for taller, more ornate buildings that resonated with the spiritual aspirations of the era [65].

The Renaissance heralded a revival of Greek and Roman ideals, driven by humanism and the desire to return to perceived cultural greatness, with a focus on symmetry and proportion. The Baroque period of the 16th century introduced lavish ornamentation and dynamic designs, reflecting the opulence and power of the ruling classes [66]. This move toward complexity was largely influenced by societal shifts towards theatricality and grandeur in both religious and political architecture.

The Neoclassical style, dominant in the 18th and 19th centuries, emphasized symmetry and classical principles, while integrating new technologies like reinforced concrete, which allowed for larger and more functional designs without sacrificing aesthetic form [67]. This balance between the old and the new was a response to Enlightenment ideals of order and rationality.

At the turn of the 20th century, Art Nouveau and Art Deco embraced nature and new materials, with Art Nouveau focusing on organic forms and Art Deco celebrating the technological advancements of the machine age [68] (see Figure 5.3). These movements marked a departure from Neoclassical restraint, as societies began to celebrate the possibilities of industrialization and mass production.

The 20th century saw the rise of Modern Architecture, which advocated for 'form follows function' and minimal ornamentation [57], reflecting the need for functional, cost-effective buildings during the industrial age. Figures like Adolf Loos and Le Corbusier championed minimalism, rejecting excessive ornamentation in favor of efficiency, influencing a generation of architects to prioritize structural honesty and simplicity [69]. However, this movement often led to uniform urban landscapes that lacked the cultural richness and diversity of their predecessors. In response

FIGURE 5.3: Transitional timeline. Sequential representation of architectural styles illustrating the shift between complexity and simplicity. From left to right: Art Nouveau[a] with its fluid lines and natural forms; Art Deco[b], marked by bold geometry and opulence; Modernism's[c] pursuit of stripped-back functionality; culminating in Postmodernism's[d] revival of historical styles and complexity (*Images edited from source*)

FIGURE 5.4: Contemporary timeline. Sequential representation of architectural styles illustrating the shift between complexity and simplicity. Era of exploration and innovation. From left to right: Deconstructivism[a], characterized by fragmentation and non-linear design; Neofuturism[b], capturing movement and technology-infused aesthetics; High-tech modernism[c], focusing on visible structural elements and technological expression; Parametricism[d], with its algorithm-based complex forms; and Pragmatic utopianism[e], blending idealistic designs with practical applications (*Images edited from source*)

to Modernism's perceived limitations, the late 1960s saw the emergence of Postmodernism, spearheaded by thinkers like Robert Venturi. Postmodernism critiqued the stark uniformity of Modernism and reintroduced complexity, ornament, and historical references, advocating for buildings that engage more deeply with their cultural and historical contexts [70]. This shift was driven by a desire to create architecture that was not only functional but also meaningful and contextually rich.

The late 20th and early 21st centuries have seen a resurgence in creativity and expression, with architects utilizing digital technologies to explore new realms of complexity and ornamentation [71] (see Figure 5.4). The fusion of digital and physical design processes signals a shift towards the democratization of complex, parametric designs, indicative of a contemporary period that values ornamentation, functionality, and human comfort [72]. This evolving trajectory of architecture suggests a future where design is deeply intertwined with societal values and technological possibilities.

Facades and ornamentation, in this context, become critical in conveying these narratives, bridging the gap between the aesthetic and the symbolic, and establishing the interface between buildings and their environments, influencing both aesthetic perception and functionality. As buildings became more energy-conscious, facade design also shifted to balance aesthetic appeal with environmental performance, such as optimizing natural light and improving energy efficiency while reflecting the building's identity [73]. The evolution of facade design and ornamentation not only reflect societal transformations, technological progress, and shifts in artistic sensibilities, but also highlight the changing cultural values toward sustainability and user comfort, each impacting how communities relate to their built environment.

In conclusion, the historical context of architectural complexity reveals a rich tapestry of styles and philosophies, from ancient grandiosity to modern minimalism and contemporary innovation. These shifts reflect the ongoing dialogue between simplicity and complexity, tradition and innovation, and functionality and aesthetics, shaping the built environment in ways that are both imaginative and responsive to societal needs.

5.2.2 Theoretical Foundations of Architectural Complexity

Previous research has extensively explored the impact of complexity in architectural design, showing that elements such as chaotic patterns and fractal geometry significantly influence user perceptions and aesthetic preferences [60]. Contemporary studies suggest that balanced complexity can create environments that are both stimulating and comfortable [62]. However, the architectural field has yet to fully develop frameworks that leverage these principles for practical design applications, particularly with modern technological advancements.

A foundational theoretical contribution to understanding architectural complexity is George David Birkhoff's theory of aesthetic measure, introduced in 1933. Birkhoff proposed that aesthetic value could be quantified through a ratio of order to complexity, expressed as $M = O/C$ (where M is the aesthetic measure, O is order, and C is complexity)[61].

This balance is central to contemporary efforts to integrate complexity into architectural design, enhancing both user satisfaction and sustainability. This theory offered architects a novel way to think about design as a balance between simplicity and ornamentation, reflecting the need for structure in increasingly complex designs. Although this framework has limitations in its applicability to modern technological contexts, it remains a cornerstone for evaluating the aesthetic appeal of architectural forms and guiding the integration of complexity into functional design[74].

Alexander et al. 's concept of 'pattern language,' introduced in the 1970s, emphasizes the importance of recurring design patterns that resonate fundamentally with human users [75]. This theory emerged in response to the chaotic urban developments of the mid-20th century, seeking to find a harmonious balance in the built environment. By focusing on universal patterns that align with human perception, Alexander laid the groundwork for biophilic design principles, which emphasize the integration of natural elements into architectural spaces to enhance human well-being [76].

Browning et al. (2014) extended this research in facade design by emphasizing the importance of balancing complexity and order in architectural design and demonstrating the importance of fractal geometries in creating environments that are visually engaging yet stress-reducing. Their studies found that specific fractal dimensions (D=1.3-1.8), found in nature, art, and architecture, are preferred by users for their ability to convey order and intrigue [58]. However, they caution against the extremes of non-fractal or overly complex designs, which can induce stress or discomfort. This work offers practical guidance for architects seeking to incorporate complexity in a way that promotes psychological and cognitive well-being.

A more recent method by Lee et al. (2023) uses fractal dimension analysis to measure the visual complexity of architectural facades, which is crucial for assessing aesthetic character and predicting attractiveness. They utilized the differential box counting method, which is better suited for handling greyscale images, to calculate fractal dimensions based on grey-level variations. These fractal dimension values are then used to predict human visual preferences, providing a reliable measure of visual complexity in architectural design [77]. Their method provides an objective, computational approach to understanding the aesthetic impact of complex forms, particularly useful in the context of digital fabrication and parametric design. Lee et al. concluded that computational measures of visual complexity (fractal dimensions) and attractive strength (visual attention simulation) can effectively quantify the visual attractiveness of architectural facades. Their findings indicate that these measures can distinguish different architectural styles, despite some limitations. Importantly, they found that visual complexity (D) and attractive strength (S) are not mathematically correlated, suggesting that engagement and appeal may be independent qualities. By predicting human visual preferences, Lee's work offers architects a tool for refining facade complexity in real-time design scenarios. Though their proposed model for predicting visual attractiveness, A = D × S, will require further validation [77].

Contemporary research continues to build on these theoretical foundations, exploring how advanced technologies like BIM and computational design methods can be used to create complex designs that are not only aesthetically but functionally effective,optimized for performance and sustainability [57]. While these tools allow architects to push boundaries, the principles established by earlier theories remain relevant in guiding the balance between complexity and usability.

In summary, the evolution of architectural complexity reflects an ongoing interplay between cultural, technological, and theoretical influences. From ancient grandiosity to modern minimalism and contemporary innovation, architects have continually sought to balance order and complexity to create meaningful and engaging built environments.

Theoretical frameworks such as Birkhoff's aesthetic measure, Alexander's pattern language, and Lee et al.'s fractal dimension analysis provide valuable insights into how complexity can be harnessed to enhance architectural design. However, these theories must now be adapted to incorporate the dynamic capabilities of modern tools, offering architects the ability to interact with complexity in real-time.

Despite these advancements, a notable gap remains in translating theoretical insights into interactive design tools that respond dynamically to user feedback. Current methodologies often lack the ability to provide real-time evaluations of facade complexity, limiting their relevance in contemporary, fast-paced design environments. Real-time interaction enables architects and designers to assess complexity dynamically, making adjustments during the design process rather than relying solely on post-design evaluations [78]. This capability is particularly valuable in environments where client preferences and functional requirements frequently shift. Immediate feedback on the impact of complexity on both aesthetic and functional outcomes leads to more informed decision-making and optimized designs.

While tools like Shared Realities [78] demonstrated the potential of integrating real-time feedback into the design process, they remain limited in scope. These tools often fall short of fully integrating environmental factors or the full complexity of design feedback into decision-making workflows, highlighting the need for more comprehensive, real-time responsive systems.

My research aims to bridge this gap by providing a more integrated, real-time approach to facade complexity analysis. By developing a comprehensive system that combines immersive VR experiences with CV algorithms embedded in the CICA system this study offers a solution that allows architects to quantify facade complexity in an interactive and dynamic manner. Unlike existing tools, this system not only evaluates complexity but also incorporates real-time user feedback, enabling designers to optimize complexity levels while accounting for both aesthetic and functional considerations. In doing so, this research pushes the boundaries of interactive design by offering architects the ability to make informed, data-driven decisions that respond to shifting user preferences and contemporary architectural practices.

5.3 Methodology

The methodology of this study, comprises three main components (subdivided into 5 key steps, as illustrated in Figure 5.1):

1. *Complexity Analysis System Development:* Outlined in Section 5.3.1 (Figure 5.1, element 3.1), this component integrates a VR framework with the CICA system. The CICA system uses CV algorithms to quantitatively assess facade design complexity, applied to both contemporary 3D-modeled facades and historical analysis. The VR component allows real-time participant interaction with facade variations, combining 3D models and CICA analysis. Key elements include the 3D modeling process (Section 5.3.1, Figure 5.6), the CICA system (Section 5.3.1, Figure 5.7), and VR integration (Section 5.3.1, Figure 5.7).

2. *Experiment Execution:* Detailed in Section 5.3.2 (Figure 5.1, element 3.2), this phase involves participants engaging with the 'Complexity Analysis' system through three stages: 'VR Interaction' Stage, 'Screen-Based Ranking' Stage, and 'Post-Experiment Survey'. This process combines quantitative CICA scores and qualitative user feedback.

3. *Data Analysis and Validation:* Detailed in Section 5.3.3 (Figure 5.1, element 3.3), this final component analyzes both CICA scores and experiment data to validate the system's effectiveness in measuring complexity and user preferences. Statistical tools are used to evaluate the alignment between CICA scores and user perceptions. The system's accuracy and its application to historical and contemporary facades are assessed through detailed complexity analysis, providing insights for architectural design practices.

With the methodology outlined, we now move forward to a comprehensive breakdown of each component.

5.3.1 Complexity Analysis System Development

The 'Complexity Analysis' system addresses the challenge of quantifying complexity in architectural facade design, playing a pivotal role in our study. To achieve this, we developed a process that integrates immersive VR experiences with CV algorithms embedded in the CICA system (see Figure 5.1, element 3.1). This approach enables real-time interaction with various facade designs while providing complexity data, offering comprehensive insights into the aesthetic and practical implications of architectural complexity.

The system comprises three integral components: '*3D Modeling and Environment Setup*', '*CICA System*', and '*VR Integration and Simulation Tools*'. These components are illustrated in Figure 5.1 (labeled 1 to 3) and are detailed in the following sections.

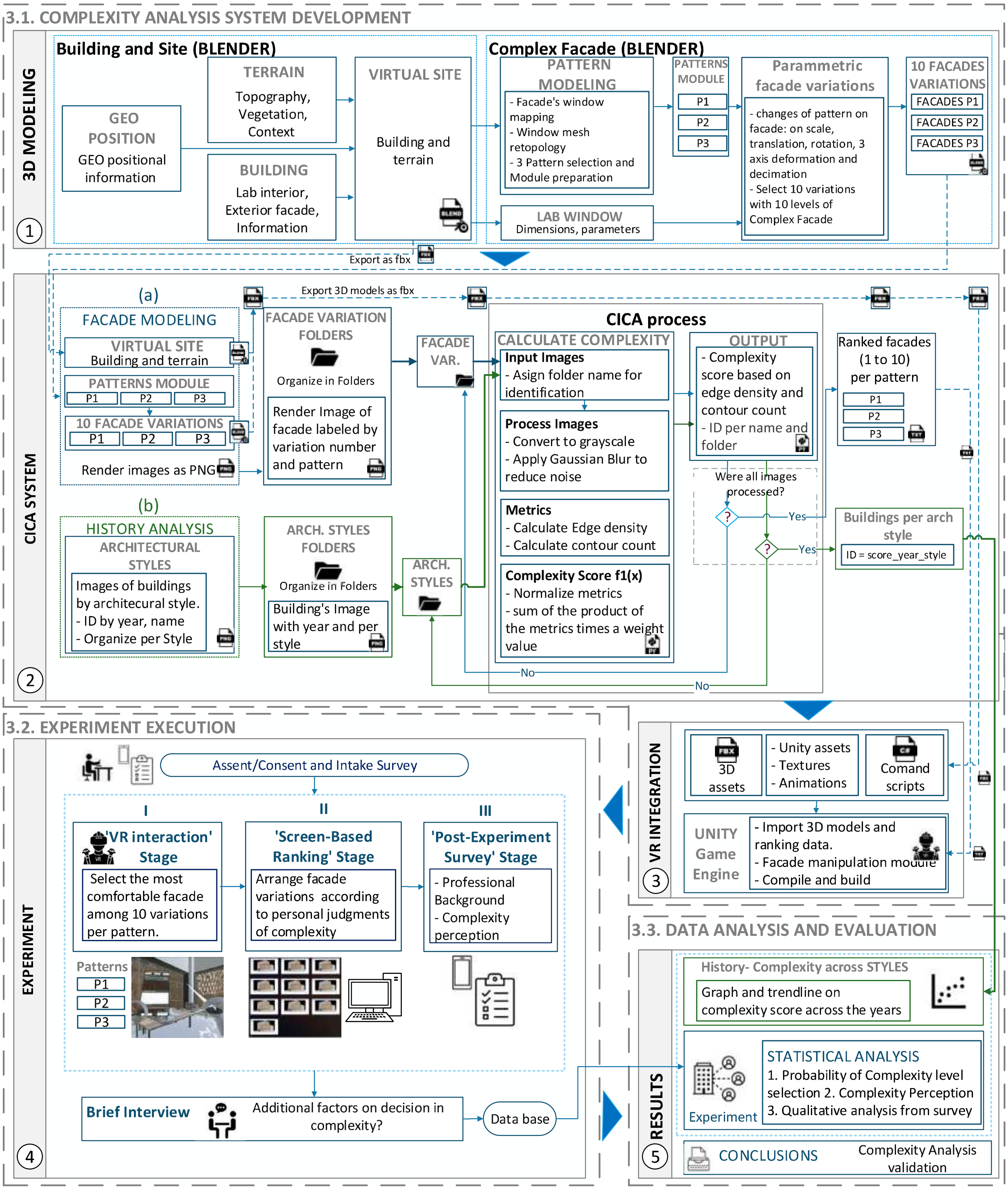


FIGURE 5.5: Detailed Unified Methodology Process Flowchart: illustrating the sequential steps of this study's approach framework designed to assess the quantification of complexity in building design and the perception of occupants in complex environemnts. It showcases the 3 main components of the methodology 'Complexity Analysis System Development'(detailed in Section 5.3.1, 'Experiment Execution' (detailed in Section 5.3.2), and 'Data Analysis and Validadtion' (detailed in Section 5.3.3).

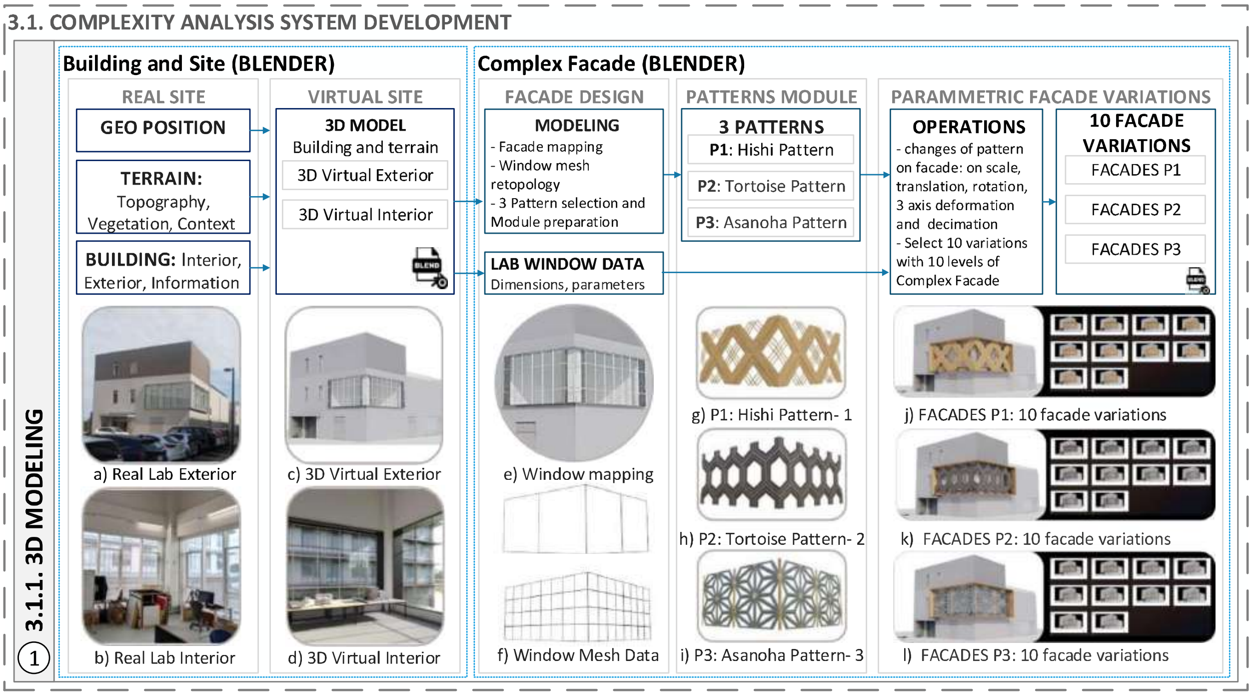


FIGURE 5.6: 3D Modeling Flowchart: This flowchart shows the process of creating a 3D model of the Architectural Environment Research Building and its facade variations in Blender (v3.6) (Section 5.3.1). The process covers geolocation, terrain modeling, and virtual replication of both exterior and interior (a-d). Facade complexity is generated through parametric operations applied to three patterns—Hishi (g), Tortoise (h), and Asanoha (i)—resulting in 10 variations per pattern (j-l), showing increasing complexity. These models are integrated into the VR environment and the CICA system for complexity assessment (Detailed record of all variations in Tables 5.1 and 5.2).

3D Modeling and Environment setup

To achieve realistic VR experiences for assessing user responses to facade complexity, a building site and facade variations were 3D modeled using Blender (v3.6). Blender was selected for its advanced rendering capabilities, support for parametric and generative design, and seamless Python integration, necessary for integrating it with the CICA and VR components of the 'Complexity Analysis' system.

The 'building site' used for this study is a detailed virtual replica of the Architectural Environment Research Building at Kyushu University, Fukuoka-Japan, including both exterior and interior elements of the existing building (Figure 5.6, elements [a] to [d]). This building was chosen because it is the location where this study takes place, contributing significantly to the sense of immersion for participants during the experiment.

To test the response of occupants to various degrees of complexity, ten facade variations across three different patterns were 3D modeled and strategically placed over the large windows of the 'building site' for maximum visual impact (see Figure 5.6, element [e] to [j]).

These patterns were selected to reflect a range of design approaches commonly seen in contemporary architecture—from minimalist to highly intricate facades reminiscent of Parametricism and Pragmatic Utopianism— representing current trends in modularity, geometric intricacy, and parametric design [57]. This ensures that the study captures a broad spectrum of facade styles relevant to contemporary architectural practices (see Figure 5.4 [d-e]).

The complexity of each facade variation was systematically increased by applying 3D modeling operations, from simple subdivisions to more advanced modifications such as rotations and decimation. These operations simulate different levels of geometric intricacy that are reflective of real-world facade design challenges, such as material usage, constructability, and cost (Figure 5.6

(element [j] to [l])and further detailed in Tables 5.1 and 5.2). Facades with higher mesh complexity represent designs that may demand more resources and construction time, making this aspect crucial for evaluating both aesthetic appeal and practical feasibility. By varying the complexity levels, the study provides insight into how architectural complexity influences user perception and decision-making in facade design.

Each facade variation is rendered and labeled for use in the CICA complexity analysis, ensuring control over complexity variability. This setup, provides a comprehensive environment for analyzing the accuracy of the 'Complexity Analysis' system and investigating user perception.

TABLE 5.1: Patterns variations for the First five levels of complexity

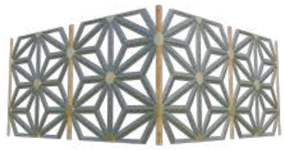
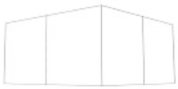
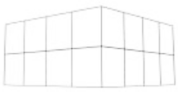
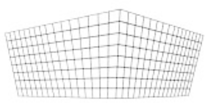
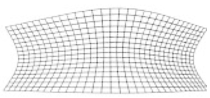
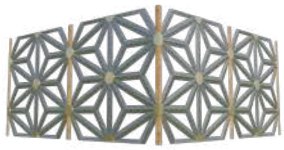
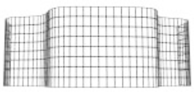
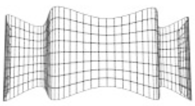
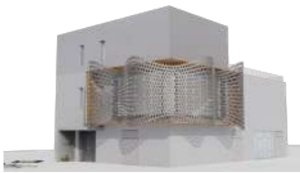
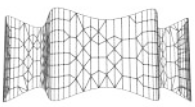
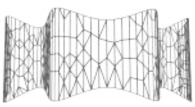
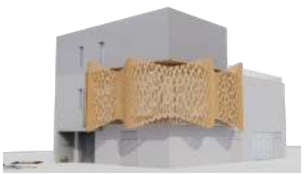
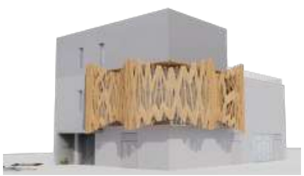
Description	*Pattern 1*	*Pattern 2*	*Pattern 3*
Pattern Name	Hishi Pattern	Tortoise shells	Asanoha Pattern
Base Module 			
Mesh complexity Level	*Pattern 1*	*Pattern 2*	*Pattern 3*
Level 1 			
Level 2 			
Level 3 			
Level 4 			
Level 5 			

TABLE 5.2: Patterns variations for the last five levels of complexity

Description	*Pattern 1*	*Pattern 2*	*Pattern 3*
Pattern Name	Hishi Pattern	Tortoise shells	Asanoha Pattern
Base Module 			
Mesh complexity Level	*Pattern 1*	*Pattern 2*	*Pattern 3*
Level 6 			
Level 7 			
Level 8 			
Level 9 			
Level 10 			

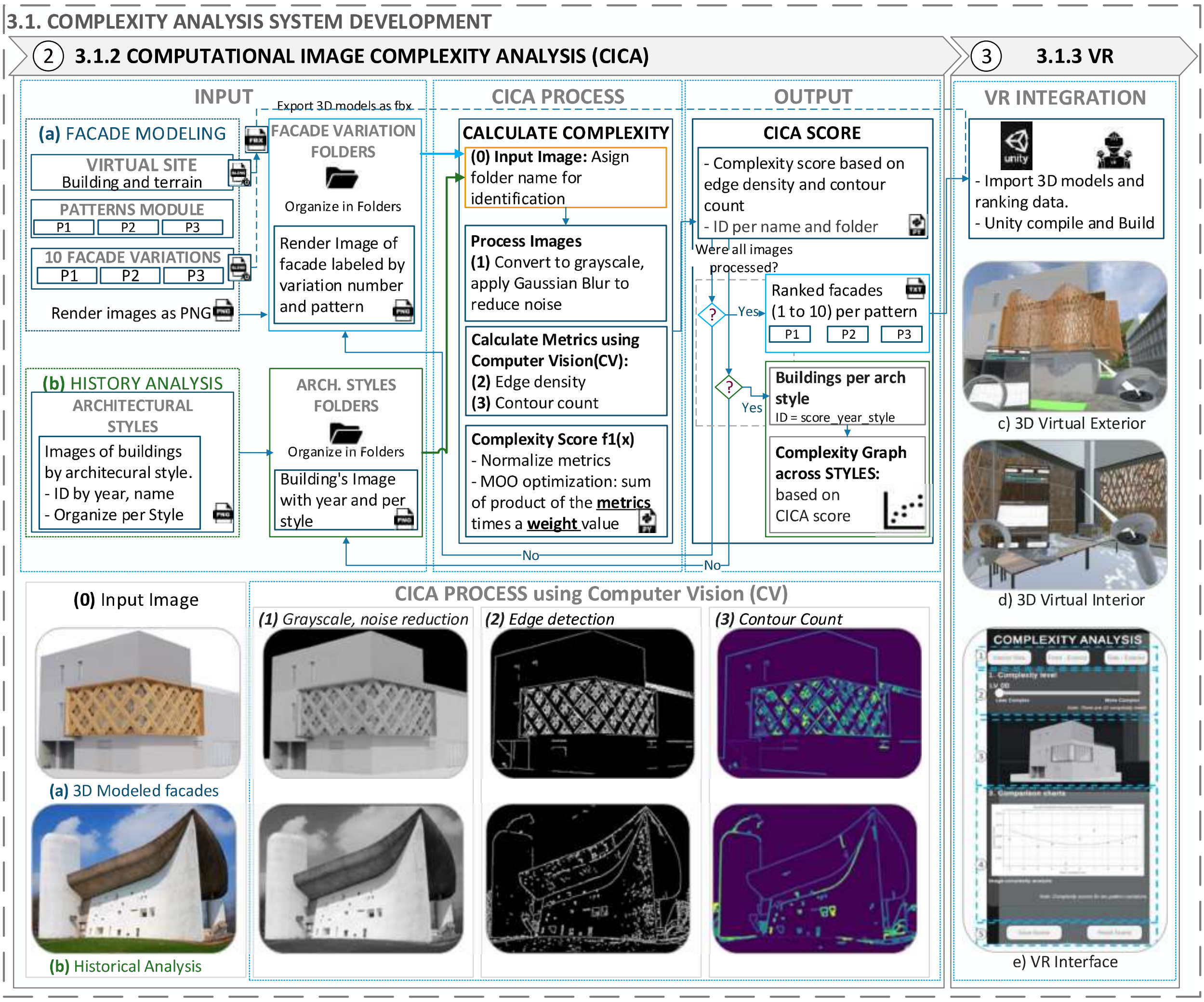


FIGURE 5.7: CICA System and VR Integration Flowchart illustrating the CICA process (element 2) and its integration into the Virtual Reality (VR) system (element 3). The CICA system, applied to 3D-modeled facades (a) and historical architectural styles (b), generates complexity scores through image processing steps: noise reduction (1), edge detection (2), and contour count analysis (3). The VR integration (Section 5.3.1) showcases 3D model views used in the immersive VR environment, including exterior (c), interior (d), and interface (e), demonstrating the combined functionality of CICA and VR for facade complexity assessment. Variations are detailed in Tables 5.1 and 5.2.

CICA System

The literature review in Section 5.2 revealed a cyclical nature in architectural evolution, alternating between complex and simple styles. Our initial goal for the CICA system is to empirically validate these trends by developing a quantifiable scoring system capable of evaluating the complexity of historical and 3D-modeled building facades (Figure 5.1, element 2).

Implemented as a Python script, the CICA system leverages Python's compatibility with Blender and its robust CV libraries, facilitating the integration of 3D models with complexity analysis scripts. Inspired by Venturi et al.'s perspective on complexity [79], the CICA system measures complexity by the mental processing time required for a building's elements.

It uses two primary metrics: edge density and contour count, selected for their relevance to human vision's edge and object contour detection [37].

Edge Density: Utilizing the Canny Edge Detection algorithm [80], this metric focuses on edge presence and density, defining architectural boundaries (Figure 5.7, element [(2)]).

TABLE 5.3: Table of Metrics and Weights for Complexity Scoring: Outlines the key criteria and corresponding weights utilized in the CICA system to determine the 'Complexity Score' of architectural facades, detailing the systematic approach to quantifying facade intricacy through edge density and contour count metrics, chosen for the critical role these metrics play in human visual perception [37]. Please refer to Section 5.3.1 for further details.

Table of Metrics and Weights for CICA Complexity Scoring on Architectural Facades				
Complexity metric	*N*	*Metric name/description*	*Quantitative method*	*Weights*
Edge Density	1	Edge detection using Canny Edge Detection algorithm for highlighting the most relevant features of a building.	Measured by dividing the number of non-zero (edge) pixels in the edges image by the total number of pixels in the image.	8
Contour count	2	Employs contour approximation algorithm for shape analysis to determine intricacy of edges.	Measure by counting the number of segments in an edge.	2
		TOTAL		**10**

Contour Count: Using contour approximation techniques [81], this metric assesses shape intricacies outlined by edges (Figure 5.7, element [(3)]).

Both metrics are essential for shaping perceived complexity and are computationally efficient for large datasets [37].

Given that both edge density and contour count metrics play critical roles in shaping perceived complexity, determining how to balance these two factors is key to assessing facade complexity. However, these metrics often have conflicting influences on the final design. For instance, increasing edge density might improve the clarity of structural boundaries but could overwhelm the overall aesthetic if not paired with appropriate contour complexity. To handle this trade-off, we used a Multi-Objective Optimization (MOO) approach.

The MOO algorithm allows us to balance these competing metrics, optimizing the trade-off between edge density and contour count. Research shows that the human eye prioritizes edge detection over contour recognition when processing visual stimuli [37]. Edge detection is more directly related to the perception of form and structure, providing a clearer representation of boundaries and spatial relationships, whereas contour count provides more nuanced, secondary information regarding shape intricacies. Given this, we assigned a higher weight (8) to edge density and a lower weight (2) to contour count, reflecting their relative importance in visual complexity perception [37] (see Table 5.3). To implement this, we applied the Analytic Hierarchy Process (AHP), a robust Multi-Criteria Decision-Making (MCDM) technique for detailed analysis and prioritization based on expert input and quantitative data [21]. AHP ensures that the weights reflect the significance of both edge density and contour count in terms of human perception and aesthetic appeal.

By assigning these weights and integrating MOO within the CICA system, we ensure that the complexity score reflects an optimal balance of the metrics, thereby offering a more holistic and nuanced measure of facade complexity. This optimization aligns with the study's goals of balancing aesthetic and functional considerations while accounting for human perception.

The MOO algorithm is represented in the 'Complexity Score' function $f_1(x)$, defined in Equation 5.1, which normalizes the metrics and combines them into a 'Unified Complexity Score':

$$f_1(x) = \text{round}\left(\sum_{i=1}^{n} w_i \cdot a_i, 2\right) = \text{complexity\_score} \tag{5.1}$$

where n is the number of performance indicators, w_i is the weight of the i-th element, and a_i is the normalized score for the i-th metric (e.g., 'Edge Density' and 'Contour Count'). This weighted sum provides the overall complexity score or 'CICA score' a quantifiable measure of facade complexity, crucial for the CICA system.

The CICA system has three main applications:

- *Historical Analysis:* Evaluates over 180 buildings from various architectural eras, creating a scatter graph of complexity scores organized by year and architecture style, showing complexity trends over time (Figure 5.7[b]). Results are presented in Section 5.4.1. Buildings were selected based on their significance in architectural history, with priority given to iconic or influential structures frequently cited in architectural discourse. Selection criteria included high-resolution images of the main facade, with minimal visual obstructions, captured from a frontal angle for consistency. Images were chosen under optimal lighting conditions to avoid distortion of architectural features. Only well-documented and widely recognized buildings were included to ensure the dataset's representativeness. Each building was represented by a single image to standardize the analysis, as multiple perspectives could introduce variability in complexity scores.

- *3D-Modeled Facades Analysis:* Analyzes 10 facade variations across 3 patterns of 3D-modeled facades with varying complexity for the VR experiment (Figure 5.7[a]). The CICA scores are used for comparison with user perceptions (Figure 5.8). Results, are presented in Section 5.4.2.

- *Urban Streetscape Analysis:* Evaluates 50 building facades across major streets in 5 cities—Barcelona, Budapest, Florence, Fukuoka, and Paris—to validate the CICA complexity score in real-world contexts. This application highlights the system's sensitivity to cultural and architectural diversity by analyzing consecutive facades along streetscapes. Selection criteria prioritized buildings with clear visibility and minimal obstructions.For each facade, CICA scores are calculated by averaging results from three perspectives—left, front, and right—captured using Google Earth imagery to ensure consistency. Results, presented in Section 5.4.4, emphasize how facade complexity reflects urban identity and cultural influences.

Through these applications, the CICA system aims to validate architectural complexity trends empirically, prepare for experiments assessing user perceptions of facade complexity, and demonstrate its robustness across historical, experimental, and real-world urban contexts.

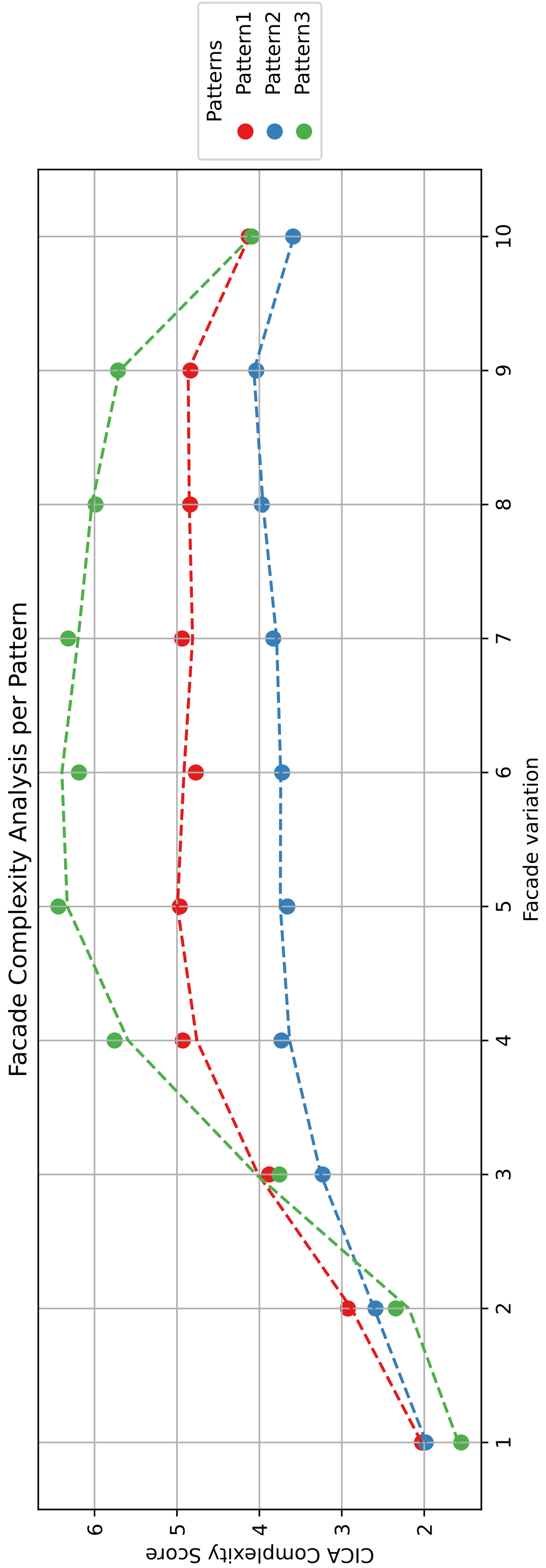


FIGURE 5.8: Scatter Graph Analysis of 3D Modeled Facade Complexity: This graph presents the CICA scores for ten variations of three distinct patterns created in Blender, with a trendline indicating the range of complexity levels among the facade designs, illustrating the nuanced relationship between design intricacy and CICA scores.

FIGURE 5.9: VR simulations of the building's exterior (left) and interior (right) as experienced during the facade complexity analysis, illustrating the transitions through various facade variations across all three patterns.

VR integration and simulation tools

The goal of this component is to integrate the virtual environment from the '3D Modeling and Environment Setup' with data from the CICA complexity analysis (Figure 5.9). This module features an immersive 'VR simulation' and a 'data visualization interface' that allows users to explore and interact with the building's interior and exterior, visualize its context, and manipulate facade variations (Figure 5.7, element 3).

The 'VR simulation,' was developed using Unity (v.2022.2.21f1) and accessible through a Head-Mounted Display (HMD), Oculus Quest 2. This software was chosen for its robust VR support, pre-built templates, and seamless integration with Python and C#, enhancing simulation interactivity and data handling.

The VR data visualization interface provides real-time feedback on facade variations, facilitating data collection on user response to varying levels of facade complexity. Structured into five key sections—Viewpoint Navigation, Facade Variation Slider, Facade Render Preview, CICA Scores Comparative Analysis Charts, and Utility Functionss (Figure 5.7, [e])—it enhances usability and interpretability, thereby optimizing the facade selection process.

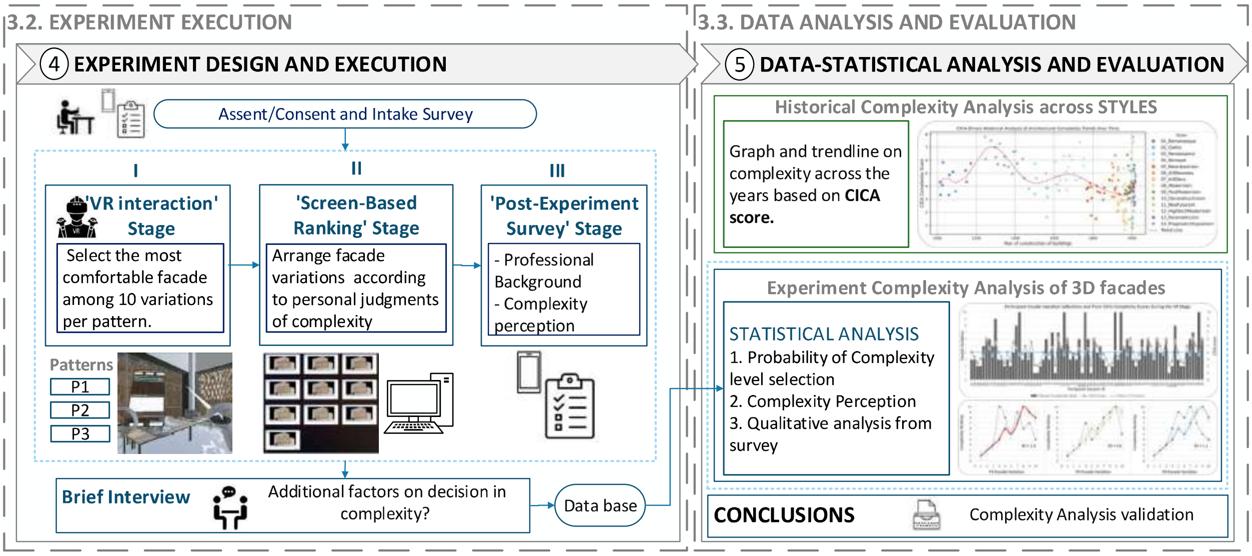


FIGURE 5.10: 'Experiment Execution' and 'Data Analysis' Flowchart: This flowchart illustrates the experiment design and transition to the 'Data Analysis and Validation' phase. It outlines the VR Interaction Stage (I), Screen-Based Ranking Stage (II), and Post-Experiment Survey (III) (Section 5.3.2). The 'Data-Statistical Analysis and Evaluation' phase highlights historical complexity analysis across styles and statistical analysis of experiment data, leading to the validation of the Complexity Analysis system (Section 5.3.3).

5.3.2 Experiment Execution

The experiment assesses participants' reactions to complex facade variations in VR, using CICA-derived complexity data (element 3.2 in Figure 5.10) and gathers their impression regarding evaluating facade complexity. The participant pool consisted of 26 individuals, comprising 13 males and 13 females, aged between 18 and 31. A majority were university students, with varied backgrounds including construction and facade design. These demographic factors are revisited in the discussion and limitations sections to assess generalizability.

The experiment consists of three stages:

1. *'VR interaction' stage:* as illustrated in the flowchart in Figure 5.10 (element I), participants engage with a VR simulation of the actual laboratory and building where the experiment takes place (see Figure 5.7, element 3). They select preferred facade variations from three patterns, each with ten complexity-labeled variations and data visualization of their CICA complexity score, considering the scenario as their permanent workplace or study location. Patterns' variations are presented in randomized order to ensure unbiased results, accessible through the VR interface.

2. *'Screen-based Ranking' Stage:* As depicted in the flowchart in Figure 5.10 (element II), participants rank the same 10 facade variations based on their perception of complexity via a screen-based interface without CICA system data. This is conducted for each of the three patterns to refine the CICA system's complexity analysis capabilities.

3. *'Post-interaction' Survey:* As shown in the flowchart in Figure 5.10 (element III), after completing the first two stages, participants answer a 15-question survey divided into Participant Background (Figures 5.12 5.13) and Complexity Perception sections(Figures 5.18 5.19), exploring qualitative perceptions of complexity and the factors influencing their choices. This section uses a 7-point Likert scale for capturing detailed responses.

The combined analysis of these stages provides a comprehensive understanding of how users engage with and perceive facade complexity. By merging quantitative and qualitative findings, we contribute to the discourse on architectural complexity and its impact on contemporary design and construction.

5.3.3 Data Analysis and Validation

The final phase of our methodology focuses on analyzing the data from the implementation of the CICA system to images of historical buildings, to the study the data collected during the experiments, and finally to the comparative analysis of urban streetscapes, aiming to validate the effectiveness of the 'Complexity Analysis' system in quantifying facade complexity and aligning it with user perceptions (see Figure 5.10, element 3.3).

- *Data Processing and Analysis:* We assess CICA scores from historical buildings to identify patterns across different architectural styles, analyze experiment data using statistical tools to understand perceptions of complexity, and evaluate the scores derived from the urban streetscape analysis to validate the system's adaptability to real-world contexts.

- *Performance Evaluation:* The efficacy of the 'Complexity Analysis' system and the CICA score is assessed through:

  - <u>Accuracy Analysis:</u> Evaluating the alignment between CICA scores and user perceptions.
  - <u>Participant Perception:</u> Analyzing user feedback to gain insights into the impact of complex facades.
  - <u>Urban Context Sensitivity:</u> Examining how CICA scores reflect cultural and architectural diversity in urban streetscapes.

- *Results Interpretation and Reporting:* Synthesizing data from historical analysis, user experiments, and urban streetscapes to confirm the validity of the CICA system and its applicability across varied architectural contexts.

While the primary focus of this phase is on validating the CICA system's ability to quantify complexity, the combined analysis of historical architectural trends and real-time user perceptions provides potential insights into future construction trends. The inclusion of the urban streetscape analysis strengthens the validation process by extending the CICA system's application beyond controlled experimental settings to real-world environments. By comparing historical architectural trends, user preferences, and urban streetscape patterns, the CICA system provides a robust framework for understanding and predicting future design shifts.

Additionally, through the system's ability to conduct accuracy analysis, architects could better identify the optimal range of complexity that appeals to users, allowing for the design of facades that align with predicted trends while balancing aesthetic interest and functional sustainability.

Over time, as more data is gathered, the CICA system's predictive capabilities could offer architects valuable foresight into emerging trends in facade design that might become prominent in future construction practices. This structured approach ensures a thorough evaluation, providing insights into the relationship between facade complexity and user perception.

5.4 Results and Discussion

Building upon the methodologies outlined in the previous sections, this section presents findings from three primary sources: the application of the CICA system to a historical dataset of architectural images across various epochs and styles, data collected from the experiment designed to gauge user responses to facade complexity, and a comparative analysis of facade complexity across urban streetscapes in five cities. Organized according to the goals set forth in the introduction, this section elucidates the evolving relationship between users and architectural complexity, providing valuable insights for future construction practices and the quantification of complexity in facade design.

5.4.1 Assessment and Implications of Facade Complexity across Architectural Eras using the CICA System and insights from literature review

While defining architectural complexity is inherently challenging due to its interconnection with various socio-economic and cultural factors influencing urban development, the CICA system was developed on the premise that analyzing a vast and diverse dataset of architectural works from different centuries could reveal patterns validating our hypothesis. This hypothesis, established on the literature review (Section 5.2.1), suggests a cyclical nature in architecture—an ongoing dialogue between simplicity and complexity—with a trend towards increased complexity in contemporary architecture. This trend is evidenced by recent architectural styles , influenced by technological advancements, computer-aided design tools, and a growing focus on sustainability.

CICA System for Quantitative Assessment

To validate this trend objectively, we conducted a quantitative analysis using the CICA system. This analysis utilized images of 177 iconic buildings across 14 architectural styles (samples illustrated in Figures 5.2 to 5.4). As outlined in the methodology (section 5.3.1), each building was represented by a single high-resolution, unobstructed frontal image of the main facade to ensure consistency. The CICA system calculated the complexity scores for all buildings and plotted the graph in just 4.54 seconds, demonstrating its efficiency.

The results are depicted in the scatter graph 'Historical Analysis of Architectural Complexity Trends Over Time' in Figure 5.11. A 9th-degree polynomial trendline, best accommodating the intricate data patterns, revealed a distinctive undulating curve. This pattern validates our hypothesis of continual oscillation between architectural complexity and simplicity, aligning with the paradigmatic shifts discussed in the Literature Review (Section 5.2.1) and showcasing a trend towards complexity in the post-modern era.

Periods of Rapid Change:

The trendline in the 'Historical Analysis of Architectural Complexity Trends Over Time' Chart (Figure 5.11) reveals dynamic oscillations between periods of ornamental richness and minimalist restraint, illustrating the unique interpretation of architectural complexity in each era. Notably, a shift is observed from the Gothic to the Renaissance period, where the trendline peaks with the ornate and vertical architecture of the Gothic era [65] and descends as the Renaissance favors harmony, proportion, and classical simplicity [66]. Additionally, the late 20th century shows spikes in complexity scores, indicating significant shifts in architectural trends associated with the transition from the minimalist aesthetics of Modernism to the more eclectic and elaborate designs of Postmodernism. Furthermore, our analysis of the last 50 years of data reveal an upward trajectory in architectural complexity, marking a departure from the uniformity of barren walls and fully glazed facades.

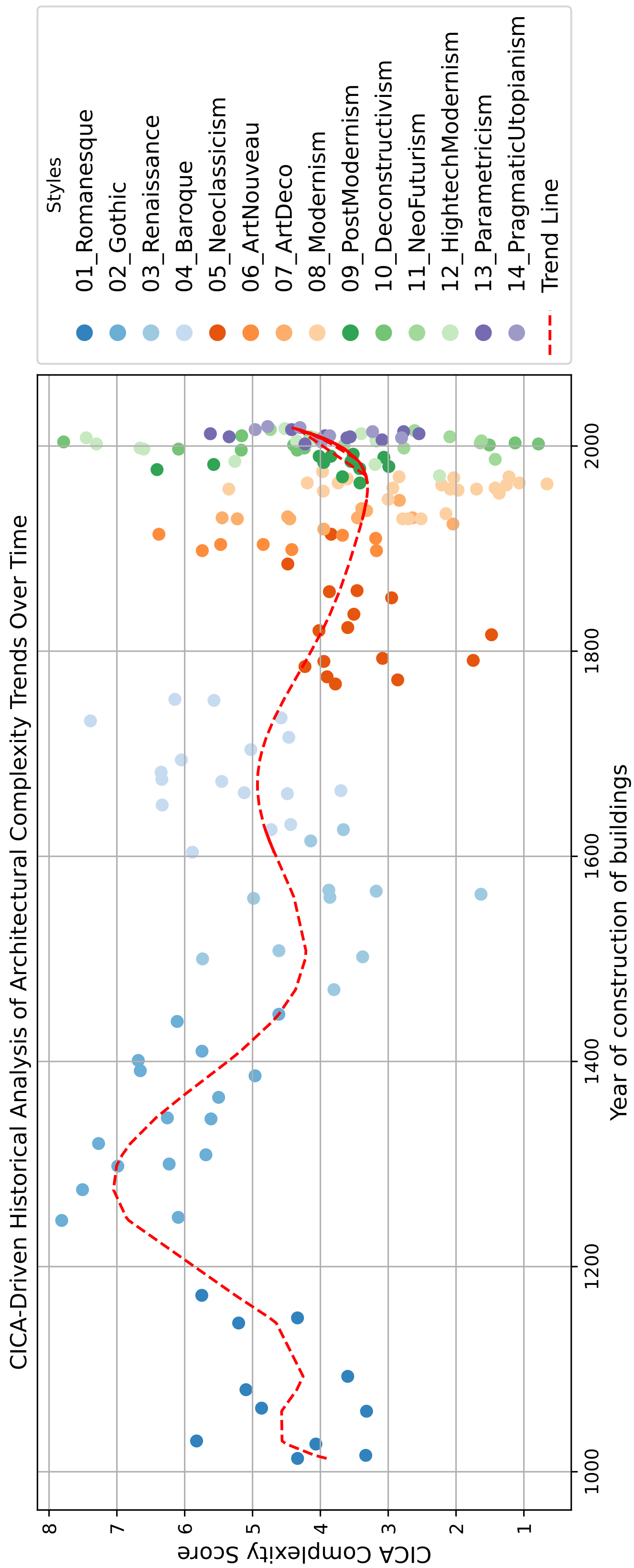


FIGURE 5.11: Scatter Graph of Architectural Complexity Over Time: This graph presents the CICA scores for 177 buildings, categorized by historical timeline and architectural style. An overlaid trendline highlights the current evolving trend towards increased complexity in architectural design as analyzed by the CICA system.

Outliers:

Certain buildings stand out with exceptionally high or low CICA scores, warranting individual examination. Our investigation into these extremes, as evidenced by the top 5 highest and bottom 5 lowest CICA scores (Table 5.4), reveals significant outliers. Westminster Abbey, exemplifying Gothic architecture, tops the chart with the highest complexity score of 7.81, underscoring the intricate design characteristic of the Gothic period [65]. However, buildings like the Seattle Central Library, ranked second with a score of 7.78, highlight certain limitations in the CICA system's current approach. Despite the library's relatively simplistic volumetric form compared to Gothic cathedrals, its grid-like facade generated a high number of edges and contours, which the algorithm interpreted as markers of complexity. This suggests that the system, which currently emphasizes edge density and contour count, may overestimate complexity in buildings with regular, repetitive patterns, as it does not differentiate between regular and irregular geometries. Conversely, the Luce Memorial Chapel in Taichung City, Taiwan, built in 1963, represents the minimalist ethos of the time with the lowest complexity score of 0.66. These buildings illustrate the broad spectrum of architectural styles and associated complexity over time, serving as critical case studies for understanding exceptional complexity or simplicity in design.

TABLE 5.4: Table of comparative CICA Historical Analysis results: Top 5 Highest and Bottom 5 Lowest CICA Complexity Scores from Historical Analysis, Including Year of Construction and Architectural Style.

Buildings with the Top 5 Highest CICA Complexity Scores

Rank	Building Name	Year of Construction	Architectural Style	CICA Score
1	Westminster Abbey	1245	Gothic	7.81
2	Seattle Central Library	2004	Deconstructivism	7.78
3	Reims Kathedrale	1275	Gothic	7.51
4	California Academy of Sciences	2008	Hightech Modernism	7.45
5	Rome Trevi Fountain	1732	Baroque	7.39

(1) (2) (3) (4) (5)

Buildings with the Bottom 5 Lowest CICA Complexity Scores

Rank	Building Name	Year of Construction	Architectural Style	CICA Score
1	Luce Memorial Chapel, Taichung City, Taiwan	1963	Modernism	0.66
2	Imperial War Museum North	2002	Deconstructivism	0.79
3	St. Mary's Cathedral, Tokyo	1964	Modernism	1.07
4	Disney Concert Hall	2003	Deconstructivism	1.13
5	Cathedral of Brasilia in Brazil	1970	Modernism	1.22

(1) (2) (3) (4) (5)

5.4.2 Quantitative Analysis on Users Response to Complex Facades

The experiment was carried out at Kyushu University, Fukuoka, Japan. The study took place in two timeframes, from October 12 to October 30, 2023, and July 1 to July 12, 2024, with experiments held between 10:00 and 18:00.

A total of 26 participants, comprising 13 males and 13 females, engaged in the experiment. The participants' ages ranged from 18 to 31, with 69.2% of participants aged between 18 and 24, and 30.8% aged between 25 and 31. The demographic distribution of the participants is illustrated in Figure 5.12. The majority (41%) were students from various disciplines, while 27% had a background in construction, and 20% had prior experience in facade design, as illustrated in Figure 5.13. The participant pool consisted largely of university volunteers, which explains the limited professional experience among participants, as most were students.

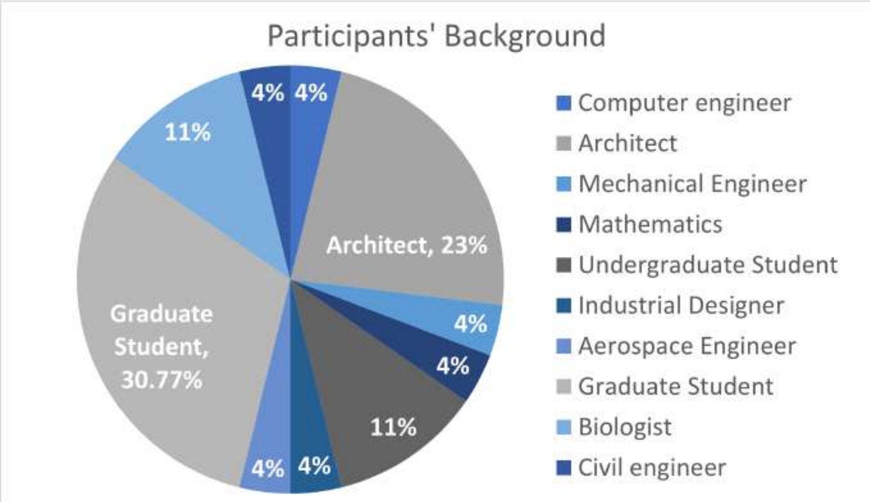


FIGURE 5.12: Participants' Background: This pie chart shows the distribution of participants' backgrounds, with architects (23%) and graduate students (30.77%) as the predominant groups (26 participants, males (50%) and females (50%), aged between 18 and 31).

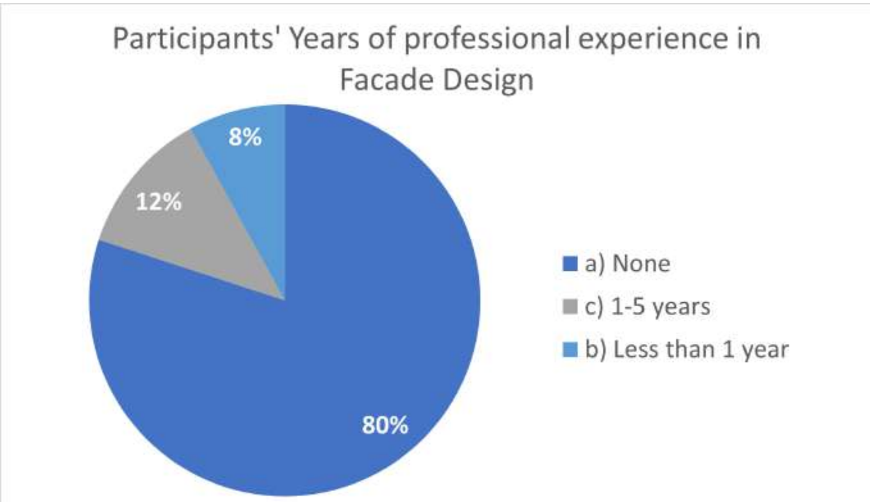


FIGURE 5.13: Participants' Professional Experience in Facade Design: This pie chart displays the distribution of experience levels, with 80% having none and 12% having 1–5 years of experience (26 participants). Most participants were university volunteers, which explains the limited professional experience.

VR to measure user preference for complexity in facade design.

In the VR Interaction stage, participants engaged with the facade selection task for all three patterns, resulting in 78 experiment sessions. For each pattern, participants selected the facade variation they found most comfortable based on its perceived complexity level.

The preferred complexity levels from the VR simulation stage were consolidated into the 'Facade variatio selection and CICA score Chart,' a bar chart, shown in Figure 5.14. Analysis of this chart reveals that most participants favored one of the first five facade variations, with only 1/3 of instances selecting options beyond this range. The results show a preference for mid-range complexity with a mean CICA score of $Mean = 4.05$, but the standard deviation of $SD = 1.2$ highlights significant variability. This deviation indicates that complexity perception is highly subjective and influenced by personal or contextual factors, such as visual tolerance or interaction with the VR environment. Notably, 'facade variation 3' emerged as the most popular choice for all three patterns among the ten variations (see Figure 5.6).

The 'Probability Distribution Graph of Preferred CICA Scores Across Patterns', showcased in Figure 5.15, provides a visual representation of the distribution of participant choices. It accentuates that there is a 40% probability of the focus group selecting an answer proximate to the calculated complexity score average,$Mean = 4.05$ with a modest standard deviation of $SD = 12\%$ in predicting individual data points or outcomes. This indicates a moderate level of predictability in participant choices suggesting that while most selections align near the average CICA score, there is still a notable range in individual preferences, indicating subjective differences in complexity perception.

The 'Comparison chart of Average Chosen Facade and CICA scores by pattern', displayed in Figure 5.16, underscores that the average choice of facade variation for each pattern hovers around the overall average complexity score, $Mean = 4.05$ and the average choice of facade variation $Mean = 4.4$, further supporting the alignment between participant preferences and the CICA system's complexity evaluation.

The results from these preliminary analysis indicate a preference among participants for facades with moderate complexity, hinting at a future architectural trend that favors a harmonious balance between intricacy and simplicity. Such designs are likely to be visually engaging without being overwhelming. Additionally, the observed deviations, though modest, suggest that individual preferences for complexity vary, reinforcing the need for flexible and customizable architectural designs tailored to meet individual preferences and needs.

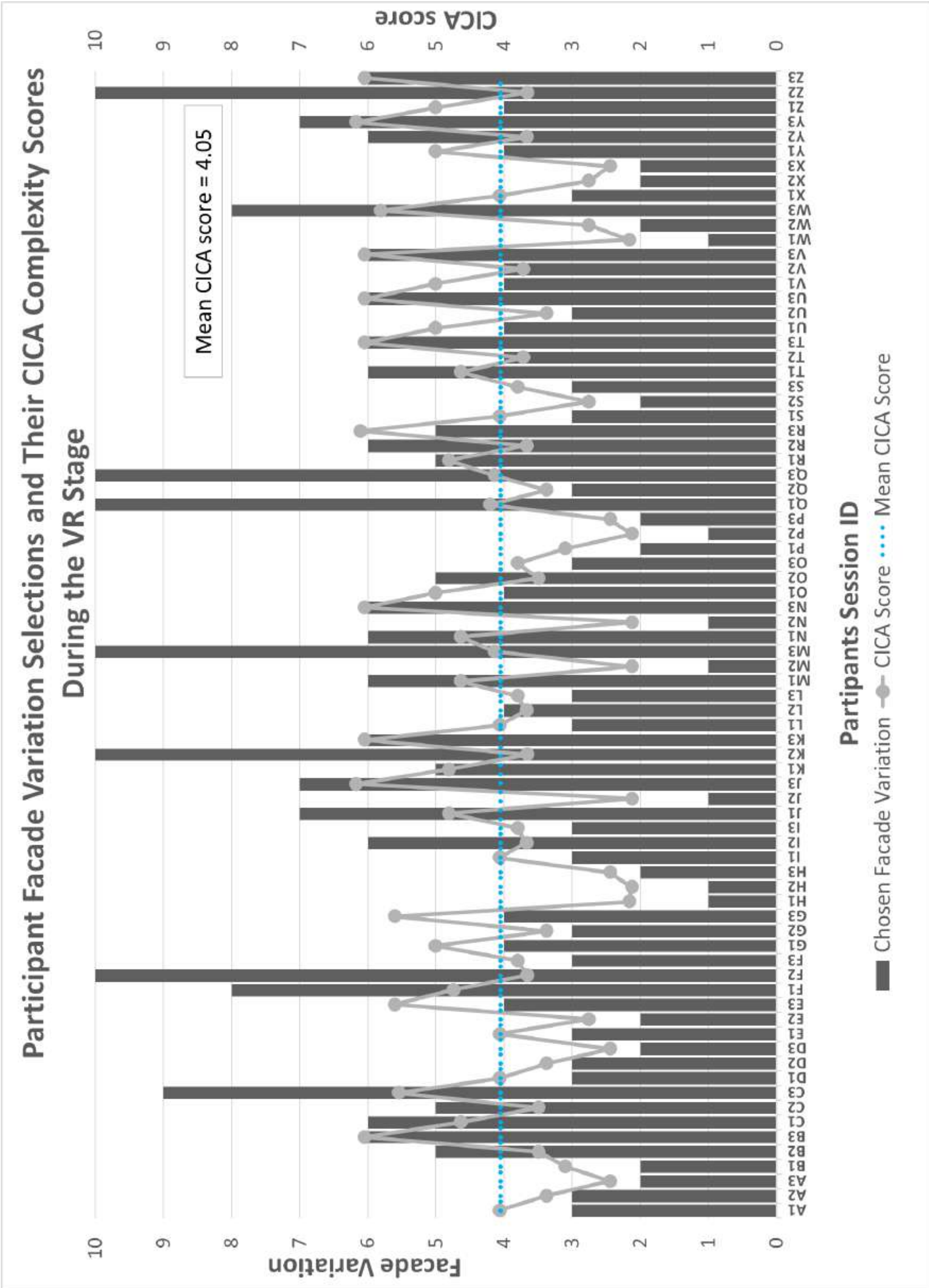


FIGURE 5.14: Facade Variation Selections and CICA Scores During VR Stage: This chart shows participants' selected facade variations (bars) and their corresponding CICA complexity scores (line) during the VR experiment. The x-axis indicates session-based IDs (1, 2, 3) per participant, with the solid line for individual scores and the dotted line for the average. It highlights the relationship between selections and complexity levels across ten facade options and three patterns (Mean CICA Score = 4.05, SD = 1.2; 26 participants, 78 sessions).

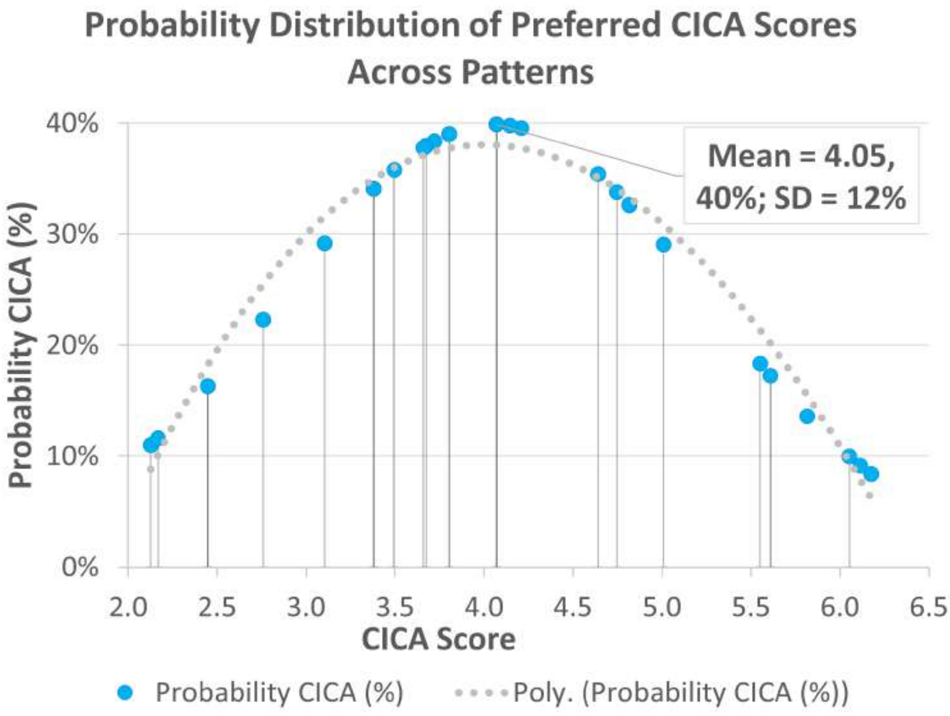


FIGURE 5.15: This scatter graph illustrates the probability distribution of preferred CICA scores for facade design across all three patterns, based on data collected during the VR stage of the experiment. (CICA score: $Mean = 4.05, withProbability = 40\%$; $SD = 12\%$) (26 participants).

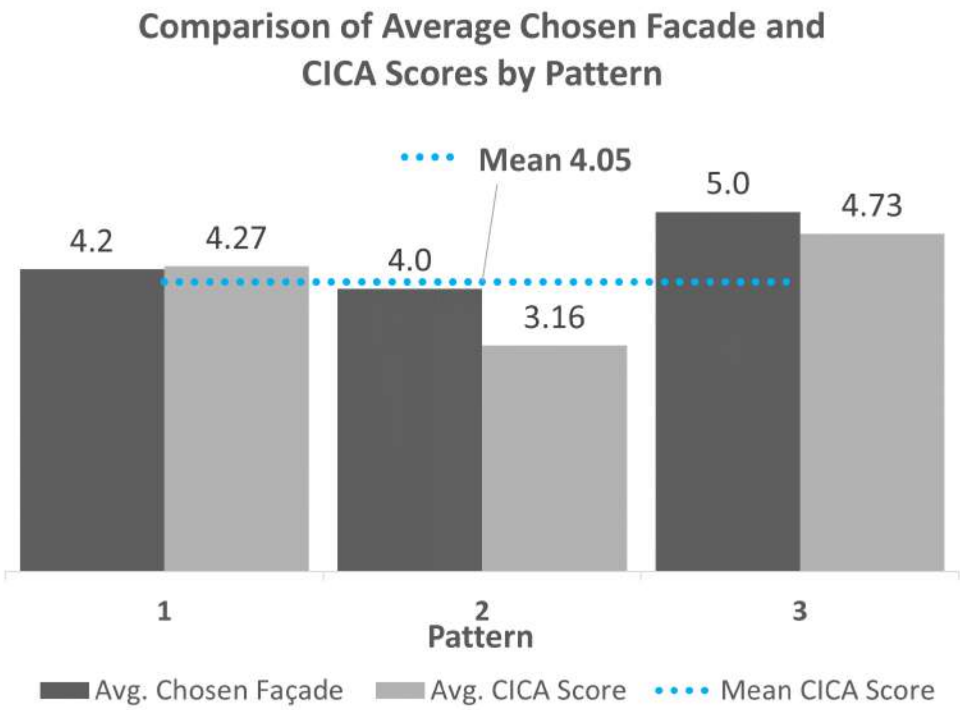


FIGURE 5.16: This bar chart presents the average chosen facade variation and corresponding CICA scores per pattern, as selected by participants during the VR stage of the experiment. (Facade variation: $Mean = 4.4$) (dotted line, CICA score: $Mean = 4.05; SD = 1.2$) (26 participants).

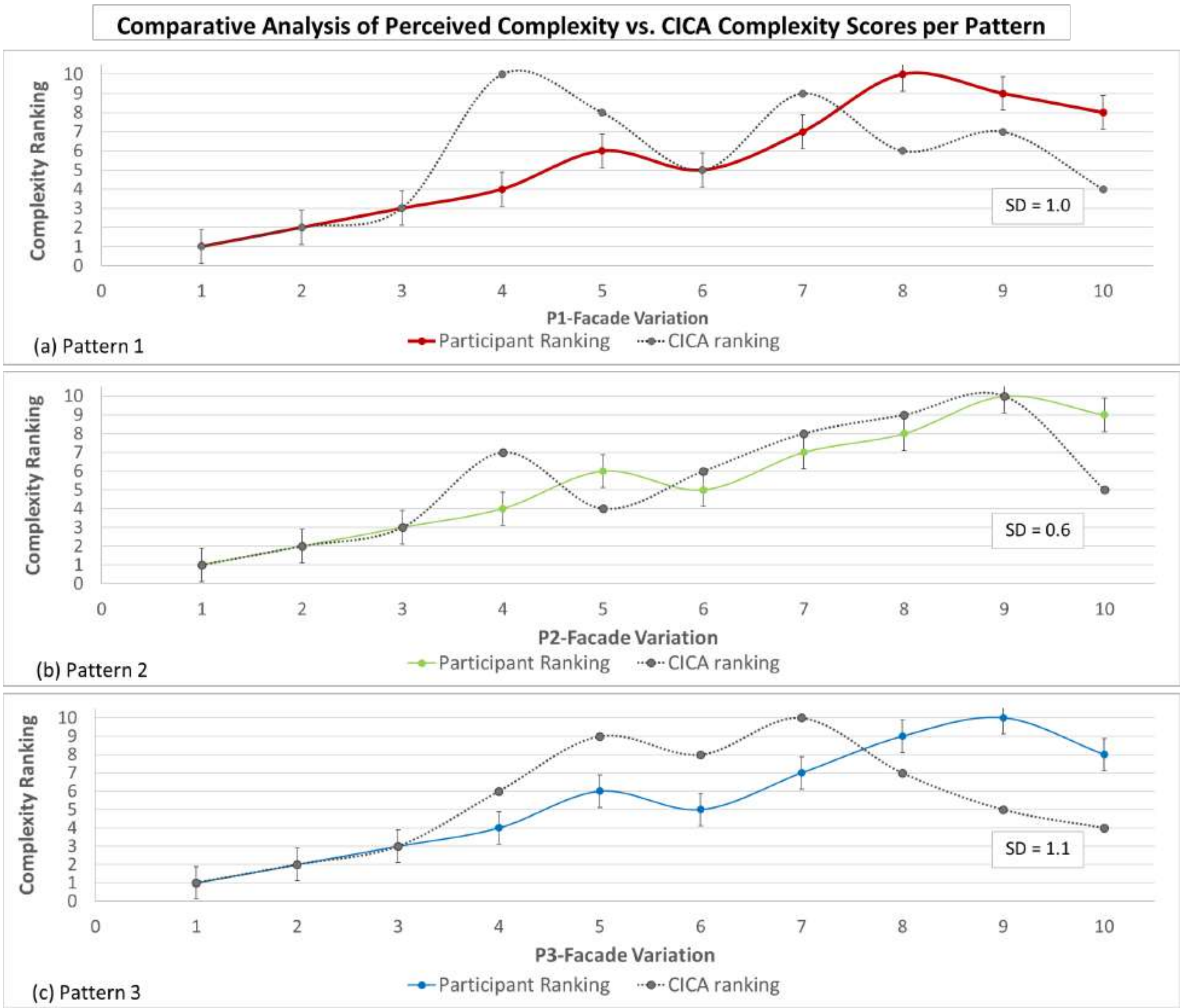


FIGURE 5.17: Comparative Analysis of Perceived vs. CICA Complexity Scores: Line graphs compare participants' perceived complexity rankings with CICA scores for facade variations within three facade patterns: Pattern 1 (a), Pattern 2 (b), and Pattern 3 (c). Rankings range from least (1) to most complex (10), highlighting contrasts between human perception and computational analysis (26 participants).

Alignment of user perception with CICA system evaluation of complexity

The accuracy of the CICA system in assessing facade complexity, compared to participant perceptions, was analyzed in Stage 2 of the experiment, the Screen-Based Ranking Stage. The results of this comparison are visually represented in the graphs in Figure 5.17. These graphs illustrate the alignment between the trendlines of the overall participants' rankings and the CICA system's rankings for all three patterns, with an average standard deviation of 9% $SD = 0.9$ in complexity level categorization.

The results reveal varying degrees of accuracy across different patterns:

In Pattern 1, in Figure 5.17(a), participants' perception of complexity rises gradually and then sharply peaks at facade variation 8, which they rated the highest in terms of complexity. The CICA system, however, peaks earlier at facade variation 4, suggesting that the system detected a higher level of complexity at an earlier stage than the participants. The standard deviation $SD1 = 1.0$ indicates that there was a considerable spread in participant responses, highlighting a divergence in complexity perception between the human participants and the CICA system, especially at higher complexity levels.

For Pattern 2, in Figure 5.17(b), the participant rankings show a peak at facade variation 9, rated as the most complex, and a near-peak score for facade variation 10. Conversely, the CICA system also recognizes variation 9's complexity but assigns higher scores to variations 7 and 8 than to variation 10. This discrepancy suggests that certain design elements in variation 10 might be perceived by users as contributing to complexity more than the CICA system's metrics capture. The smaller standard deviation $SD2 = 0.6$ here indicates a closer alignment between participants' perceptions and the CICA scores, suggesting a more consistent agreement on complexity rankings for this pattern among the participants.

In Pattern 3, as illustrated in Figure 5.17(c), participant rankings highlight one peak in perceived complexity, with facade variation 9 rated highest and variation 8 closely behind. However, the CICA system assigns the highest complexity score to variation 7 and ranks variation 5 as the second most complex, diverging significantly from participant rankings for variations 8, 9, and 10. This mismatch, along with the standard deviation $SD = 1.1$, similar to Pattern 1, underscores the variability in how participants perceive complexity as opposed to the CICA system, particularly at the upper end of the complexity scale.

The analysis across patterns demonstrates that while the CICA system provides a systematic approach to complexity measurement, it does not always reflect the human perception, particularly at higher complexity variations. The differences between participant responses and the CICA system are most pronounced in Patterns 1 and 3, suggesting subjective nuances in complexity perception that the CICA system might not capture. These insights highlight the importance of integrating subjective human input with objective algorithmic assessments in the architectural design process.

While these results primarily demonstrate the CICA system's capability to quantify facade complexity, its application also holds promise for sustainable design. By quantifying complexity, architects can balance visual appeal with material efficiency, reducing unnecessary resource use and minimizing a building's carbon footprint. More complex designs often require more materials and energy, but the CICA system enables architects to control this complexity, selecting levels that enhance aesthetics while maintaining environmental sustainability. Furthermore, optimizing facade designs for durability and adaptability can reduce the need for frequent renovations, supporting long-term sustainable building practices. When combined with tools for energy efficiency, the system can also contribute to improved environmental performance, such as enhancing natural light and thermal regulation, while ensuring user satisfaction.

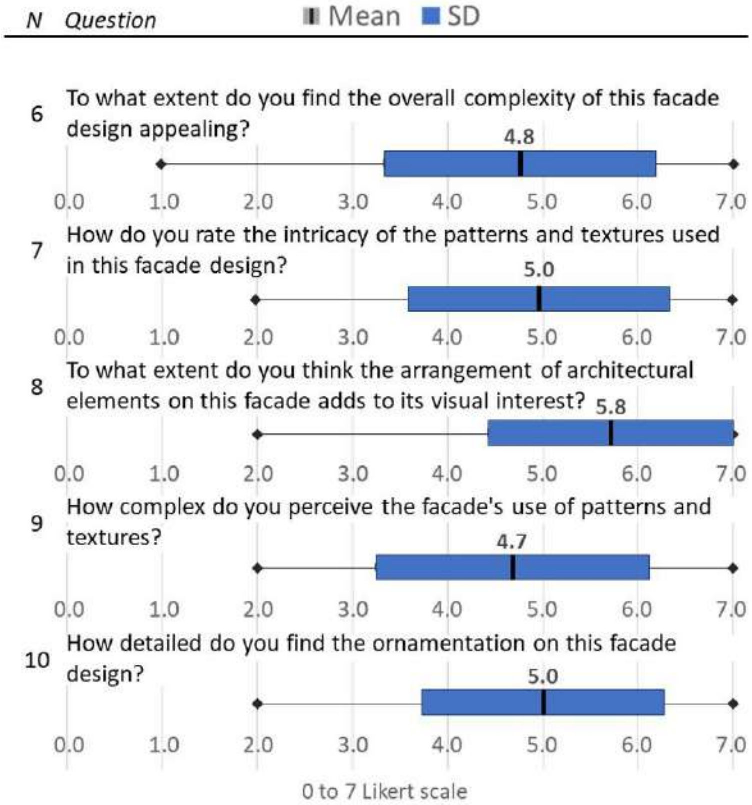


FIGURE 5.18: Questions 6 to 10 of the Complexity perception section from the Post-Experiment Survey. (n = 10), 1 - strongly disagree, 7 - strongly agree.

5.4.3 Qualitative Analysis on Users Perception to Complex Facades

We gathered additional insights through a survey and interviews, presenting a multifaceted view of user perceptions regarding architectural complexity. The responses to the 'complexity perception' section of the survey have been summarized in Figure 5.18 and Figure 5.19, with evaluations conducted using a 7-point Likert scale.

Survey responses show a moderate to high endorsement of complexity in facade designs, with average ratings above 3.5 and mean scores around $Mean = 5.2$. However, the standard deviation of $SD = 1.3$ reveals considerable variations in participant responses, underscoring the subjective nature of architectural complexity. These deviations reflect the diverse perspectives and preferences among participants, which is significant in understanding that the perception of facade complexity is not uniform across users. This range of responses suggests that while some participants are more attuned to intricate designs, others may prefer simpler structures, thus reinforcing the need for adaptable design approaches in architecture.

Survey Insights and Post-Experiment Reflections

Participants rated the appeal of facade complexity positively, with an average score indicating moderate to high appeal ($Q_{6\text{mean}}$ = 4.8; Figure 5.18). This suggests that complex facade designs have the potential to attract and satisfy user preferences, aligning with broader architectural discourse and highlighting the potential for integrating such designs into future practices.

The survey also revealed that the intricacy of patterns and textures in the facade designs was well-received, scoring above the midpoint on the Likert scale ($Q_{7\text{ mean}}$ = 5.0; Figure 5.18). This indicates that these design elements significantly contribute to user satisfaction and visual engagement, encouraging their exploration in future projects. Participants rated the contribution of architectural element arrangement to the facade's visual interest highly ($Q_{8\text{ mean}}$=5.8; Figure 5.18),

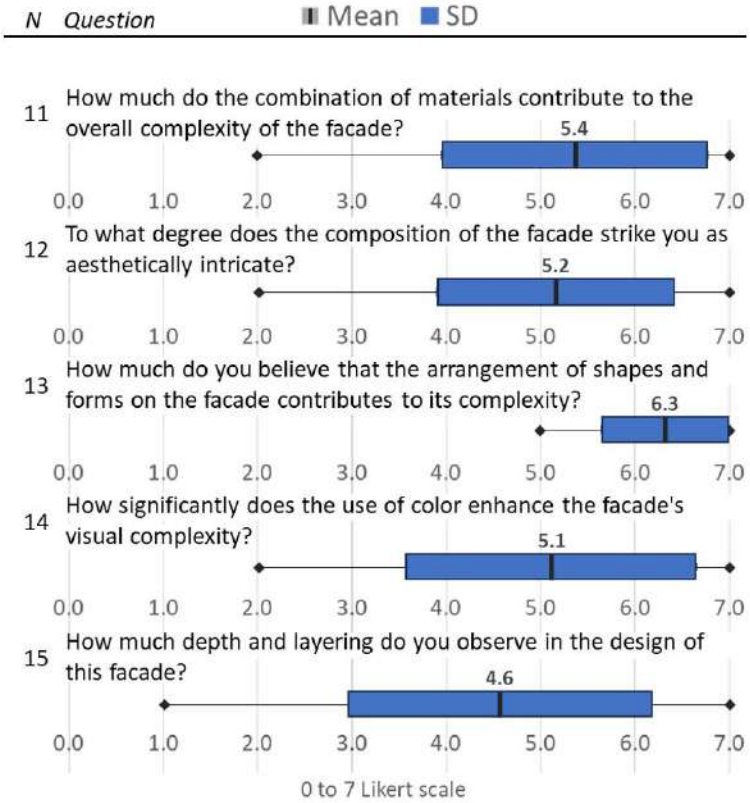


FIGURE 5.19: Questions 11 to 15 of the Complexity perception section from the Post-Experiment Survey. (n = 10), 1 - strongly disagree, 7 - strongly agree.

suggesting that thoughtful composition can greatly enhance a facade's appeal. The complexity of patterns and textures was perceived as moderate to high appeal ($Q_{9\ mean}$=4.7; Figure 5.18), reflecting a balanced approach where complexity is appreciated but not overwhelming. This points to the importance of finding the right complexity level that resonates with users.

The detail in ornamentation received a score that indicates users found it moderately detailed ($Q_{10\ mean}$=5.0 ; Figure 5.18). This suggests a user preference for ornamentation that contributes to the visual richness of a facade without dominating the design. The combination of materials was seen as an important factor in contributing to facade complexity ($Q_{11\ mean}$=5.4; Figure 5.19), underscoring the role of materials in defining a facade's character and aesthetic appeal.

The aesthetic intricacy of the composition received a moderately high rating ($Q_{12\ mean}$=5.2; Figure 5.19), emphasizing the value of thoughtful arrangement of design elements in enhancing a facade's visual complexity. Participants placed significant value on the role of shapes and forms in adding to facade complexity ($Q_{13\ mean}$=6.3; Figure 5.19). It solidifies the notion that the strategic placement of visual elements holds substantial sway over how a facade is perceived, highlighting the need for architects to consider geometric aspects when designing complex facades. The use of color was considered to moderately enhance visual complexity ($Q_{14\ mean}$=5.1; Figure 5.19). While not as impactful as form or texture, color is still an important design tool influencing complexity perception. Depth and layering were perceived as contributing moderately to facade complexity ($Q_{15\ mean}$=4.6; Figure 5.19), indicating that while not rated as highly significant as other factors, three-dimensionality and interplay of different design layers can enhance perceived complexity.

These insights suggest that participants appreciate complexity that is intelligently integrated into design through form, texture, and color, yet still desire a certain level of clarity without being overwhelmed by excessive details. These findings can guide architects in creating facades that are complex yet coherent, appealing to a broad spectrum of users. However, while participants were prompted to assess shapes and forms on the facade, the survey did not address the overall volumetric complexity or building massing. The focus remained on surface details such as patterns and textures, rather than the three-dimensional geometry of the entire building. This suggests that the impressions reflect mostly two-dimensional visual factors, potentially missing how volumetric complexity—like the building's size, shape, and articulation—affects perception.

In post-experiment interviews, participants articulated a clear preference for the role of form in facade design, assigning it significantly more importance than materials at an 80:20 ratio, emphasizing form as a dominant influence in their assessment of facade complexity and aesthetic value.

Interestingly, when discussing complex facades, participants gained a more comprehensive understanding of how complexity is perceived in different contexts, thanks to the VR experiment, which allowed them to assess facades from both interior and exterior perspectives. They agreed that intricate designs were appreciated when viewed from the exterior and generally favored more complex facades from an outside viewpoint. However, after experiencing them from the inside, participants tended to prefer simpler designs—particularly when enjoying the simulated unobstructed views of the campus. This distinction highlights that users may desire more visual complexity on facades facing non-critical or less scenic areas, while favoring simplicity on facades that interact with prominent external views to maintain visual comfort and openness from within. The results of the VR experiment align with these findings, reinforcing the notion that the perception of facade complexity shifts depending on the viewer's position. This underscores the need for context-sensitive design strategies that account for both indoor and outdoor experiences.

These interviews reveal a nuanced understanding of facade design among participants, highlighting the need for context-sensitive approaches that align architectural form and complexity with the functional and aesthetic needs of building users. Complex designs can enhance privacy or visual interest where appropriate, while simpler facades can preserve the aesthetic experience of key external views.

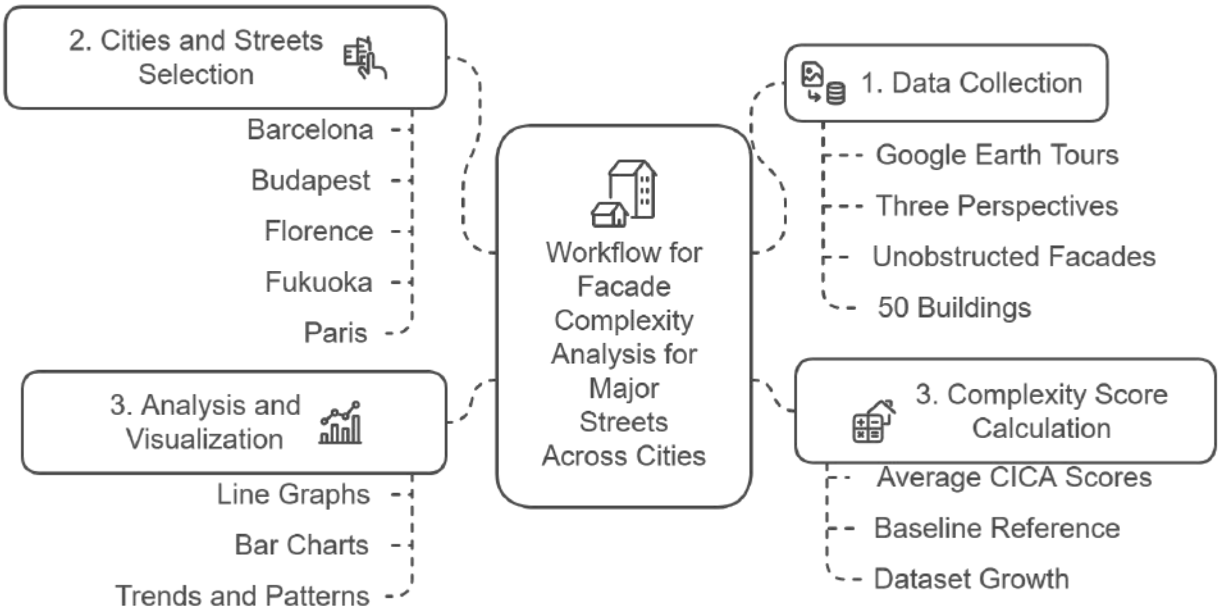


FIGURE 5.20: Workflow of the 'CICA Complexity analysis of building lineups across multiple cities' for validating the CICA Complexity Score applciability to real scenarios.

5.4.4 Validating the CICA Complexity Score in Urban Streetscapes

Building upon the findings from the previous subsections, which demonstrated the historical evolution of facade complexity using the CICA system and explored user responses to complex facades through experimental analysis, this section aims to validate the applicability and reliability of the CICA complexity score in a real-world context. While prior analyses focused on specific historical datasets and controlled experiments, this study extends the application of the CICA system to evaluate building facades along major streets in diverse urban environments.

The objective of this analysis is twofold: first, to assess how the CICA system performs when applied to actual streetscapes with varying architectural styles and urban contexts; and second, to identify patterns and trends in facade complexity across cities. By analyzing ten consecutive building facades along major streets in five cities—Barcelona, Budapest, Florence, Fukuoka, and Paris—this section demonstrates the versatility of the CICA system in quantifying complexity across different cultural and architectural settings. This analysis not only tests the robustness of the CICA system but also provides valuable insights into urban facade design trends that can inform future architectural practices.

Methodology

The goal of this analysis is to evaluate facade complexity across major urban streets using the CICA system, thereby validating its applicability in real-world contexts. This involves quantifying the complexity of building facades along selected streets and comparing trends across cities to uncover broader patterns. The key steps of the workflow for this analysis are as follows (see Figure 5.20): 'Data Collection', 'Cities and Streets Selection', 'CICA Complexity Score Calculation', and 'Analysis and Visualization'.

For the 'Data Collection', the primary source for facade images was Google Earth, leveraging its virtual tour feature to capture high-resolution visuals from multiple perspectives. To ensure accuracy, images with minimal obstructions—such as trees, vehicles, or pedestrians—were prioritized. For each building, three perspectives were captured: left, front, and right, providing a comprehensive view of the facade. In total, 50 buildings were analyzed, with 10 buildings selected per street and city.

The main criteria for the 'Cities and Streets Selection' process focused on diversity in architectural and cultural contexts. Five cities were chosen: Barcelona (La Rambla), Budapest (Szent István), Florence (Piazza del Duomo), Fukuoka (Otemon), and Paris (Boulevard Haussmann). While most selected streets are iconic and globally recognized for their architectural significance, the choice of Otemon in Fukuoka was guided by the fact that the study was conducted in this city. By selecting a regular street in Fukuoka rather than a world-renowned one, this study offers an interesting perspective on how iconic streets compare to a more typical urban road. Along each street, ten consecutive building facades were identified and labeled sequentially from 1 to 10, creating a dataset of 50 facades spanning all cities (see Figure 5.21).

The method for 'CICA Complexity Score Calculation' involved applying the CICA system to each building facade by averaging the scores derived from the left, front, and right perspectives. This ensured a comprehensive representation of each facade's complexity. To validate these scores, the system referenced a dataset of 177 historical buildings established in the historical analysis section (see Section 5.4.1). This comparative baseline allowed the scores to reflect a broad spectrum of architectural styles and periods. As the dataset grows to include more buildings, the accuracy and representativeness of the scores will improve further. By anchoring complexity evaluations within this evolving historical dataset, the methodology ensures both quantitative rigor and contextual relevance. Finally, the average complexity score of the ten facades was calculated for each city to enable trend comparisons.

The approach to 'Analysis and Visualization' included plotting complexity scores for individual facades on line graphs to illustrate variations across the ten buildings in each city (see Figure 5.21). A bar chart was also created to display the average complexity score for each city, highlighting overall trends (see Figure 5.22). These visualizations were analyzed to identify patterns in facade complexity between cities and to explore unique architectural characteristics that influenced the scores.

FIGURE 5.21: Scatter Graph of CICA Complexity analysis of building lineups across multiple cities: This graph presents the CICA scores for 50 buildings, across major streets in 5 diferent cities. The buildings are categorized by city and labeled from 1 to 10 in accordance to the way they line up in the selected major street of each city. An overlaid trendline highlights the range of complexity levels among the facades of each street across cities.

Quantifying Facade Complexity Variation Across Cities and Streets

Trends in Facade Complexity Along Streets

The scatter graph 'CICA Complexity Analysis of Building Lineups Across Multiple Cities,' shown in Figure 5.21, illustrates the variation in facade complexity scores for the ten consecutive buildings along each selected street. The graph reveals distinctive patterns in facade complexity across the ten buildings for each city, highlighting both consistency and variability in architectural styles:

Barcelona (La Rambla) displays a relatively steady trend with minor fluctuations in CICA scores. The lineup reflects a cohesive architectural language characterized by consistent ornamentation and rhythmic facade arrangements. This uniformity mirrors the cultural and historical significance of La Rambla as an iconic urban promenade.

Budapest (Szent István) shows a stable trend with relatively moderate variations, indicating a uniformity in facade designs along the street. The inclusion of the Comedy Theatre of Budapest at position 3, a Neo-Baroque landmark with intricate detailing, contributes to the overall richness of the streetscape without introducing sharp contrasts in complexity scores.

Florence (Piazza del Duomo) demonstrates a sharp increase in complexity scores from position 5 onward, coinciding with the dominance of the Florence Cathedral (Duomo) in the lineup. The Cathedral's richly detailed Renaissance facade significantly elevates the scores for these positions, contrasting sharply with the simpler structures in positions 1 through 4.

Paris (Boulevard Haussmann) highlights a moderate peak at position 3, attributed to the Palais Garnier Opera House, a Beaux-Arts masterpiece known for its elaborate ornamentation. The subsequent buildings maintain moderate complexity, reflecting the structured elegance of Haussmann's urban design principles.

Fukuoka (Otemon) exhibits the lowest complexity scores among the cities, with sharp variations between some positions. The absence of historical landmarks and the predominance of contemporary modernist facades contribute to the overall simplicity of the streetscape, offering a stark contrast to the historical richness of the European streets.

Iconic buildings, such as the Florence Cathedral, the Palais Garnier Opera House, and the Comedy Theatre of Budapest, demonstrate the significant influence of architectural landmarks on facade complexity scores, underscoring their role in shaping the character and identity of urban streetscapes.

Variation in Facade Complexity Across Cities

The bar chart 'Average CICA Complexity Score of Building Facades on Major Streets by City,' shown in Figure 5.22, provides an aggregated view of the average complexity scores for each city. The results highlight notable differences in facade complexity across the selected urban streetscapes:

Barcelona (La Rambla) has the highest average CICA complexity score (6.4), indicating rich architectural detailing and visual intricacy in its streetscape. The cohesive blend of historical and ornamental features contributes to its standout complexity.

Budapest (Szent István) follows closely with an average score of 6.1, reflecting a similarly intricate yet distinct architectural style. The street's consistent and decorative facades underline Budapest's architectural richness.

Florence (Piazza del Duomo) and Paris (Boulevard Haussmann) present moderate complexity scores, at 5.1 and 5.7 respectively. Florence's score reflects a mix of Renaissance harmony and simpler surrounding facades, while Paris balances ornamental elegance with structured urban coherence.

Fukuoka (Otemon) has the lowest average complexity score (4.1). This result is likely influenced by the prevalence of contemporary and minimalist architectural styles, which contrast sharply with the historical richness of the European streets.

The observed variations emphasize the cultural and architectural diversity among the selected cities. European cities such as Barcelona, Budapest, and Paris demonstrate a higher emphasis on

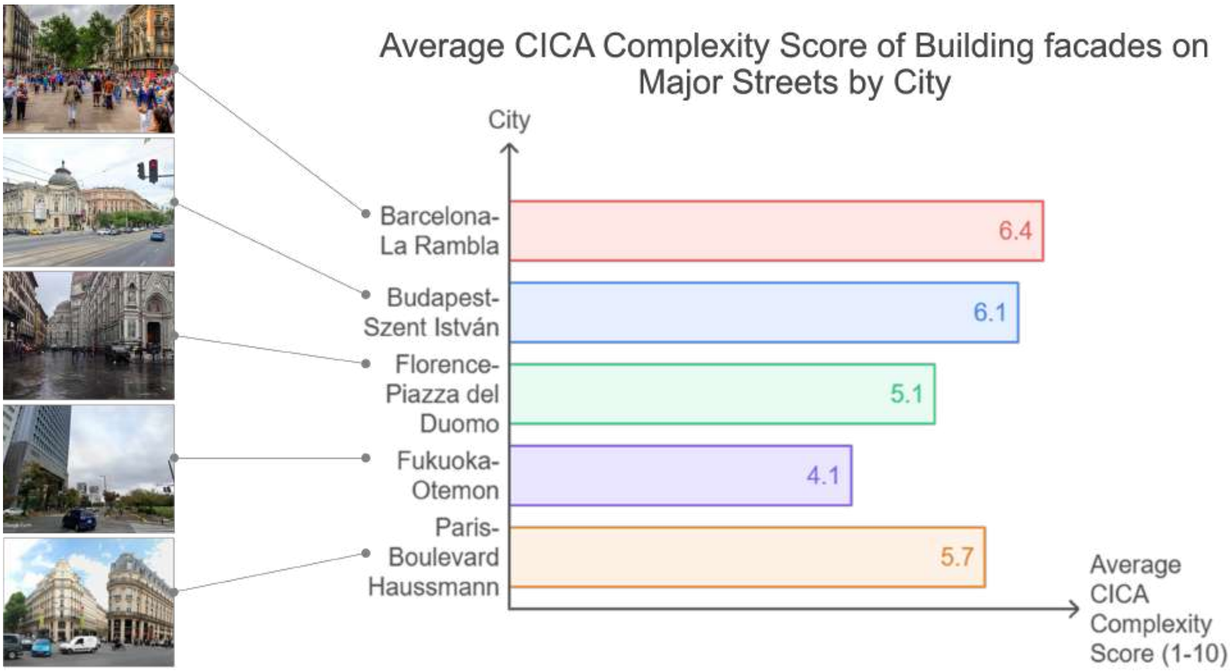


FIGURE 5.22: Average CICA Complexity score of buildings in major street across cities. (50 buildings, 5 cities).

intricate facade designs rooted in historical and cultural significance, while Fukuoka highlights the simplicity often seen in modern urban environments.

Cultural and Architectural Influences on Facade Complexity

The relationship between facade complexity and design intricacy reflects the cultural and architectural contexts of each city. Using the CICA complexity score as a basis, this study identifies patterns in facade complexity and design approaches across urban streetscapes. The findings are visually summarized in the scale diagram 'Comparing Architectural Complexity Across Cities' (see Figure 5.23), which compares high-complexity cities emphasizing cultural aesthetics and ornate facades with low-complexity cities prioritizing functional urban planning and modern simplicity.

Barcelona's La Rambla falls on the high-complexity side of the spectrum, reflecting its strong focus on cultural aesthetics and architectural expression. The facades along this iconic promenade exemplify Modernisme (Catalan Modernism) style influences, with ornate details and vibrant aesthetics that reflect the city's cultural emphasis on artistic expression and architectural innovation.

Budapest's Szent István street similarly aligns with ornate, intricate facades but displays a slightly lower overall complexity. Characterized by structured, uniform facades enriched with Neo-Baroque and Neo-Renaissance elements. These designs emphasize elegance and craftsmanship without overwhelming the streetscape with excessive complexity.

Florence's Piazza del Duomo reflects a balance between high facade complexity and cultural significance. The sharp rise in facade complexity due to the dominance of the Florence Cathedral illustrates how singular architectural landmarks can define the visual identity of a streetscape. The balance between simpler and more elaborate facades further reflects the city's Renaissance heritage, where architectural landmarks coexist with more restrained urban designs.

Paris's Boulevard Haussmann represents a unique approach to achieving complexity through simplicity and consistency. Haussmann's urban planning principles, which prioritize symmetry, proportions, and consistency, result in facades that achieve visual richness through balance and coherence rather than intricate detailing. The Palais Garnier Opera House (Figure 5.21, position

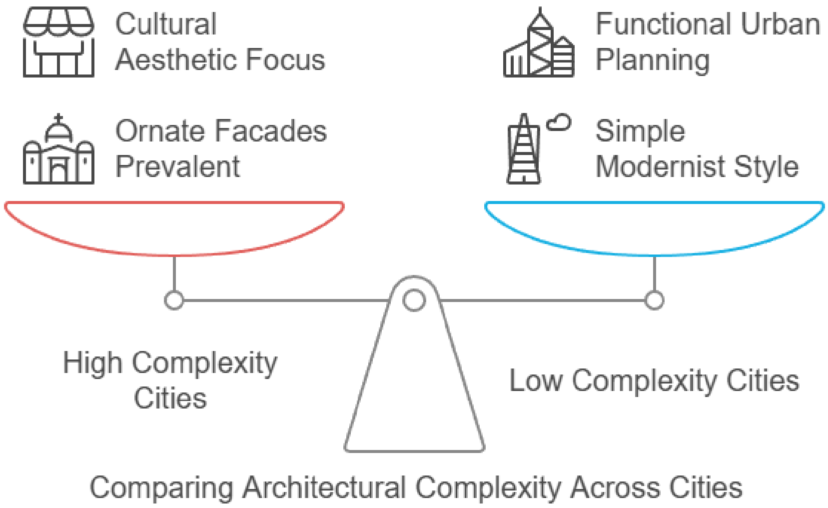


FIGURE 5.23: Scale diagram 'Comparing Architectural Complexity Across Cities'. Key considerations Cultural and Architectural Influences on Facade Complexity (50 buildings, 5 cities).

3) serves as a notable exception, enriching the overall complexity of the street with its elaborate Beaux-Arts style.

In contrast, Fukuoka's Otemon street occupies the lower-complexity side of the scale, where the minimalist and modern facades reflect contemporary urban development priorities. This simplicity underscores the functional focus of modern Japanese architecture, contrasting sharply with the historical ornamentation prevalent in European cities.

The scale diagram (Figure 5.23) highlights the contrasting priorities between cities emphasizing cultural and aesthetic expression versus those focusing on functional urban planning and modern simplicity. These findings reveal how tradition and modernity shape urban streetscapes. European cities such as Barcelona, Florence, Budapest, and Paris maintain cultural identity through varying balances of intricacy and complexity, while Fukuoka reflects evolving priorities in modern architecture, where minimalism emphasizes practicality and adaptability.

The CICA complexity score provides a structured way to quantify these visual characteristics, serving as both a marker of cultural heritage and a tool for analyzing evolving architectural trends. By combining the measurable insights of CICA with conceptual interpretations of design intricacy, this study offers a comparative framework for understanding how cultural and architectural factors influence the aesthetic and functional characteristics of urban streetscapes.

Insights for Urban Design

The findings of this study underscore the critical role of facade complexity and design intricacy in shaping urban identity, aesthetic appeal, and functionality. By analyzing patterns across culturally and architecturally diverse cities, this research provides valuable lessons for urban design, highlighting how facade complexity reflects a balance between tradition, modernity, and evolving urban priorities.

Cities such as Barcelona, Florence, and Paris demonstrate the enduring value of intricate facades in preserving cultural identity and enhancing the visual richness of urban environments. The ornate details and cohesive designs seen in these cities illustrate how architectural complexity can evoke a sense of place and history. Iconic landmarks like the Florence Cathedral or the Palais Garnier Opera House reinforce the importance of integrating visually striking elements within urban streetscapes to maintain cultural significance and attract public engagement.

Moreover, these cities highlight the success of cohesive urban planning approaches that harmonize complexity across streetscapes. By maintaining a balance between individual building intricacies and overall street uniformity, cities can create visually engaging yet orderly environments.

In contrast, Fukuoka's Otemon offers lessons in simplicity and functionality. Modernist facades prioritize clarity and practicality, emphasizing the importance of efficient, adaptable urban environments. While these designs lack the intricate detailing seen in historical contexts, they showcase opportunities for innovation in minimalist architecture, such as using clean lines and modular elements to achieve visual appeal without excessive ornamentation. This approach can be especially relevant in rapidly developing or space-constrained urban areas.

The challenge of integrating historical richness with contemporary priorities is central to urban design. The findings of this study suggest that achieving this balance requires thoughtful planning and a nuanced understanding of cultural and architectural contexts. Data-driven tools like the CICA complexity score offer a powerful means of quantifying visual characteristics and guiding design decisions. Urban designers can use such tools to evaluate how proposed developments align with historical aesthetics or contribute to contemporary urban priorities.

The CICA system's ability to quantify facade complexity offers significant potential for urban design practices, including evaluating new developments to ensure facade designs align with the desired visual and cultural identity of an area, revitalizing historical districts by using complexity insights to guide restoration projects that respect historical aesthetics while accommodating modern needs, and integrating complexity metrics into urban development policies to promote aesthetically and culturally responsive design. By incorporating these quantitative metrics into design processes, urban planners and architects can create cohesive and engaging urban environments that balance heritage with innovation.

The insights derived from this study highlight the interplay between tradition and modernity in urban design. Facade complexity serves as both a reflection of cultural heritage and a tool for shaping visually engaging, functional streetscapes. By leveraging data-driven approaches like the CICA system, urban designers can craft sustainable and culturally responsive cities that honor the past while embracing the future.

Reliance of the CICA system

The findings from this study highlight the reliability and versatility of the CICA complexity score in analyzing facade complexity across diverse urban contexts. By consistently capturing the visual intricacies of facades and adapting to cultural and architectural differences, the CICA system demonstrates its robustness as a tool for urban analysis.

The consistent scoring patterns observed within cities reinforce the reliability of the CICA system. For instance, the relatively stable trends along streets like Barcelona's La Rambla and Budapest's Szent István suggest that the system effectively quantifies facade intricacies while accounting for architectural uniformity. These results confirm the system's ability to produce repeatable and coherent scores across varied urban environments.

Differences in scoring trends between cities underscore the sensitivity of the CICA system to cultural and architectural diversity. For example: High scores in Barcelona and Florence reflect the rich detailing and ornate designs characteristic of their historical and cultural contexts. Moderate scores in Paris and Budapest illustrate the balance between ornamentation and structural elegance in their cohesive urban plans. Lower scores in Fukuoka align with the minimalist, functionality-driven aesthetic of modern Japanese architecture. This sensitivity validates the CICA system's application for comparative studies, offering a robust framework for analyzing urban streetscapes with diverse architectural influences.

5.5 Conclusions, Limitations, and Future Works

This study investigates architectural design at the intersection of digital fabrication, VR assessment, and CV algorithms, aiming to deepen our understanding of complexity in facade design. Our primary goal is to verify the practical application of a VR and CV based 'Complexity Analysis' system for facade design, offering insights into user acceptance of complex facades.

A literature review theorized a current trend towards increasing complexity in contemporary architecture, moving away from the uniformity of barren walls and fully glazed facades approach of the modernist movement. The CICA system quantitatively analyzed this same timeframe, proving this theory and revealing the existence of an upward complexity trendline since the late 20th century (see Figure 5.8). Furthermore, the historical analysis using the CICA system underscored the cultural and historical significance of facades, indicating that architectural complexity is not merely a matter of quantitative metrics but also involves cultural resonance and historical context.

This study contributes to architectural design theory by bridging qualitative perceptions of complexity with a quantifiable,data-driven approach. The CICA system offers a novel method for assessing facade complexity using CV algorithms, providing adaptable, quantitative insights across different contexts. By validating historical trends with empirical data and demonstrating a clear rise in complexity in recent decades, the study advances the theoretical understanding of architectural complexity. Moreover, the integration of complexity metrics with VR technologies enhances user-centered design, allowing for more interactive assessments of how complexity influences user satisfaction and aesthetics.

Participants in the experiment showed a preference for facades with moderate complexity, suggesting that future architectural trends may favor designs that balance intricacy with simplicity. On average, participants preferred a moderate level of complexity, with a mean CICA complexity score of 4.05 (out of 10) and a 40% probability of selecting a score close to this value.

Discrepancies between participant perceptions and the CICA system's complexity rankings, with an average standard deviation of 9%, were more evident at higher complexity levels, highlighting the subjective nature of complexity perception and the need to integrate human feedback into architectural assessments. Qualitative data suggest a shift towards customizable and user-responsive architectural solutions, with participants favoring form over materials and preferring facades that consider views and privacy.

By expanding the analysis to include urban streetscapes in Barcelona, Florence, Paris, Budapest, and Fukuoka, the CICA system demonstrated its robustness in capturing facade complexity across diverse cultural and architectural contexts. The results showed that historical cities exhibit higher complexity scores driven by ornamentation and cohesive urban planning, while modernist cities prioritize simplicity and functionality. This comparative analysis underscores the potential of the CICA system to inform urban design by identifying patterns and cultural influences that shape facade complexity.

The CICA system's ability to consistently capture facade complexity across cities, combined with its sensitivity to architectural and cultural diversity, reaffirms its potential as a reliable tool for urban design and analysis. Its application extends beyond theoretical analysis, offering valuable insights into public space development, urban renewal projects, and historic building renovations.

Limitations

While this research provides valuable insights into architectural complexity, certain limitations warrant cautious interpretation of the results:

The study involved a relatively small sample of 26 participants, primarily composed of university students, with 69.2% aged between 18 and 24. Most participants lacked extensive professional experience in architecture, particularly in facade design. This limited demographic representation may affect the generalizability of the findings, as preferences for complexity could vary significantly with broader participant pools, including professionals with diverse levels of expertise and experience.

The use of VR offered a controlled and immersive environment but may not entirely capture the experience of interacting with real-world facades. VR settings could affect perceptions of complexity and comfort, leading to different results compared to real-world interactions.

The CICA system, while effective in evaluating facade complexity using metrics like edge detection and contour count, may not capture all elements influencing perceived complexity. These metrics focus on two-dimensional visual data and might not fully address the subjective nature of complexity perception, which is shaped by individual aesthetic preferences, prior experiences, and cultural factors—factors that CV algorithms struggle to encapsulate. Furthermore, the system lacks tools to analyze three-dimensional articulation and hierarchical design elements, which are crucial to volumetric complexity and the overall form of buildings. This omission limits the system's ability to fully represent how buildings are perceived in terms of spatial interaction and three-dimensionality.

The survey questions focused mainly on surface-level details, such as patterns and textures, without addressing the building's overall form and three-dimensional geometry. Incorporating questions and metrics related to volumetric complexity would provide a more complete understanding of how architectural complexity is perceived in real-world settings.

The historical evaluation is based on single images of each facade, which limits the ability to fully grasp the overall complexity of a building, as different perspectives might reveal additional elements that contribute to its perceived intricacy. This choice was made to standardize the analysis, but multiple images from different angles could provide a more comprehensive understanding of architectural complexity. The limited dataset of 177 historical buildings may restrict the comprehensiveness of the complexity assessment. Expanding the dataset could yield a more detailed understanding of trends in architectural complexity over time.

For the analysis of urban streetscapes was based on facades from five cities and selected streets, limiting its generalizability. Expanding the dataset to include more cities, streets, and diverse architectural styles could improve its representativeness.

This study concentrated on facade design, which is just one aspect of architectural complexity. While the insights into patterns, textures, and materials are valuable, the CV models developed for specific facade features might not generalize well to other architectural elements or styles.

Future Works

The findings and limitations of this study provide opportunities for further exploration in architectural complexity:

Future studies should involve a larger and more diverse group of participants to broaden the generalizability of the findings. Conducting long-term studies could also shed light on the evolution of preferences for architectural complexity over time.

Future research could compare VR-based assessments with evaluations of physical facades to better understand the correlation between virtual experiences and real-world perceptions. Leveraging emerging technologies in Extended Reality (ER), such as Mixed Reality (MR) and Augmented Reality (AR), could further bridge the gap between virtual simulations and reality enhancing the assessment and prediction of user preferences in complexity in architectural design.

Future works could improve the accuracy of the CICA system by incorporating additional metrics such as color, texture, and contextual integration, providing a more nuanced understanding of facade complexity. In particular, incorporating volumetric complexity, such as the three-dimensional articulation, massing, and hierarchical design elements, would significantly enhance the system's ability to capture how buildings are perceived holistically in real-life contexts. This could be achieved by developing tools that assess not just the surface-level details but also the overall building form and its spatial interaction with the environment. Developing methodologies that integrate user feedback more directly into the design process could lead to more personalized and culturally sensitive architectural solutions. Future iterations should consider both the quantitative aspects of facade complexity and the cultural resonance and historical context to provide a comprehensive evaluation of architectural evolution.

Furthermore, future research should encompass additional elements, such as interior design and spatial organization, to achieve a more holistic understanding of architectural complexity. Investigating the relationship between architectural complexity and sustainability could also provide insights into how complex designs impact sustainable building practices, helping architects balance intricate aesthetics with environmental considerations.

Conclusion

In conclusion, this study successfully addressed the challenge of quantifying complexity in architectural facade design through the integration of VR and CV technologies. The practical application of the CICA system extends beyond theoretical analysis, offering architects a tool for informed decision-making in real-world design contexts. By enabling the quantification of facade complexity, the CICA system provides insights into how visual interest, user satisfaction, and material efficiency can be balanced to create sustainable and adaptable designs. Architects can apply these findings across various design scenarios. Future applications of the system include urban heritage preservation, where facade complexity insights could guide the restoration of historical districts, and contemporary urban planning, where the CICA system could ensure new developments align with cultural identity and modern needs. Its potential for cross-disciplinary research further expands its relevance, offering opportunities to explore how architectural complexity impacts urban aesthetics, pedestrian behavior, and sustainability.

Additionally, by integrating the CICA system with existing energy efficiency tools, the system could be instrumental in designing facades that optimize natural light, thermal performance, and environmental comfort while maintaining aesthetic appeal. This capability makes the system relevant for a wide range of building projects, helping architects make more DBD decisions that align with both functional and cultural contexts. This can prove useful for guiding the optimization of building design towards a more user-centric approach in architectural design, catering to the evolving demands of modern society.

By addressing its limitations and expanding its applications, the CICA system has the potential to reshape architectural and urban design practices, enabling culturally responsive, visually engaging, and functionally efficient building design.

The development and application of the CICA system exemplify the versatility of the Data-Driven Immersive Design Optimization (DIDO) framework. The DIDO framework integrates computational precision with immersive visualization tools, bridging the gap between data-driven insights and stakeholder engagement. This dual capability makes DIDO a transformative method for architectural workflows, enhancing both the aesthetic and functional dimensions of design. As demonstrated in this study, DIDO's flexibility enables it to address varying contexts, from urban streetscapes to individual facade designs, aligning with cultural, historical, and user-centered priorities.

Chapter 6

Conclusions, Limitations, and Future Works

6.1 Introduction

The evolution of architectural practices in recent decades has been marked by the growing integration of computational technologies and immersive tools, responding to the increasing complexity of design demands in the Architecture, Engineering, and Construction (AEC) industry. This thesis aimed to validate the Data-Driven Immersive Design Optimization (DIDO) framework, a pioneering methodology that bridges the gap between technical precision and user-centered design through the convergence of Data-Driven Building Design (DBD), Virtual Reality (VR), and Computer Vision (CV).

By addressing both macro-level urban challenges, such as 'Site Layout Planning' (SLP), and micro-level architectural details, like 'Facade Complexity', this research has demonstrated the versatility and adaptability of the DIDO framework. Through the development of case studies, the research explored how immersive technologies and computational insights can complement each other to optimize architectural outcomes while engaging stakeholders in meaningful ways.

This chapter concludes the thesis by summarizing the key findings, revisiting the research objectives, and evaluating the DIDO framework's contributions to architectural practices. It also highlights the limitations encountered during the research and proposes avenues for future exploration to further refine and expand the applicability of the DIDO framework.

6.2 Summary of Research Contributions

This section highlights the significant contributions of the research, focusing on the development and application of the DIDO framework, advancements in site layout planning (SLP), and innovations in 'Facade Complexity Analysis', as well as their broader impacts on the Architecture, Engineering, and Construction (AEC) industry (see Figure 6.2).

Development of the DIDO Framework

The DIDO framework represents a pioneering integration of Data-Driven Building Design (DBD), Virtual Reality (VR), and Computer Vision (CV), offering a robust solution to contemporary challenges in architectural workflows. By combining computational precision with user-centered experiential tools, the framework bridges the gap between technical optimization and intuitive decision-making, ensuring that performance-based metrics resonate with stakeholders' insights and preferences. This fusion of analytical rigor and immersive engagement fosters a deeper understanding of design trade-offs, enabling architects and planners to create designs that are both efficient and user-friendly.

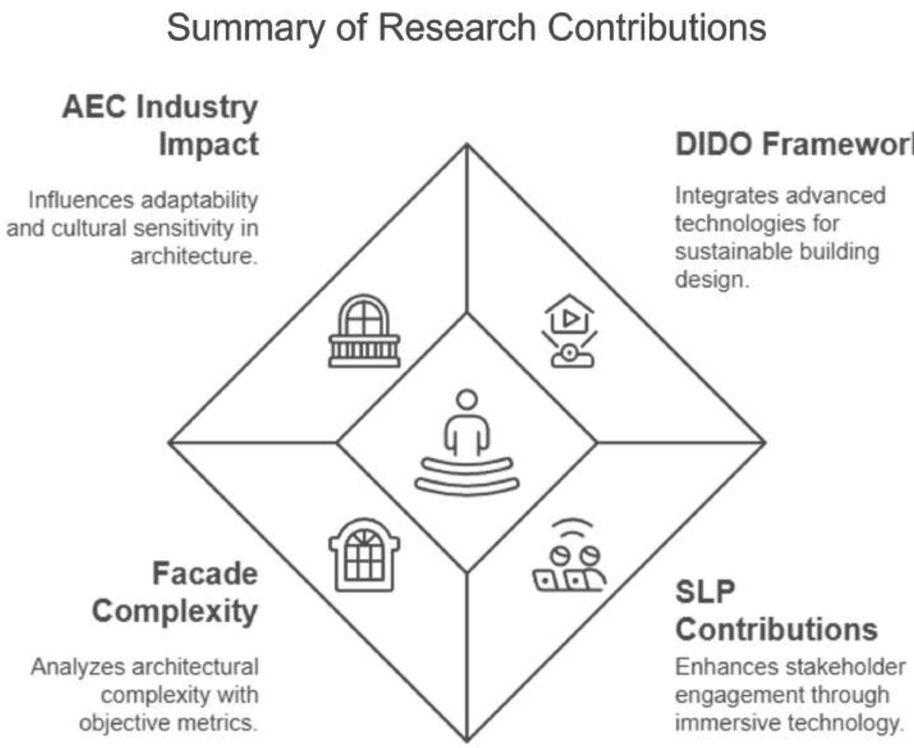


FIGURE 6.1: Flowchart illustrating the summary of research contributions.

A defining feature of the DIDO framework is its versatility, demonstrated by its applicability across diverse architectural scales, from macro-level site planning to micro-level facade optimization. By integrating immersive visualization tools with data-driven methodologies, the framework enhances collaboration and decision-making throughout the design process. This adaptability allows DIDO to address a wide range of challenges, facilitating more informed, cohesive, and sustainable design practices that align with the evolving needs of the Architecture, Engineering, and Construction (AEC) industry.

Contributions to SLP from implementation of DIDO framework

The integration of Multi-Objective Optimization (MOO) with VR within the DIDO framework has significantly enhanced stakeholder engagement in site layout planning. By offering stakeholders an immersive environment to interact with data-driven recommendations, the study enabled more precise and informed decision-making. The use of VR allowed participants to intuitively explore spatial arrangements and assess the impact of various layout configurations, fostering greater trust and understanding of optimization processes.

The research further demonstrated that VR-based immersion reduces deviations between computationally optimized layouts and user-selected outcomes. Stakeholders found it easier to align with data-driven solutions when presented with dynamic, visually enriched scenarios, which enhanced their ability to evaluate trade-offs and make decisions that balance technical efficiency with experiential considerations. This alignment highlights VR's transformative role in bridging the gap between abstract optimization models and stakeholder preferences.

Contributions from Implementation of DIDO for 'Facade Complexity Analysis'

A key innovation of this research was the creation and validation of the 'Computational Image Complexity Analysis' (CICA) system, a tool designed to objectively quantify facade complexity using advanced Computer Vision (CV) algorithms. The system combines quantitative metrics, such as edge density and contour count, with qualitative insights derived from historical data and user preferences. The study validated the robustness of the CICA system across different contexts, establishing it as a reliable tool for analyzing architectural intricacy.

Through empirical analysis, this study uncovered oscillations between simplicity and complexity across architectural history, while also documenting an upward trend in complexity over the past several decades. The application of the CICA system to urban streetscapes in five culturally and architecturally diverse cities further demonstrated its effectiveness in capturing the nuanced interplay between facade design and urban identity. This analysis not only highlighted the system's scalability but also revealed how cultural and contextual factors shape perceptions of complexity.

Moreover, the research aligned complexity metrics with user preferences by integrating VR-based experiments into the facade analysis process. By validating the CICA scores against participant feedback, the study confirmed that moderate levels of complexity are generally preferred, emphasizing the importance of designing facades that balance intricacy with usability. This insight is particularly valuable for architects seeking to create designs that resonate with both functional and aesthetic considerations.

Broad Impacts on the AEC Industry

The DIDO framework offers a pathway for integrating advanced technologies into the architectural workflows of the AEC industry. By combining data-driven methodologies with immersive tools, the framework addresses longstanding challenges in stakeholder engagement, decision-making, and sustainability. It provides a practical approach to harmonizing computational rigor with human-centered design, enabling architects and planners to make more informed decisions while fostering collaboration among project stakeholders.

One of the most significant contributions of this research is its emphasis on adaptability and cultural responsiveness. By providing tools for balancing material efficiency, energy optimization, and user satisfaction, the research highlights the potential for DIDO to enhance architectural workflows while remaining sensitive to both functional and aesthetic needs. The CICA system, in particular, demonstrates how complexity metrics can inform facade design decisions and support projects focused on urban renewal or historical preservation. These applications ensure that new developments respect cultural heritage and align with contemporary urban demands, offering a means to integrate architectural innovation with context-sensitive planning.

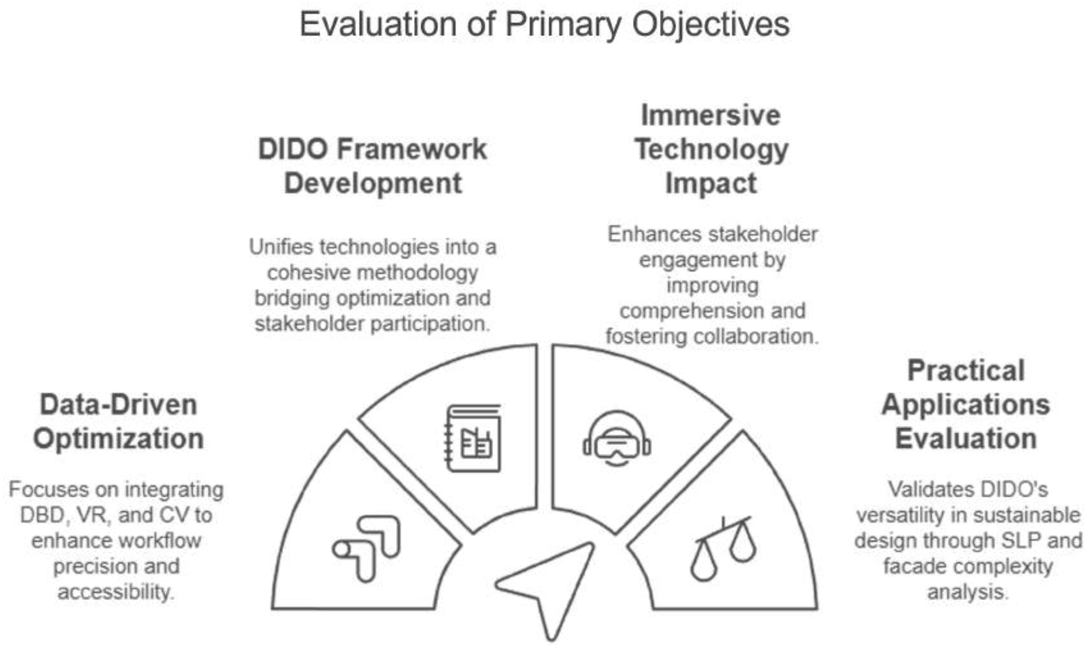


FIGURE 6.2: Flowchart illustrating the evaluation of the primary objectives.

6.3 Evaluation of Research Objectives

The objectives outlined in this study, as detailed in Chapter 1 (Section 1.3), were designed to address critical gaps in the architectural design process by integrating advanced computational techniques and immersive technologies. Through the Data-Driven Immersive Design Optimization (DIDO) framework, the research aimed to explore, implement, and validate innovative methods for enhancing decision-making in architectural workflows. The evaluation presented here reflects on the achievement of these objectives, structured into primary goals and specific targets for Site Layout Planning (SLP) and 'Facade Complexity Analysis'. By analyzing the findings in light of these goals, this section highlights the contributions of the study, identifies challenges encountered, and underscores opportunities for further advancement.

6.3.1 Evaluation of Primary Objectives

The primary objectives of this study, as outlined in Section 1.3, were centered on advancing architectural design through the integration of data-driven methodologies, immersive visualization tools, and computational analysis. The discussion highlights how the DIDO framework successfully addressed these goals while offering insights into future possibilities (see Figure 6.2).

Exploration of Data-Driven Optimization Techniques with VR and CV in Architectural Design

The exploration of integrating data-driven design (DBD), Virtual Reality (VR), and Computer Vision (CV) through the DIDO framework demonstrated its capacity to address complex architectural workflows. The framework effectively merged computational analysis with immersive visualization, allowing for data-informed yet intuitive decision-making. Findings confirmed the value of this approach in improving design outcomes, particularly through the alignment of computational optimization with user-centric feedback.

The implications of these findings emphasize the transformative role of combining computational methods with experiential tools in modern architectural design practices. By bridging the gap between analytics and human interaction, the study highlights how architects can achieve both precision and accessibility in design workflows.

However, challenges were observed in adapting these techniques across varying design scales and project contexts. Further research could explore how data-driven optimization can integrate with other emerging technologies, such as AI-enhanced design tools, to broaden its application.

Development of the DIDO Framework

The research successfully established the DIDO framework, unifying DBD, VR, and CV to create a comprehensive methodology for architectural design. This framework demonstrated its effectiveness in aligning technical performance metrics with user-centered design objectives, balancing computational precision with human engagement.

The broader implications of DIDO's development lie in its ability to redefine design processes across the AEC industry. The framework bridges the traditionally separate realms of technical optimization and stakeholder participation, making it a versatile tool for fostering collaborative workflows.

Challenges include scalability across diverse design scenarios. While DIDO performed well in the tested applications, further refinement is required to adapt the framework to other complex projects, such as large-scale infrastructure planning or hyper-localized interior designs.

Impact of Immersive Technology on Stakeholder Engagement

The research demonstrated how VR and CV can significantly enhance stakeholder engagement in architectural decision-making. Immersive technologies made complex spatial and visual data more accessible, improving comprehension and fostering collaborative feedback. Case studies in Site Layout Planning (SLP) and 'Facade Complexity Analysis' showcased how these tools improved user satisfaction and decision-making accuracy.

The implications of these findings are profound for democratizing architectural processes. Immersive technologies empower a wider range of stakeholders, regardless of their technical expertise, to participate meaningfully in design decisions.

However, the reliance on VR and CV revealed certain technical and logistical challenges, such as the need for user training and potential hardware limitations. Future studies should focus on refining these tools for broader adoption, including solutions for low-cost or mobile-based immersive experiences.

Evaluation of DIDO's Practical Applications and Limitations

Case studies on SLP and 'Facade Complexity Analysis' validated the DIDO framework's versatility and adaptability. The findings showcased how DIDO could address both macro-level challenges in urban planning and micro-level considerations in aesthetic optimization.

The practical implications of these results are significant for the AEC industry. DIDO's capacity to integrate diverse datasets, align stakeholder feedback with computational metrics, and streamline workflows positions it as a transformative tool for sustainable and efficient design practices.

However, limitations in applying DIDO to untested scenarios were noted. Expanding the framework's scope to include diverse architectural scales and real-time stakeholder feedback would enhance its practical relevance and adaptability.

6.3.2 SLP-Specific Objectives

Optimization of Site Layout Decisions Using DBD and MOO

The application of DIDO to SLP demonstrated that Multi-Objective Optimization (MOO) significantly enhanced the precision and efficiency of layout planning. The alignment between stakeholder-selected layouts and MOO-driven recommendations in the VR environment was evident, with an average improvement in decision-making accuracy of 48.3% compared to traditional screen-based methods (Figure 4.13). This alignment underscores DIDO's potential to streamline spatial planning, ensuring layouts satisfy both technical and user-defined goals.

Interestingly, improvements varied across sites, correlating with the topographical complexity of the locations. Site 2, which featured the most challenging terrain, saw the highest accuracy improvement (57.2%), while Site 1 exhibited the lowest improvement (42.1%; Figure 4.15). This suggests that the visual and interactive features of VR are particularly valuable in navigating complex spatial conditions, where traditional methods might struggle.

The findings also emphasize the resource-saving potential of DIDO, as reduced deviation from MOO recommendations minimizes costly redesigns and optimizes land use efficiency. Future research should explore integrating dynamic environmental factors, such as real-time traffic patterns or energy simulations, to further expand DIDO's applicability in SLP. By incorporating these adaptive metrics, the framework could offer even greater precision and adaptability in addressing evolving site planning challenges.

Evaluation of VR's Role in Stakeholder Engagement

The study revealed that VR immersion significantly enhanced stakeholder engagement, leading to greater confidence and satisfaction in layout decisions. Participants consistently reported higher levels of understanding regarding spatial relationships within their selected layouts, with survey responses highlighting a mean usability score of 5.1 (Figure 4.17). This suggests that VR's intuitive visualization capabilities enable stakeholders to grasp complex site dynamics more effectively than traditional 2D representations.

Moreover, the probability graph (Figure 4.14) showed a 40% likelihood of participants achieving high alignment with MOO recommendations, further reflecting VR's influence in improving decision-making precision. While these findings demonstrate VR's potential as a transformative tool for participatory urban design, challenges remain. Variability in user responses, as indicated by the standard deviation of 44.1% in accuracy improvements (Figure 4.13), underscores the importance of developing training protocols and intuitive interfaces to bridge gaps in user familiarity with VR technology.

Future work could explore integrating VR with other immersive tools, such as AR, to create hybrid environments for site analysis. These tools could further enhance stakeholder comprehension and interaction, fostering more collaborative and inclusive decision-making processes in urban planning.

Impact of Data-Driven Immersive Design on Layout Planning Outcomes

The integration of immersive design tools in SLP resulted in marked improvements in decision-making accuracy and user satisfaction. The VR-based approach achieved an average improvement of 48.3% in decision accuracy compared to screen-based methods, with particularly strong results observed for complex sites like Site 2 (57.2%; Figure 4.15). These findings highlight the potential for immersive tools to optimize urban planning outcomes by aligning stakeholder preferences more closely with data-driven recommendations.

Survey responses further validated this impact, with participants rating VR's effectiveness in aiding SLP at 5.4 out of 7 (Q15 in Figure 4.18). This aligns with qualitative feedback emphasizing the enhanced comprehension and confidence VR provided during decision-making. The usability metrics also reflect a generally positive user experience, though some participants noted challenges related to navigation and interface intuitiveness.

The broader implications of these findings suggest that immersive tools like VR can foster more inclusive, efficient, and data-informed design processes in urban planning. However, scaling these tools to larger projects will require integrating real-time data feedback, such as environmental or traffic simulations, to ensure decisions remain contextually relevant. Future studies should also address the variability in user experiences by incorporating adaptive learning interfaces tailored to diverse participant backgrounds.

6.3.3 'Facade Complexity Analysis'-Specific Objectives

Integration of CV, DBD, and VR for 'Facade Complexity Analysis'

The creation and validation of the 'Complexity Image Complexity Analysis' (CICA) system marked a significant milestone in integrating Computer Vision (CV) with Data-Driven Design (DBD) and Virtual Reality (VR) under the Data-Driven Immersive Design Optimization (DIDO) framework. The system efficiently quantified facade complexity across diverse architectural styles and contexts, processing 177 buildings in 4.54 seconds (see Section 5.3.1), showcasing both its computational efficiency and adaptability.

The integration of CICA within the DIDO framework emphasizes the potential to blend computational rigor with user-centered design insights. By aligning data-driven metrics with subjective user preferences observed during the VR experiments, the system has demonstrated its capability to create designs that harmonize aesthetic and functional goals.

Future directions include expanding the system's capabilities to account for three-dimensional and volumetric complexity. This enhancement could address current limitations, such as the inability to analyze spatial hierarchy and massing, which were highlighted in the limitations of the CICA system (see Section 5.5). Incorporating additional metrics like materiality and environmental performance could further advance its relevance in sustainable design practices.

Quantification of Facade Complexity and User Preference Alignment

The CICA system quantitatively demonstrated a preference for moderate facade complexity, with an average *CICA complexity score of 4.05/10* (see Section 5.4.2). This preference was corroborated by the VR-based user experiment, where participants consistently selected facades with moderate intricacy across three patterns. The probability distribution graph (Figure 5.15) highlighted a 40% likelihood of users selecting a design with a complexity score near this average, despite individual variability (standard deviation of $SD = 1.2$).

This balance between intricacy and simplicity provides critical insights for designing facades that are visually engaging yet approachable. These findings guide sustainable and user-responsive architectural practices by emphasizing a balance between aesthetic appeal and functionality. For instance, the moderate complexity preference aligns with the need for adaptable designs that cater to diverse user groups while maintaining efficient resource utilization (see Section 5.4.3).

Future research should explore cultural and environmental factors influencing complexity perception. Expanding the dataset to include diverse cultural and geographic contexts could yield localized insights, enabling architects to tailor complexity levels to specific user and environmental needs.

Extending 'Facade Complexity Analysis' to Urban Streetscapes

The application of the CICA system to urban streetscapes revealed distinct patterns in facade complexity across five cities—Barcelona, Budapest, Florence, Fukuoka, and Paris. Complexity scores ranged from 4.1 in Fukuoka to 6.4 in Barcelona (see Figure 5.22), highlighting the influence of cultural and architectural contexts. Barcelona's ornate 'Catalan Modernisme' facades maintained high scores, while Fukuoka's minimalist modernist designs exhibited lower scores, emphasizing functionality over ornamentation. This analysis confirmed the CICA system's reliability in capturing both visual intricacy and urban cohesion across diverse settings.

These findings underscore the role of facade complexity in preserving cultural identity and guiding urban renewal. Iconic cities with higher complexity, like Barcelona and Florence, demonstrate the value of intricate designs in enhancing visual richness and fostering cultural continuity. Conversely, the regular street from Fukuoka, with a modern and less intricate design, highlight the potential for contemporary designs to prioritize clarity and adaptability while showcasing room for improvement of aesthetic appeal. The ability of the CICA system to identify these patterns offers practical insights for architects and planners, informing both preservation efforts and the integration of contemporary elements into historic urban fabrics.

Future research should extend this analysis to additional cities and diverse street typologies to enhance the generalizability of the findings. Incorporating volumetric complexity and environmental performance metrics into the CICA system could provide a more comprehensive assessment of urban environments. These advancements would strengthen its application in designing sustainable streetscapes that balance cultural heritage with modern demands, ensuring the system's utility in diverse urban renewal and planning scenarios.

Validation of CV Metrics in Assessing Architectural Complexity

The application of the CICA system to historical datasets, experimental user evaluations, and urban streetscape analysis validated its reliability in quantifying architectural complexity across varied contexts. In the historical analysis (Figure 5.11), the system identified a rising complexity trendline in postmodern architecture, corroborating the hypothesis of increasing complexity in contemporary design (see Section 5.4.1). In urban streetscapes, it consistently captured the nuanced interplay of cultural and architectural influences, as illustrated by the average complexity scores across cities, ranging from 4.1 (Fukuoka) to 6.4 (Barcelona) (see Figure 5.22).

The discrepancies observed between participant preferences and CICA rankings, particularly at higher complexity levels (standard deviation of 9%; see Section 5.4.2), underscore the importance of integrating user feedback with algorithmic assessments. These results highlight the potential for refining facade optimization practices by blending quantitative data with subjective input.

Future work should focus on expanding the dataset to include more architectural styles and contexts, as recommended in Section 5.5. This expansion would enhance the system's generalizability and applicability, ensuring its utility in both historical preservation and contemporary design optimization.

6.3.4 Integration of Findings

This subsection combines results stemming from both the primary and specific objectives, putting into focus how data-driven methodologies and immersive technologies are working together to change architectural practices. By combining computational precision and immersive interaction, the DIDO framework has proven to be versatile in different contexts, starting from site layout planning (SLP) to the analysis of facade complexity.

Collaborative Impact of Data-Driven Insights and Immersive Technologies

The integration of data-driven insights and immersive tools, as explored in both SLP and 'Facade Complexity Analysis', illustrates the transformative potential of DIDO in architectural design. The findings reveal that VR technologies significantly enhanced decision-making accuracy, reducing deviations in SLP by an average of 48.3% (Section 4.4, Figure 4.13) and aligning user-selected designs more closely with multi-objective optimization (MOO) recommendations. Similarly, the use of VR in 'Facade Complexity Analysis' enabled participants to engage with CICA-based evaluations, revealing a pattern in preferred level of complexity, the otherwise subjective interpretation of complexity in facade design now backed by a measurable CICA complexity score with 40% of users consistently selecting facades rated near the mean CICA score of 4.05 (Section 5.4.2, Figure 5.15), contributing to refine the predicting computational model.

These findings highlight the synergistic relationship between computational tools like MOO algorithms and CICA metrics, and experiential technologies like VR. While computational systems provided data-driven precision, VR's immersive environment bridged the gap between abstract metrics and human-centered design, enabling users to intuitively assess spatial layouts and facade aesthetics.

Adaptability of the DIDO Framework

The adaptability of the DIDO framework across diverse scales and design challenges underscores its versatility. At the macro-level, SLP demonstrated how VR and MOO integration can improve urban planning efficiency, reducing resource waste and fostering stakeholder engagement (Section 4.5). At the micro-level, 'Facade Complexity Analysis' showed how CV-based metrics could capture intricate architectural patterns, as seen in the urban streetscapes analysis (Section 5.4.4, Figure 5.22).

This adaptability reflects DIDO's capacity to address both functional optimization and aesthetic refinement, balancing quantitative metrics with qualitative user feedback. For example, SLP participants valued real-time feedback for its role in spatial exploration (Section 4.4), while facade complexity participants emphasized the importance of moderate intricacy in designs and considerations for views (Section 5.4.3). The consistent application of the DIDO framework across these contexts highlights its potential as a standardized tool for participatory and data-driven architectural design.

Future Directions for Cross-Disciplinary Applications

While DIDO's successes demonstrate its robustness, challenges identified in its implementation offer opportunities for refinement. For example, differences in user perceptions—such as the variability in VR interaction outcomes in SLP ($SD = 44.1\%$, Figure 4.14) and the standard deviation in facade complexity preferences ($SD = 1.2$, Figure 5.15)—emphasize the need for more intuitive interfaces and adaptive feedback loops.

Looking ahead, expanding DIDO to incorporate emerging technologies like augmented reality (AR) and mixed reality (MR) could bridge the gap between immersive virtual environments and real-world applications. For urban renewal, DIDO could integrate facade complexity metrics to guide the restoration of historical districts (Section 5.4.4). Similarly, combining MOO-driven SLP with facade optimization could foster holistic urban design practices, balancing efficiency with cultural and aesthetic considerations.

By synthesizing computational insights with immersive technologies, the DIDO framework has proven its potential to foster inclusive, efficient, and culturally responsive architectural practices. The integration of these approaches not only enhances decision-making but also empowers stakeholders to engage meaningfully in design processes, paving the way for sustainable and adaptive design innovations.

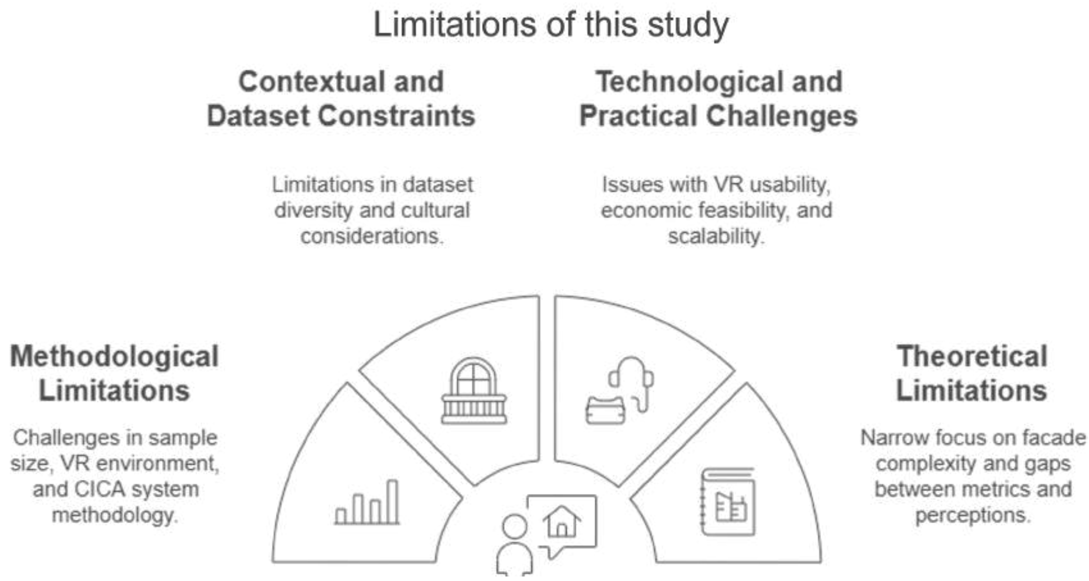


FIGURE 6.3: Flowchart illustrating the limitations of this study.

6.4 Limitations of the Study

This study has provided significant insights into the integration of data-driven methodologies and immersive technologies in architectural design, yet several limitations must be acknowledged for advancing the methodologies and expanding the impact of data-driven immersive design in the architectural, engineering, and construction (AEC) industry (see Figure 6.3).

Methodological Limitations

One of the key limitations of this study lies in its sample size and demographics. The SLP experiments involved only 17 participants, while the 'Facade Complexity Analysis' included 26 participants. Most participants were university students and faculty members, with limited representation from diverse professional backgrounds and age groups. This homogeneity restricts the generalizability of findings to broader stakeholder groups, such as experienced urban planners, architects, and non-academic users. A larger and more diverse participant pool is necessary to validate the findings and expand their applicability.

The virtual reality (VR) environment, while effective in facilitating immersive decision-making, introduces its own constraints. The controlled experimental setting may not fully replicate the complexities of real-world conditions, such as environmental distractions or dynamic urban contexts. Moreover, participants' familiarity with VR technology varied, leading to potential biases in decision-making outcomes. Some participants reported mild discomfort, such as motion sickness, which could impact their performance and engagement. These challenges underline the need for more robust VR systems and standardized user protocols.

Similarly, the CICA system demonstrated limitations in its current methodology. The reliance on two-dimensional (2D) images for complexity analysis omits crucial three-dimensional (3D) architectural features, such as volumetric articulation and spatial hierarchy. Additionally, the metrics used—such as edge detection and contour density—do not fully encapsulate subjective aesthetic preferences, which are deeply influenced by cultural and individual factors. These constraints highlight areas for refinement in both experimental design and algorithmic approaches.

Contextual and Dataset Constraints

The datasets used in this study present contextual limitations. The SLP experiments were conducted using hypothetical site scenarios rather than real-world urban environments, which limits the practical applicability of the findings. For 'Facade Complexity Analysis', the historical dataset comprised 177 architectural facades, while urban analysis focused on five streetscapes from selected cities. While these datasets provided valuable insights, their scope does not fully capture the global diversity of architectural styles or urban contexts. Expanding these datasets to include a wider range of building types, geographic regions, and cultural influences would enhance the robustness of the results.

Furthermore, the analysis did not deeply explore cultural or environmental considerations in user preferences. For instance, while the CICA system identified a preference for moderate complexity (mean score of 4.05/10, Section 5.4.2), it did not account for how cultural backgrounds might shape these preferences. Similarly, the environmental implications of facade complexity, such as energy efficiency and material sustainability, were not integrated into the analysis. Addressing these aspects in future studies could offer a more holistic understanding of facade design.

Technological and Practical Challenges

The usability of VR systems posed a significant challenge, with participants displaying varying levels of comfort and proficiency. Designing universally intuitive interfaces for such a diverse group of users remains a critical challenge. While survey results highlighted the potential of VR for enhancing decision-making (Section 4.4, Figure 4.18), they also pointed to areas requiring improvement, such as better visualization of design flaws and enhanced navigation controls.

Economic feasibility is another practical limitation. Implementing advanced VR and computer vision (CV) systems at scale requires substantial financial and technical resources, which may hinder their adoption in smaller architectural and urban planning firms. This constraint underscores the need for cost-effective solutions to democratize access to these technologies.

Lastly, scalability emerged as a challenge, particularly for the DIDO framework. While this study demonstrated the effectiveness of DIDO in focused applications like SLP and facade complexity, its adaptability to large-scale urban planning projects or multi-site analysis has not been tested. Understanding how DIDO performs in such scenarios is essential for its widespread implementation.

Theoretical Limitations

This study's focus on facade complexity represents another limitation. While it provided valuable insights into patterns, textures, and user preferences, the narrow scope may overlook other critical aspects of architectural design, such as interior spaces, urban integration, and landscape interactions. Future research should adopt a more comprehensive approach to address these interconnected design elements.

Moreover, discrepancies between computational metrics and user perceptions underscore the ongoing gap between quantifiable data and experiential insights. For instance, while the CICA system provided systematic complexity scores, it occasionally diverged from participants' subjective evaluations, particularly at higher complexity levels (Section 5.4.2, Figure 5.17). Bridging this gap will require advancements in algorithms that better incorporate human-centered and culturally sensitive factors into data-driven methodologies.

This comprehensive discussion of limitations provides a clear pathway for addressing the constraints of the study while aligning future research directions with the evolving needs of the architectural, engineering, and construction (AEC) industry.

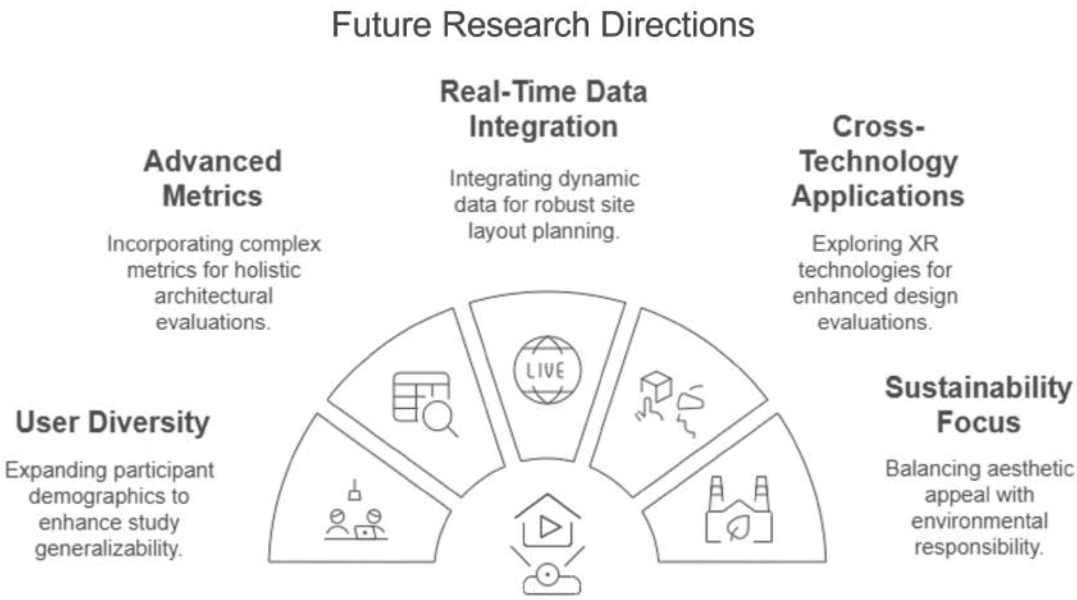


FIGURE 6.4: Flowchart illustrating Future Research Directions of this study.

6.5 Future Research Directions

Building on the findings and limitations identified in this study, future research offers numerous opportunities to refine and expand the applications of the Data-Driven Immersive Design Optimization (DIDO) framework. By addressing key gaps, such as participant diversity, advanced metrics for facade complexity, and the integration of dynamic data, researchers can enhance the robustness and scalability of DIDO, making it a transformative tool for architectural design (see Figure 6.4).

To improve the generalizability of this study's findings, future research should expand participant demographics to include diverse user groups with varying professional expertise, cultural backgrounds, and geographic representation. This would provide a more comprehensive understanding of how different user profiles influence decision-making in SLP and 'Facade Complexity Analysis'. Additionally, testing DIDO in large-scale, real-world applications, such as urban planning projects or high-density developments, will help assess its scalability and adaptability across diverse architectural contexts.

Enhancing the capabilities of the Computational Image Complexity Analysis (CICA) system represents a critical area for future exploration. Incorporating volumetric and three-dimensional complexity metrics would allow for a more holistic evaluation of architectural designs. Additional metrics, such as materiality, energy efficiency, and environmental performance, could further align the CICA system with sustainable design goals. Expanding datasets to include a broader range of cities, architectural styles, and geographic regions will enhance the system's applicability and reliability in diverse contexts.

The inclusion of dynamic, real-time environmental data offers the potential to improve the robustness of site layout planning (SLP) models. Future research could integrate data such as traffic flow, energy consumption, and climatic conditions into multi-objective optimization (MOO) processes. These inputs would allow stakeholders to evaluate how designs perform under varying conditions, providing a more realistic basis for decision-making in immersive virtual reality (VR) environments.

Exploring the potential of extended reality (XR) technologies, such as augmented reality (AR) and mixed reality (MR), could complement VR-based workflows by enabling real-time, in-situ evaluations of design proposals. Integrating DIDO with generative design algorithms and advanced simulation tools could further enhance its computational workflows, opening up new possibilities for iterative, data-driven design optimization.

Future research should focus on refining the human-computer interaction (HCI) aspects of DIDO to enhance accessibility and user engagement. This includes developing alternative visualization paradigms tailored to users with varying levels of expertise and exploring innovative interaction techniques to make VR environments more intuitive. Long-term studies on the cognitive and psychological impacts of immersive technologies in professional settings could provide valuable insights into their usability and effectiveness.

DIDO's potential for advancing sustainable architectural practices warrants further investigation. Future studies could examine the interplay between facade complexity, energy performance, and material efficiency to identify design strategies that balance aesthetic appeal with environmental responsibility. The framework's adaptability to projects such as adaptive reuse, urban renewal, and green building certification processes also represents a promising avenue for research.

The interdisciplinary nature of architectural workflows calls for broader collaboration across related fields. Future research could explore how DIDO enhances communication and collaboration between architects, engineers, urban planners, and other stakeholders. Expanding the framework's applications to adjacent disciplines, such as industrial design or interior architecture, could reveal additional opportunities for innovation.

Future works delineated in this section seek to realize the comprehensive capabilities of the DIDO framework, establishing it as a fundamental element in contemporary architectural practice. By tackling the recognized deficiencies and broadening its scope of applications, DIDO has the potential to reconcile computational accuracy with human-centric design, thereby fostering innovation within the field of architecture and beyond.

6.6 Final Thoughts

This thesis, titled *'Enhancing Architectural Design through Data-Driven Building Design using Virtual Reality and Computer Vision,'* set out to explore how computational precision and user-centered design could converge to redefine architectural practices. Through the development and application of the Data-Driven Immersive Design Optimization (DIDO) framework, the study demonstrated the transformative potential of integrating data-driven methodologies with immersive tools like Virtual Reality (VR) and Computer Vision (CV). By addressing Site Layout Planning (SLP) and 'Facade Complexity Analysis', the research validated how the DIDO framework enables informed, efficient, and collaborative decision-making processes, fulfilling the initial vision of harmonizing technological innovation with human-centric design principles.

Beyond its specific contributions to SLP and facade design, the broader implications of this work extend into the future of architectural workflows. By adopting immersive technologies, architects and planners can tackle contemporary challenges such as sustainability, urban renewal, and cultural sensitivity. The findings highlight that tools like the CICA system and VR not only enhance analytical capabilities but also foster deeper stakeholder engagement, paving the way for more inclusive, adaptive, and resilient architectural solutions. This intersection of computational rigor and experiential insights exemplifies a shift towards design methodologies that prioritize both precision and empathy.

As architecture evolves to meet the demands of a dynamic world, this research underscores the need for continuous innovation. The DIDO framework, as articulated in this thesis, serves as a foundational model for bridging the gap between advanced computation and human creativity, inspiring researchers and practitioners alike to push the boundaries of what is possible. By embracing such integrative approaches, the field of architecture can unlock new possibilities for collaboration, sustainability, and design excellence.

In conclusion, this study not only advances theoretical understanding but also provides practical tools and methodologies for real-world application. Its journey reflects a commitment to exploring the convergence of data and design, offering a vision for architecture that is as grounded in human experience as it is in technological progress. The work presented here aspires to influence not just the projects of today but the architectural landscapes of tomorrow, driving the field toward a future that is innovative, inclusive, and impactful.

Appendix A

Appendix for Virtual Reality-based Site Layout Planning for Building Design

A.1 Post-interaction Survey of experiment for Site Layout Planning

The evaluation survey had three sections. The first one task with identifying the professional background of the participants (see A.1). The second one, a 10 question survey using a 7-point Likert scale to measure the usability of the system (see A.2) and perception of the influence that said system had on their solution (see A.3).

TABLE A.1: Multiple choice survey for professional background

	Participant background section. Multiple choice questions
1	What is your current occupation? a) Architect b) Civil engineer c) Construction manager d) Urban planner e) Other (please specify)
2	How many years of professional experience do you have in site layout planning? a) None b) Less than 1 year c) 1-5 years d) 6-10 years e) More than 10 years
3	What is the highest level of education you have completed? a) High school diploma b) Associate degree c) Bachelor's degree d) Master's degree e) Doctoral degree
4	Which software tools have you used for site layout planning? (Select all that apply) a) AutoCAD b) SketchUp c) Revit d) Rhino e) ArcGIS f) Other (please specify)
5	What challenges have you encountered when designing site layouts? (Select all that apply) a) Limited space b) Limited budget c) Site constraints d) Client preferences e) Environmental factors f) Other (please specify)

TABLE A.2: User satisfaction section from Usability survey for VR simulation for site layout planning design

	User satisfaction section. 7 - Likert scale
6	Overall, how satisfied are you with the virtual reality simulation for site layout planning design? 1) Very dissatisfied 2) Moderately dissatisfied 3) Slightly dissatisfied 4) Neither satisfied nor dissatisfied 5) Slightly satisfied 6) Moderately satisfied 7) Very satisfied
7	To what extent did the virtual reality simulation enhance your ability to visualize the site layout plan? 1) Not at all 2) Slightly 3) Moderately 4) Neither 5) Somewhat 6) Very 7) Extremely
8	How easy was it to use the virtual reality simulation for site layout planning design? 1) Very Difficult 2) Moderately Difficult 3) Slightly Difficult 4) Neither Easy nor Difficult 5) Slightly Easy 6) Moderately Easy 7) Very Easy
9	To what extent did the virtual reality simulation allow you to explore different design options? 1) Not at all 2) Slightly 3) Moderately 4) Neither 5) Somewhat 6) Very 7) Extremely
10	How helpful was the virtual reality simulation in identifying potential design flaws or issues? 1) Not at all helpful 2) Slightly helpful 3) Moderately helpful 4) Neither helpful nor unhelpful 5) Somewhat helpful 6) Very helpful 7) Extremely helpful

TABLE A.3: User-System Influence Perception section from Usability survey for VR simulation for site layout planning design

	Influence perception section. 7 - Likert scale
11	To what extent did the suggested solutions presented through the virtual reality simulation influence your decision regarding the site layout planning design? 1) Not at all 2) Slightly 3) Moderately 4) Neither 5) Somewhat 6) Very 7) Extremely
12	How valuable were the suggested solutions presented through the virtual reality simulation in improving the site layout planning design? 1) Not valuable at all 2) Slightly valuable 3) Moderately valuable 4) Neither valuable nor invaluable 5) Somewhat valuable 6) Very valuable 7) Extremely valuable
13	How likely are you to implement the suggested solutions presented through the virtual reality simulation in the final site layout plan? 1) Very unlikely 2) Moderately unlikely 3) Slightly unlikely 4) Neither likely nor unlikely 5) Slightly likely 6) Moderately likely 7) Very likely
14	How likely are you to use a virtual reality simulation for site layout planning design in the future? 1) Very unlikely 2) Moderately unlikely 3) Slightly unlikely 4) Neither likely nor unlikely 5) Slightly likely 6) Moderately likely 7) Very likely
15	How would you rate the overall effectiveness of the virtual reality simulation for site layout planning? 1) Very dissatisfied 2) Moderately dissatisfied 3) Slightly dissatisfied 4) Neither satisfied nor dissatisfied 5) Slightly satisfied 6) Moderately satisfied 7) Very satisfied

Appendix B

Appendix for Facade Complexity Analysis for Building Design

B.1 Post-interaction Survey of experiment for Facade Complexity Analysis

Survey conducted for the experiment related to Facade Complexity analysis in Chapter 5. The evaluation survey had two sections. The first one tasked with identifying the professional background of the participants (see TableB.1). The second one, a 10 question survey using a 7-point Likert scale to measure the degree of complexity and pattern arrangement within facade design tailored for digital fabrication (see TableB.2).

TABLE B.1: Multiple choice survey for professional background

	Participant background section. Multiple choice questions
1	What is your current occupation? a) Architect b) Civil engineer c) Construction manager d) Urban planner e) Other (please specify)
2	How many years of professional experience do you have in facade design? a) None b) Less than 1 year c) 1–5 years d) 6–10 years e) More than 10 years
3	What is the highest level of education you have completed? a) High school diploma b) Associate degree c) Bachelor's degree d) Master's degree e) Doctoral degree
4	Which software tools have you used for facade design? (Select all that apply) a) AutoCAD b) SketchUp c) Revit d) Rhino e) ArcGIS f) Other (please specify)
5	What challenges have you encountered when designing facades? (Select all that apply) a) Limited space b) Limited budget c) Building program constraints d) Client preferences e) Environmental factors f) Other (please specify)

TABLE B.2: Perception section from survey for facade complexity analysis

	Complexity perception section. 7 - Likert scale
6	To what extent do you find the overall complexity of this facade design appealing? Strongly Disagree (1) ——— Strongly Agree (7)
7	How do you rate the intricacy of the patterns and textures used in this facade design? Not Intricate at All (1) ——— Extremely Intricate (7)
8	To what extent do you think the arrangement of architectural elements on this facade adds to its visual interest? Not at All (1) ——— Adds Significantly (7)
9	How complex do you perceive the facade's use of patterns and textures? Not Complex at All (1) ——— Very Complex (7)
10	How detailed do you find the ornamentation on this facade design? Not Detailed at All (1) ——— Extremely Detailed (7)
11	How much do the combination of materials contribute to the overall complexity of the facade? Minimally (1) ——— Significantly (7)
12	To what degree does the composition of the facade strike you as aesthetically intricate? Not Intricate at All (1) ——— Extremely Intricate (7)
13	How much do you believe that the arrangement of shapes and forms on the facade contributes to its complexity? Not at All (1) ——— A Great Deal (7)
14	How significantly does the use of color enhance the facade's visual complexity? Not Significantly (1) ——— Very Significantly (7)
15	How much depth and layering do you observe in the design of this facade? None (1) ——— A Great Deal (7)

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