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TITLE:

CoFAB: An Integrated Human-AI Collaboration Prototyping and Fabrication System for Designers in Early Design Stages

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CoFAB:

An Integrated Human-AI Collaboration Prototyping and Fabrication System for Designers in Early Design Stages

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Abstract

The rapid development of generative AI is fundamentally and revolutionally transforming design workflows. However, significant technical and cognitive barriers still exist in translating conceptual ideas into digital and physical prototypes. Existing AI tools inadequately support the comprehensive design-to-fabrication process, particularly for designers without extensive technical backgrounds. This research introduces an innovative prototyping workflow that strategically integrates generative AI, parametric modeling platforms, and robotic fabrication systems to mitigate these challenges and streamline design translation.

The study focuses on the reconfiguration of designer-fabrication tool interactions through developing a novel intelligent system driven by natural language interfaces. By employing a mixed approach combining user surveys, workflow analysis, and comparative experimental design, the research comprehensively evaluates the system's impact on task completion efficiency, operational complexity reduction, and creative exploration. The developed end-to-end prototyping platform enables designers to generate fabrication-ready models through intuitive natural language instructions, facilitating a seamless transition from conceptualization to physical prototype.

Empirical results demonstrate the system's significant potential in reducing technical barriers and cognitive load. Non-expert users can now rapidly iterate diverse design alternatives, substantially expanding their exploratory design capacities. Beyond its immediate technological contributions, this research establishes a continuous platform bridging design conception, digital modeling, and physical fabrication. By proposing novel methodological frameworks for assessing human-AI collaborative workflows, the study provides a foundational reference for future explorations into generative AI and intelligent fabrication integration.

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1 Introduction

1.1 Context

The rapid development of generative AI in recent years is bringing a revolutionary transformation in creative workflows. AI-powered tools such as ChatGPT and Midjourney are now capable of assisting with a wide range of tasks, from conceptual ideation to visual generation, they significantly lower the barrier to participation in design and expand both the speed and breadth of design exploration. Machine learning algorithms can analyze vast design databases, extract patterns, and generate novel solutions, thereby challenging traditional design constraints. Simultaneously, digital fabrication technologies are also evolving. The decreasing cost of access to desktop fabrication devices, such as 3D printers and robotic arms, is introducing new means for transforming digital models into tangible products outside of professional production contexts, seemingly eliminating the barriers posed by conventional manufacturing.

Despite these advances in these separate domains, there is still no efficient integration between generative AI and digital fabrication, which remains a technically demanding and consequently insufficiently widespread practice. In traditional digital fabrication workflow, designers are often required to install dozens of specialized software programs on their computers, configure complex system environments, and navigate a labyrinthine ecosystem of tools and each requiring distinct technical expertise. The journey from conceptual design to physical prototyping demands proficiency across multiple technical domains, including parametric modeling, simulation, toolpath generation, and robotic control. Each stage of the design-to-fabrication pipeline entails

different technical knowledge, making it necessary for designers to possess an unprecedented breadth of expertise that goes far beyond traditional skills in ideation and creativity.

As the pace of technological innovation accelerates, the cognitive load has also been placed on designers. Every new tool or platform requires substantial time investment to learn, master, and adapt to emerging workflows. The expectation to master a rapidly evolving software and hardware ecosystem introduces not only mental fatigue but also financial strain. This ongoing pressure diverts designers' focus from creative exploration to system management, creating a tension between imaginative thinking and technical execution.

1.2 Statement of Question

The context addressed above presents both a challenge and an opportunity. Given the transformative potential of generative AI and digital fabrication technologies, this research aims to address a critical gap in the current design-to-fabrication ecosystem: the absence of an integrated, user-friendly platform that seamlessly connects AI-driven design generation with accessible digital fabrication processes. Specifically, this study focuses on how generative AI can be utilized to streamline and democratize the design-to-fabrication workflow, reduce the technical barriers that prevent creative professionals and non-technical users from translating digital concepts into physical prototypes, and thereby accelerate iteration and broaden participation in digital fabrication.

Based on the foundation, the central research question is stated:

> *How to improve current human–AI–robot collaborative workflows to reduce the technical barriers and cognitive load faced by designers during early-stage modeling and prototyping, while increasing workflow continuity to enhance the efficiency of rapid prototyping?*

To explore this overarching question, the research further investigates the following:

1. What are the main challenges and pain points that designers currently face in the workflow from conceptual design to physical prototyping? What expectations do they have regarding the role of generative AI in this process?
2. How can generative AI algorithms be utilized to automate and simplify complex technical stages in digital manufacturing workflows, such as parametric modeling, toolpath generation, and robotic control?
3. To what extent can an integrated human-AI-robot workflow reduce the cognitive load and technical complexity associated with translating digital designs into physical objects, and how can this transformation be effectively measured?

By addressing these questions, this research aims to propose a new framework that expands the potential of generative AI and digital fabrication in early-stage prototyping, reducing technical complexity while enhancing iteration speed and creative productivity. The ultimate goal is to develop a proof-of-concept system that demonstrates the feasibility of a more inclusive, efficient, and creativity-centered design-to-fabrication ecosystem.

1.3 Outline

This thesis is structured to systematically address the research questions outlined above and to explore the integration potential of generative AI and digital fabrication workflows. A multi-phase methodology is adopted, comprising background research, early user inquiry, system development, implementation, and evaluation, following a logical progression from theoretical framing to experimental validation and critical analysis.

Chapter 2 “**Background”** establishes the theoretical and technological foundation of the study. It critically reviews existing research across four key domains: generative AI applications in 3D design, rapid prototyping strategies for early-stage design, AI-enhanced human-machine collaboration, and AI approaches to lowering design entry barriers. Through this review, current limitations are identified and the research gap this study aims to fill is clearly articulated.

Chapter 3 “**Hypothesis”** formulates the central research question and supporting hypotheses. It discusses the technical challenges inherent in traditional design-to-fabrication workflows, explores the opportunities of human-AI-robot integration, and defines the scope of human-AI collaboration in this context. By adding measurable assumptions about technology accessibility and developing reliable metrics for assessing the performance of the proposed framework, this chapter transforms the initial research questions into testable propositions.

Chapter 4 “**Method”** outlines the approach used to explore the hypotheses. It detailly introduces the initial user research, the development of a natural language to digital modeling system, and the experimental setup for transforming digital designs into physical prototypes. Through iterative testing and system refinement, this chapter demonstrates the feasibility and design logic of the proposed “workflow.

Chapter 5 “**Results”** presents the outcomes of the study, including user survey results, the implementation of the AI-assisted prototyping platform, the standardized workflow, and the results of fabrication experiments. It includes both qualitative feedback and quantitative metrics that assess the system’s effectiveness in reducing cognitive load and improving design iteration speed.

Chapter 6 “**Conclusion and Reflection”** summarizes the key findings, outcomes, and implications of the research. It discusses the limitations and challenges of the current system, proposes avenues for refinement, and outlines future research directions. The contributions are situated within broader discussions of design innovation and human-AI-robot collaboration.

Appendices provide supplementary materials, including detailed surveys, technical documentation, and experimental scripts, are provided to support the transparency and replicability of the study.

2 Background

2.1 Overview

In the ongoing era of digital transformation, the design and fabrication fields are undergoing restructuring. With the rapid development of generative artificial intelligence (Generative AI) and additive manufacturing (i.e., 3D printing), the boundary between creative ideation and physical realization is becoming increasingly blurred. AI technologies are reshaping the way creative ideas are generated during the early stages of design, while devices such as 3D printers and robotic arms are unlocking new possibilities for physical prototyping. This dual evolution signifies not only an expansion of technical capabilities but also a paradigmatic shift in the overall design-to-fabrication workflow.

Specifically, generative AI tools such as Midjourney (Midjourney, 2023), DALL·E (Ramesh et al., 2022), and ChatGPT (OpenAI, 2022) have demonstrated remarkable capabilities in multimodal generation tasks, including text, images, and code, greatly accelerating the speed of conceptual development and enhancing expressive freedom (Antonio et al., 2022). At the same time, the increasing accessibility of desktop 3D printers and robotic fabrication equipment has enabled non-expert users to engage in physical prototyping. Representative initiatives such as Fab@Home (Evan & Lipson, 2006) and MakerBot (MakerBot, 2011) have promoted the notion of "manufacturing for everyone." 3D printing technology has not only introduced new tools but also redefined the role of designers by enabling real-time transformation of ideas into manufacturable forms, thus serving as a catalyst for a new design paradigm (Lipson et al., 2013).

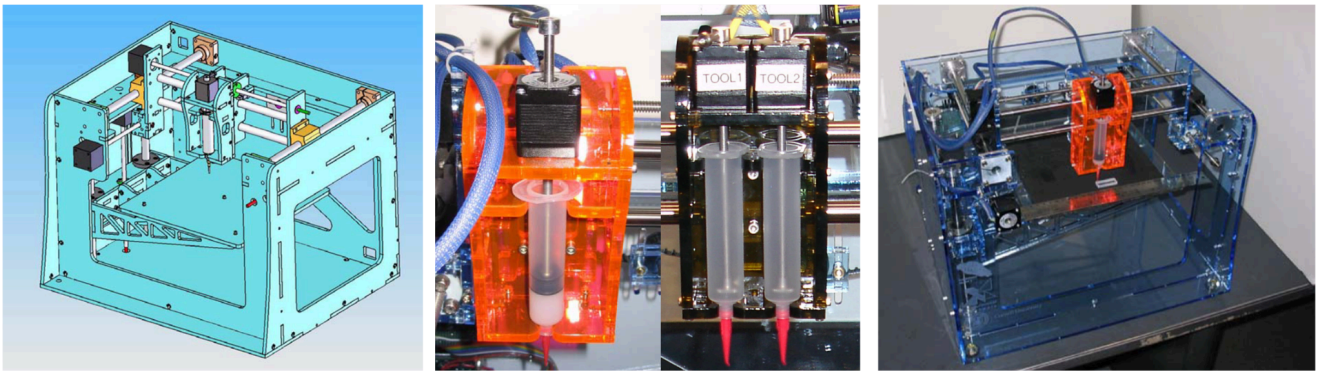


Figure 2.1 Fab@Home: A low-cost solution to access 3D printing equipment (Evan & Lipson, 2006)

However, these technologies still largely exist in isolated development silos. The current design-to-fabrication workflow faces numerous significant technical and cognitive barriers. Traditional digital fabrication processes are often highly fragmented: designers must navigate across multiple software platforms, such as Grasshopper, Fusion 360, or Rhinoceros, while possessing a wide range of skills, including parametric modeling, G-code generation, and robotic control. The complexity of configuring these systems and integrating various tools presents a steep learning curve, particularly for non-technical users. The disconnection between "intelligent generation" and "precise execution" results in a fragmented prototyping pipeline that requires extensive software manipulation, data conversion, and equipment coordination. More critically, the increasing cognitive load imposed by these processes diverts designers' focus from creative exploration to system operation.

Under the circumstance, both academia and industry have begun to explore the paradigm of Human-AI-Robot Collaboration, aiming to bridge the gap between design generation and physical fabrication by integrating AI capabilities with human creativity and machine execution. Recent research has explored natural language interfaces to lower entry barriers to modeling and fabrication, embedding AI into parametric modeling (Ko et al., 2023), path planning, and robotic control workflows (Abdi et al., 2023). This cross-disciplinary system architecture not only simplifies operational processes but also holds the potential to expand creative opportunities in education, maker culture, architecture, and industrial design.

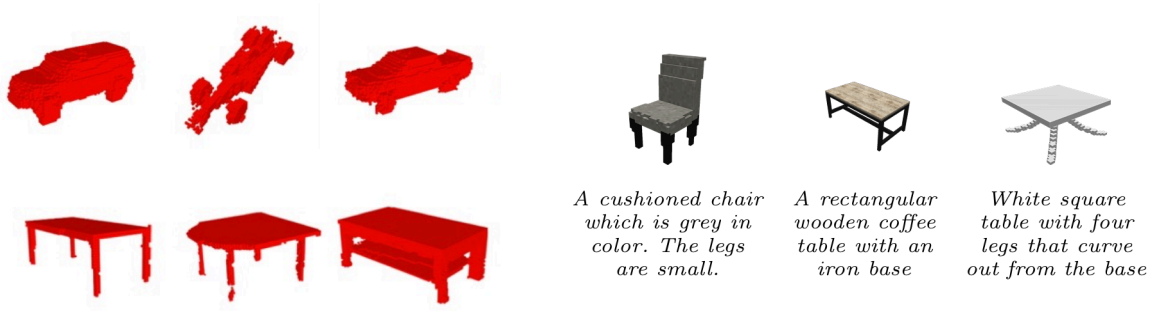
This study aims to systematically examine and integrate these emerging technological trends by proposing a user-centered, integrated intelligent prototyping platform. By combining natural language understanding, generative AI, parametric modeling environments, and robotic fabrication devices, the research seeks to construct a continuous pipeline from “creative expression” to “physical output.” The goal is to lower the professional threshold while enhancing workflow integration, thereby promoting the democratization and accessibility of concept-to-prototype design.

2.2 Current Research Progress

2.2.1 Generative AI in 3D Design

Recent developments in generative artificial intelligence are significantly reshaping 3D design workflows. Through extensive dataset training and algorithm optimization, generative AI has reduced operational complexity, while enhancing designers' iteration speed and ideation breadth. This section reviews research progress on generative AI in 3D design, examining its impact on the 3D design industry and advancements in facilitating interactions between designers and fabrication systems.

Generative AI broadly refers to computational models capable of autonomously producing new content or artifacts. Among these, Generative Adversarial Networks (GANs)(Goodfellow et al., 2014) and diffusion models(Dhariwal & Nichol, 2021) have enabled designers to create 3D geometries with unprecedented ease. Early GAN-based methods, exemplified by exemplified by 3D-GAN(Wu et al., 2017), have demonstrated the ability to generate diverse 3D models from limited inputs, while Text2Shape(Chen et al., 2018) realized text-driven generation of 3D voxels. However, despite these advances, GAN-based approaches revealed limitations in complex 3D structure generation, including unstable training, weak textual constraints, and inefficiencies with high-dimensional data. These limitations prompted a shift toward diffusion models as a more promising technological pathway.



(a) Geometries generated by 3D-GAN (b) Geometries generated by Text2Shape

Figure 2.2 Early GAN-based text-to-3D approaches' generation outputs (Wu et al., 2016; Chen et al., 2018)

Current research on diffusion models in text-to-3D generation has increasingly matured, showing significant advantages over previous approaches. DreamFusion (Poole et al., 2022) pioneered methods utilizing pre-trained 2D diffusion models to generate neural radiance fields (NeRF) from textual descriptions, although its intensive computational requirements limited practical use. Magic3D (Lin et al., 2022) subsequently introduced a two-stage optimization approach, enhancing mesh resolution while reducing computational load. GET3D (Gao et al., 2022) further improved practical usability by generating high-quality textured meshes with complex topologies directly from 2D images through differentiable surface modeling. Parallel research has focused on generation efficiency and representational flexibility. Point-E (Nichol et al., 2022) generates 3D point clouds from text inputs within minutes, while Shap-E (Jun & Nichol, 2023) synthesizes multi-representational implicit functions, rendering outputs either as textured meshes or neural radiance fields.

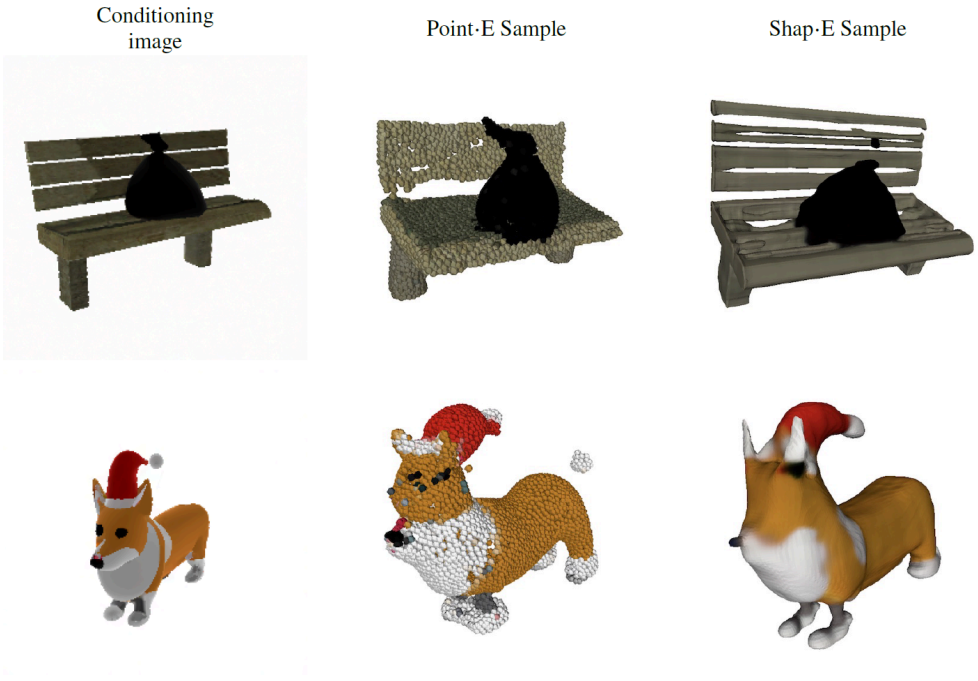


Figure 2.3 Conditioning images for which both ShapE and PointE succeed. (Jun & Nichol, 2023)

DreamGaussian (Tang et al., 2023) further accelerates high-quality 3D mesh generation via Gaussian splatting. Recent frameworks like TRELLIS (Xiang et al., 2024) and InstantMesh (Xu et al., 2024) exemplify integrated generative approaches. TRELLIS introduced structured 3D latent spaces supporting multiple unified representations, while InstantMesh streamlined single-image-to-3D workflows without object-wise optimization, demonstrating potential for real-time design prototyping (Liu et al., 2023).

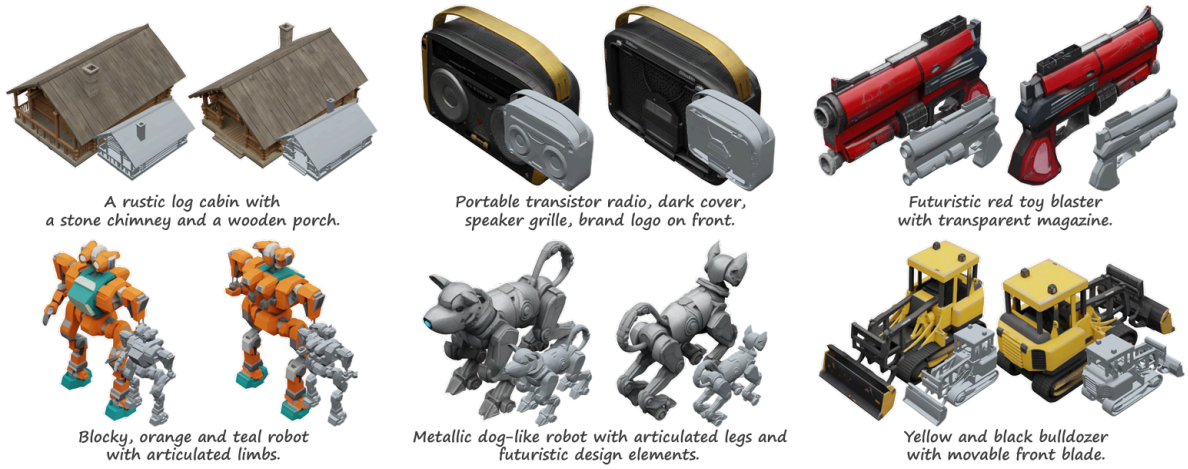
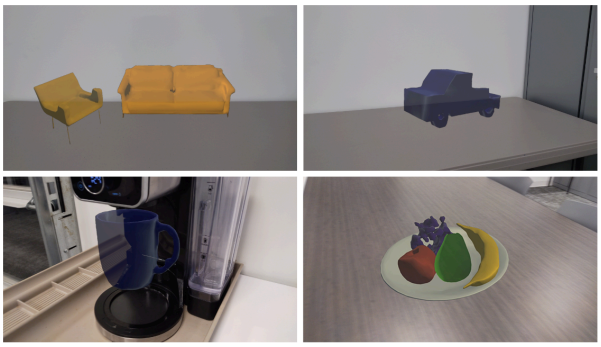
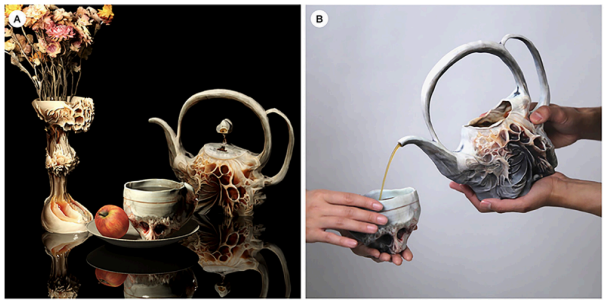


Figure 2.4 High-quality 3D assets generated from text input with TRELLIS(Xiang et al., 2024)

The technological advancements have accelerated the integration of generative AI into design workflows. 3DALL-E (Liu et al., 2023) integrates text-to-image models into CAD software, enabling designers to generate innovative reference images. Depthfusion (Danry et al., 2025) utilizes diffusion modeling to create detailed 3D models directly supporting digital fabrication methods like PolyJet and ceramic printing, enhancing detail and manufacturing utility. The PREDO framework (Wong et al., 2024), combining diffusion models with evolutionary algorithms, improved the practicality of generated 3D automotive models by addressing reliability issues. Research on “Text-to-Architecture” (Bono, 2024) transforms AI-generated geometry into architectural elements, promoting diversified exploration of architectural spaces and structures through generative AI. Additionally, the Matrix framework (Behravan & Gračanin, 2025) integrates the Shap-E model to achieve real-time speech-to-3D object generation within augmented reality environments, enriching immersive experiences.



(a) MATRIX AI: generate 3D models in an AR environment with integrated voice input



(b) The Depthfusion system generates biomimetic tableware with text input and can be 3D-printed using PolyJet 3D technology.

Figure 2.5 Exploration of Text-to-3D generative AI based on Diffusion Modeling for applications in design fields (Danry et al., 2025; Behravan & Gračanin, 2025)

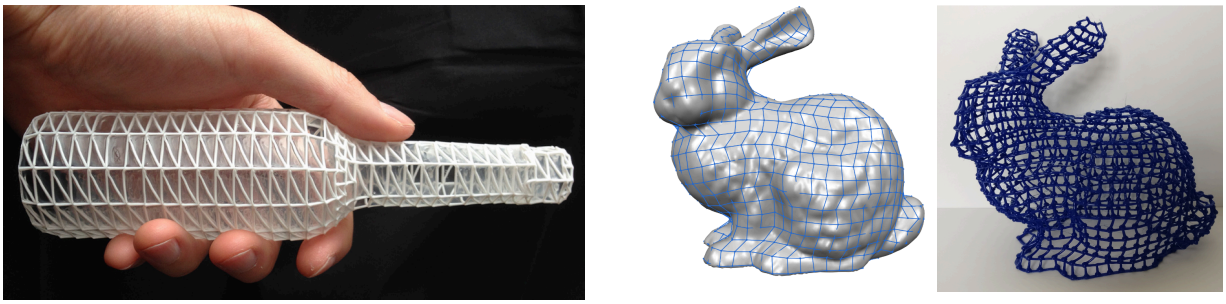
In conclusion, text-to-3D generative AI has progressed from theory to practice, creating a comprehensive framework in design. This progression moved from early GAN research through diffusion model breakthroughs to today's practical design and fabrication applications. Now integrated across the entire design workflow, these technologies reduce barriers while expanding creative possibilities for designers. Future research will likely focus on improving semantic control, multimodal processing, and CAD integration, aiming to create more intuitive human-machine collaboration that balances computational power with human creativity and expertise.

2.2.2 Rapid Prototyping in Early Design Stages

Rapid prototyping technologies have participated in and reshaped designers' workflows considerably earlier than generative artificial intelligence, which has only recently begun to develop rapidly. The evolution of rapid prototyping has progressed from traditional physical modeling to the integration of digital technologies, continuously improving manufacturing efficiency and convenience. This evolution has redefined how designers externalize concepts,

test hypotheses, and gather feedback with minimal resources (Camburn et al., 2017). Sass and Oxman (2006) documented the transition from manual manufacturing to digital methods, noting how technologies such as three-dimensional printing have fundamentally altered the materialization of design.

Research has consistently focused on accelerating prototyping processes and expanding use cases. Mueller et al. (2014) introduced WirePrint, the system successfully reduced printing time from hours to minutes by transforming complete 3D meshes into wireframes, significantly enhancing prototyping efficiency. Untzelmann and Kobbelt (2018) optimized wireframe generation methods based on WirePrint, demonstrating better performance in support structures and sampling point processing. Similarly, Tao et al. (2017) proposed WeaveMesh, enabling rapid production of simplified three-dimensional models through flexible assembly. Bhattacharya et al. (2024) presented the FabRobotics framework, demonstrating the integration of 3D printing with mobile robotics, extending manufacturing capabilities beyond static equipment.



(a) Lo-Fi 3D Model printed with WirePrint

(b) Printed Models with optimized algorithm from mesh to path

Figure 2. 6 By simplifying 3D models into meshes for 3D printing, the speed of prototyping is significantly increased. (Mueller et al., 2014; Untzelmann and Kobbelt, 2018)

Another research focus is reducing technical barriers to prototype creation, enhancing participation and accessibility. Hudson et al. (2016) examined challenges for ordinary users when using 3D printing technology, identifying complex operational workflows and technical aspects as obstacles. They advocated for integrated systems combining modeling, printing, and feedback support, while incorporating operational guidance into interface design to lower entry barriers.

Bousseau et al. (2016) studied novice designers' prototyping behaviors, suggesting design tools should feature automatic graphic assistance, material-aware feedback, and dynamic collaborative support to help beginners more efficiently design and implement physical prototypes. Stemasov et al. introduced the concept of "Ephemeral Fabrication" (2022), proposing a method for instantaneously manufacturing temporary physical objects with minimal barriers through the wearable device Draupnir, emphasizing immediacy and rapid manufacturing in specific environments.

The combination of digital technology with physical prototyping is another significant advancement. Research indicates that augmented reality technology enables real-time interaction with digital prototypes in actual physical environments, supporting more intuitive and efficient iterative prototype development processes (Nee et al., 2012; Omaia et al., 2024). Kim et al. (2021) explored how multimodal interaction systems combining AR and Internet of Things (IoT) technologies facilitate prototype experiences with enriched perceptual capabilities. Weichel et al. proposed MixFab (2014), a personal manufacturing system in mixed reality environments that allows users to directly manipulate virtual objects in physical space through an AR interface combined with natural gesture recognition and 3D scanning functionality, supporting precise 3D modeling and print previewing. DebRoy et al. (2017) proposed using digital twin technology for high-fidelity simulation and continuous synchronization between physical and digital counterparts, enabling more accurate prediction, optimization, and refinement of manufacturing processes. Snider et al. (2022) demonstrated through case studies how immersive technologies, including AR and MR, seamlessly integrate physical and digital prototyping workflows, enhancing manufacturing speed and interactivity.

Overall, these developments in rapid prototyping—from accelerating workflows and integrating digital-physical systems to reducing technical complexity—indicate significant progress in improving prototyping efficiency, lowering entry barriers, and increasing creative possibilities in early design phases. However, opportunities remain in exploring deeper integration with emerging technologies such as generative artificial intelligence and robotic manufacturing. The establishment of more comprehensive, seamless workflows and ecosystems continues to merit exploration.

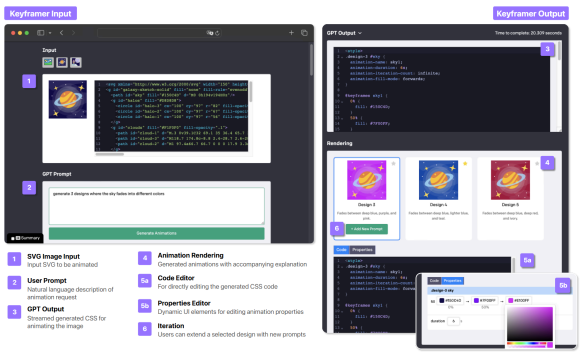
2.2.3 Human-AI Collaboration in the Design Process

As previously mentioned, the rapid development of generative AI has significantly transformed designer's workflows. Recent studies have explored the relationship between AI and designers, as well as methods to optimize user experience and perception in collaborative systems, thereby expanding the boundaries of designer-AI collaboration capabilities. Guzdial and Riedl (2019) developed a turn-based interaction framework to precisely describe and compare different Human-AI collaborative systems; Haase and Pokutta (2024) defined a four-level collaborative model of Human-AI Co-Creativity, proposing that future Human-AI collaborative systems should focus on enhancing human capabilities rather than replacing humans, strengthening human leadership in creative outcomes; Zhou et al. (2024) revealed through research that human collaboration in creative design has highly non-linear characteristics, and subsequently developed the OptiMuse system, which proposes that AI can play four roles in co-creation: executor, optimizer, colleague, expert, emphasizing that artificial intelligence should adapt its interaction methods and output strategies based on users' dynamic behaviors in Human-AI collaboration.

Regarding specific interaction methods, Rezwana and Maher (2022) experimentally verified that AI systems with voice, text, and virtual avatar communication capabilities can significantly enhance users' trust in AI, sense of cooperation, and creativity evaluation during Human-AI collaboration, highlighting the importance of interaction methods; Rezwana and Maher (2023) proposed the COFI framework, pointing out that current system interactions are predominantly unidirectional, calling for enhanced bidirectional communication mechanisms between AI and users; Gmeiner et al. (2023) introduced "team learning" and "human-machine collaboration" strategies into Human-AI interaction processes, proposing design recommendations for enhanced perception, heuristic feedback prompts, and multimodal interaction support.

Furthermore, recent research increasingly recognizes that AI capabilities represent new design materials that designers can utilize and shape. Kulkarni et al. (2023) explored the central role of prompts in human-AI interaction, studying how designers develop, refine, and iterate prompts to

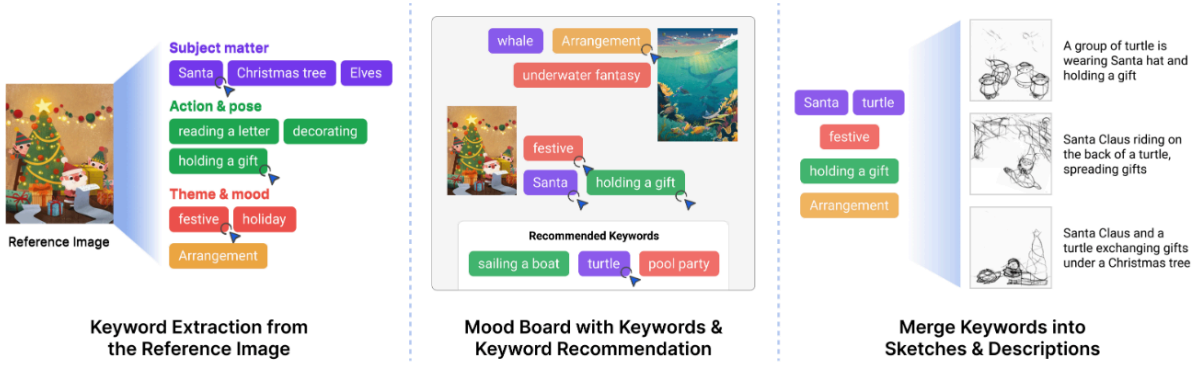
achieve expected outcomes; the PromptInfuser system (Petridis et al., 2023) demonstrated how AI and intuitive interaction interfaces can improve designers' expressive abilities and design iteration efficiency; simultaneously, several comprehensive Human-AI collaborative workflows have been developed. CreativeConnect (Choi et al., 2024) provides graphic designers with a generative AI workflow for concept design through keyword extraction and combination, with the system generating keywords based on images, providing keyword recommendations, and combining keywords into sketches and textual descriptions, aiming to inspire designers in divergent creation during the conceptual stage; PlantoGraphy (Huang et al., 2024) introduced AI collaboration into landscape design processes, supporting designers in jointly controlling scene composition and plant arrangement through text and graphical interfaces, utilizing diffusion models to achieve controllable generation from text to high-quality landscape rendering; in the animation industry, the Keyframer system (Tseng et al., 2024) was proposed as a prototype design tool combining natural language prompts with code generation, allowing users to control SVG animation generation through text, and providing property editors and code editors to support highly flexible iterative design.



(a) Keyframer: An AI-assisted tool using natural language prompts to generate codes and SVG animation



(b) PlantGraphy: Human-AI collaborative platform for landscape rendering



(c) CreativeConnect: A system utilizing Human-AI Collaboration in Text-to-Image Workflows to Improve Generation Accuracy

Figure 2.7 Human-AI collaborative system in design fields (Tseng et al., 2024, Choi et al., 2024, Huang et al., 2024)

In conclusion, the above research has established normative frameworks for Human-AI collaborative systems and provided instructive recommendations, including respecting and emphasizing human creativity and agency, adopting multimodal input and interaction interfaces to reduce technological barriers, and establishing clear and immediate feedback to promote the efficiency of human-machine collaboration.

2.2.4 Design Cognition Load and Evaluation

Despite the apparent advantages brought by rapid technological development, designers face increasing cognitive load as interfaces and workflows become increasingly complex. Balancing this development with cognitive load has become important. Cognitive Load Theory, introduced by Sweller in 1988 (Sweller, 1988), examines the allocation of cognitive activities during problem-solving and learning tasks. The research established the foundation of Cognitive Load Theory, significantly influencing design processes and tool development. Chandler and Sweller (1996) investigated cognitive load when learning computer programs, revealing that poorly designed interfaces create substantial cognitive loads, impeding learning and performance improvement. Martin-Michiellot and Mendelsohn (2000) further explored this phenomenon in graphical computer interfaces, finding that complex systems directly impact cognitive load and task performance. As design systems continuously increase in functionality at the expense of usability, Chandrasegaran et al. (2013) studied this evolutionary process, analyzing how different

interaction methods in design systems affect cognition. Tang et al. (2011) conducted comparative research between digital and traditional design environments, evaluating through the "Function-Behaviour-Structure" framework and discovering that digital environments create higher cognitive load, emphasizing the importance of maintaining intuitive operations and preserving traditional workflow characteristics in digital tools.

In order to quantify and evaluate cognitive load, researchers have developed various methods. Most notably, the NASA-TLX method (Hart & Steveland, 1988) is a multidimensional assessment tool measuring perceived workload across six dimensions: mental demand, physical demand, temporal demand, performance, effort, and frustration. This tool has been widely used to evaluate design interfaces and workflows, providing standardized metrics for comparing different systems and methods.

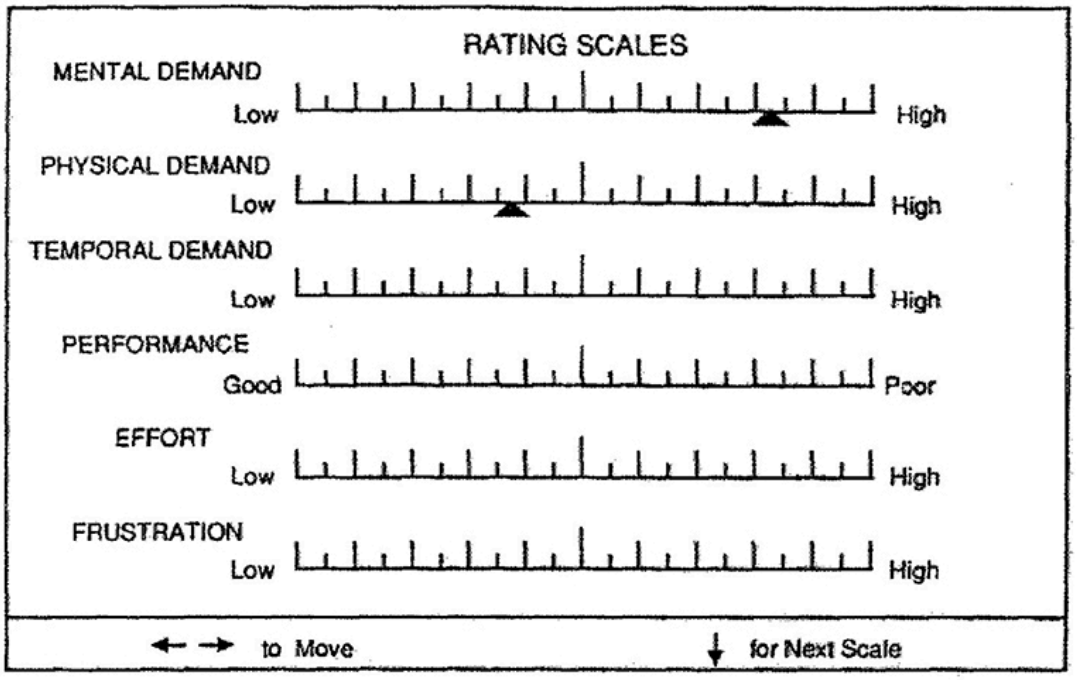


Figure 2.8 The NASA Task Load Index(NASA-TLX).

Sharit and Cuomo (1988) introduced a cognitive-based approach for evaluating human-machine interaction performance in CAD environments, including quantitative measurements of mental workload, situational awareness, and decision quality. Soliman et al. (2001) continued exploring human-machine interaction in CAD/CAM systems, proposing and constructing eight key success

factors for evaluating system integration, emphasizing the cognitive load caused by dispersed workflows and inconsistent interfaces.

Based on Cognitive Load Theory, some research has begun exploring methods to reduce cognitive load in design environments. Sweller and Chandler (1994) made further contributions to this field, proposing design strategies of “integrated format” and “simplified processing paths,” offering key design recommendations for constructing design tools to reduce unnecessary cognitive load. Niu et al. (2022) reviewed human-machine interfaces in CAD design environments, finding that multimodal interaction methods including voice, gesture, and gaze have tremendous potential in reducing cognitive demands. These multimodal interfaces can better distribute cognitive load across different sensory channels, potentially improving overall performance and reducing mental fatigue. Fillingim and Feldhausen (2023) studied how designers and operators develop intuition, form strategies, and achieve effective collaboration in high cognitive load environments within digital manufacturing contexts. The authors proposed “Operator 4.0” and “Operator 5.0” concepts, indicating that future design systems should follow users' intuition development and experience transfer, adopting reasonable feedback and evaluation to optimize cognitive load allocation between human operators and intelligent systems. Murtaza et al. (2025) studied the effects of large language models on learning outcomes and cognitive load, showing that well-designed large language models can help eliminate complex distractions in the environment, significantly reducing extraneous cognitive load in complex technical domains.

With the development of generative artificial intelligence and manufacturing technologies, the functionality and complexity of design systems continue to grow simultaneously. How to reduce cognitive load stemming from complexity for designers participating in new technology workflows presents an important challenge for future design system development. The literature provides significant theoretical foundations and methodological references for research in this field, supporting this study's exploration of goals to reduce cognitive load in design processes and improve rapid prototyping efficiency.

2.3 Research Gap and Significance

2.3.1 Research Gap

Despite the previous literature review demonstrating the significant advancements in the fields of generative AI, digital fabrication, and human-AI collaboration, there are some critical gaps remain. Currently, these important domains are developing relatively independently, and users in the design fields lack an integrated and seamless software ecosystem and workflow, which results in inefficiency and cognitive load.

First, while text-to-3D generative AI has made great progress, this progress is still largely constrained in research contexts, lacking integration with practical design and fabrication processes. Models such as DreamFusion, Shap-E, and TRELLIS already have decent generative capabilities, but integration in the design-to-manufacturing process is still limited. Designers seeking to transform concepts from digital models to physical prototypes still require extensive technical expertise in parametric modeling, G-code generation, and robot control, etc. These technical implementations are often dispersed across different software platforms, with complex equipment configurations and conversion steps, leaving designers to spend extra time on non-creative work. How to bridge this divide and create a seamless workflow becomes an important research gap.

Secondly, advancements in rapid prototyping technologies such as WirePrint, MixFab, etc. have succeeded in reducing fabrication time, lowering the technical barrier, and increasing interactivity. This dissertation focuses on further exploring how these rapid prototyping technologies, through integration with generative AI and large language models, can improve the accessibility of design tools and interfaces, thereby addressing the cognitive load problems caused by complex multi-software workflow.

In addition, while some research has established standards and evaluation systems for Human-AI collaboration in design processes as well as in broader creative tasks, such collaboration systems primarily address separate stages of the design process, such as concept generation, 3D modeling, or graphic design, rather than providing continuous support for the entire workflow

from ideation to physical realization. Therefore, this thesis will explore the Human-AI-Robot collaboration framework spanning from conceptualization to physical prototyping, testing and evaluating the effectiveness of the system in terms of collaboration efficiency, cognitive load reduction, etc.

2.3.2 Research Significance

This thesis proposes an integrated human-AI–robot workflow to enhance seamless integration from conceptual ideation to physical prototype fabrication, while reducing designers' cognitive load in the process. By doing so, it addresses the research gaps outlined above and contributes in the following two areas:

First, the study introduces a continuous, seamless workflow that connects designers, generative AI, and digital fabrication processes. By integrating functionalities, which are currently dispersed across multiple software tools, into a single streamlined pipeline, it aims to eliminate the numerous technological barriers in prototype design. This integration significantly reduces the time required to transition from design to manufacturing, allowing designers to iterate and produce multiple design solutions more swiftly and with lower technical overhead. For non-expert users, the system removes specialized software or technical requirements, thereby democratizing rapid prototyping.

Second, the study explores how human-AI collaboration can alleviate cognitive load within the design environment, assessing this dynamic using quantitative measures. Through natural language interactions and AI-driven support, both professional designers and individuals without technical expertise gain easier access to rapid prototyping capabilities. Consequently, they can focus more on creative exploration and iterative refinement rather than complex technical operations, potentially enhancing both the quality and diversity of their designs. To quantify these improvements, this research employs assessment instruments such as NASA-TLX to measure gains in task efficiency and creative exploration.

By examining both workflow integration and cognitive load assessment, this research aims to establish a feasible pathway for effective collaboration among designers, generative AI, and digital fabrication, while expanding rapid prototyping opportunities for non-expert users.

Additionally, by monitoring and managing cognitive load, designers can dedicate more attention to creative ideation and iterative problem-solving. Ultimately, this work addresses existing fragmentation and complexity that hinder the broader adoption of advanced design and manufacturing technologies, laying the groundwork for a more intuitive, efficient, and cognition-manageable design-to-fabrication process.

3 Hypothesis

3.1 Statement of Hypothesis

Based on the research questions presented in Chapter 1 and the gaps identified in Chapter 2, this study posits that developing a seamlessly integrated human-AI-robot framework can enhance workflows in the early design stage. The main hypotheses are as follows:

1. Barrier Reduction with AI Integration: Integrating natural language interfaces and generative AI into 3D design workflows can substantially reduce technical complexity. By accepting natural language commands or image inputs, the system can automatically produce 3D models ready for additive manufacturing.

2. Speed and Iterative Efficiency Enhancement: By combining an improved rapid prototyping method with a human-AI collaborative system, the proposed workflow can transition from conceptual design to physical prototypes more swiftly than traditional approaches, thus enhancing fabrication speed and iterative efficiency.

3. Cognitive Load Minimization: Consolidating previously fragmented workflows—including ideation, modeling, path generation, and manufacturing device control—into a single, uninterrupted pipeline can reduce designers' cognitive load. Consequently, designers can devote more energy to creative exploration, thereby increasing both the quantity and creativity of design outcomes.

3.2 Scenarios and Evaluation Metrics

This research explores the prototyping workflow with human-AI-robot collaboration system during early design stages, therefore, the main scenarios are designers' or non-technical users' practical working process during which works from conceptualization to the physical prototypes. To validate the hypotheses outlined in 3.1, the research will conduct user tests on several practical work scenarios and evaluate the effectiveness of the proposed collaborative system.

3.2.1 User Testing Scenarios

The evaluation employs structured testing scenarios and participant configurations to assess the system's effectiveness across diverse work contexts and user demographics. Participants are stratified into three distinct groups representing varying levels of expertise:

- **Group 1:** Amateur makers with basic manufacturing interest but no design background
- **Group 2:** Individuals with design backgrounds and experience using 3D modeling software, but lacking architectural training and Grasshopper modeling/programming experience
- **Group 3:** Participants with architectural or related disciplinary backgrounds and intermediate Rhino/Grasshopper proficiency

Building on this participant framework, test scenarios focus on design tasks relevant to architectural design processes and are organized into two primary categories, with all participant groups required to complete both testing categories:

- **Secario 1:** Design Brief to Digital Model: Modeling and Creative Exploration Under Complex Design Requirements

  In this testing category, participants receive specific design briefs containing detailed design descriptions. Participants first convert these design briefs into digital models using methods of their choosing. Subsequently, they utilize CoFAB's text and image input capabilities to transform the same concepts and ideas into digital models. The effectiveness of the system in improving efficiency, reducing technical barriers, and

lowering cognitive load is evaluated by recording work duration, success rates, and cognitive load for both self-selected methods and CoFAB approaches. Additionally, participants are tasked with generating multiple outcomes using the CoFAB system to assess the quantity and diversity of generated results. Participant satisfaction with these generated outcomes is documented to verify the system's potential for creative exploration.

- **Scenario 2:** Design Concept to Physical Prototype: Complete Workflow from Design Concepts to Digital Models to Physical Prototypes

  In this testing category, participants receive simplified, outline-based design requirements that allow substantial creative freedom. Participants transform the design brief into digital models based on their interpretation. They then utilize CoFAB's integrated tools for mesh optimization, wireframe generation, and rapid prototype manufacturing, converting digital models into physical prototypes using both CoFAB's wireframe 3D printing and conventional slicing-based 3D printing methods. The system's effectiveness in enhancing efficiency and reducing cognitive load throughout the complete design-to-physical prototype process is evaluated by recording work duration, cognitive load, and satisfaction levels for both manufacturing approaches.

3.2.2 Evaluation Metrics

To measure the effectiveness of the CoFAB system in addressing the research hypotheses, the following evaluation metrics will be employed, with primary emphasis on time efficiency improvement, secondary focus on complexity and cognitive load reduction, and creative exploration:

1. Time Efficiency Metrics
    a. **Time to Completion:** Total time required to complete each scenario task
    b. **Iteration Cycles:** Number of design iterations achievable within a fixed time period
    c. **Command Success Rate:** Percentage of natural language commands successfully interpreted and executed by the system
    d. **Technical Operation Time:** Percentage of total time spent on technical operations versus creative activities
    e. **Workflow Transition Time:** Time spent switching between different tools or interfaces

2. Cognitive Load Assessment
    a. **NASA Task Load Index (NASA-TLX):** Standardized assessment tool measuring perceived workload across six dimensions:
        - Mental Demand: How mentally demanding was the task?
        - Physical Demand: How physically demanding was the task?
        - Temporal Demand: How hurried or rushed was the pace of the task?
        - Performance: How successful were you in accomplishing what you were asked to do?
        - Effort: How hard did you have to work to accomplish your level of performance?
        - **Frustration:** How insecure, discouraged, irritated, stressed, and annoyed were you?

b. **Cognitive Interruptions:** Frequency of workflow interruptions due to technical issues or system complexity
c. **Technical Knowledge Dependency:** Assessment of specialized knowledge required (measured through surveys)

3. Creative Exploration Metrics
    a. **Design Variation:** The number and diversity of design outcomes explored
    b. **Feature Richness:** The complexity and sophistication of generated architectural elements
    c. **Creative Satisfaction:** User-reported satisfaction with design possibilities (measured through surveys)

These metrics will be collected through a combination of objective measurements (time tracking, system logs, output analysis) and subjective assessments (surveys, interviews, think-aloud protocols). Together, they will provide a comprehensive evaluation of the CoFAB system's effectiveness in addressing the central research question and supporting hypotheses.

4 Methods

4.1 Methods Overview

In order to examine the questions mentioned above and to validate the hypotheses, the thesis utilized a comprehensive research approach. Initially, a preliminary study was conducted to investigate the experiences, contexts, and challenges of designers from various background prototyping in the early design stages. The data was analyzed to identify current pain points in prototyping, with the objective of developing an improved system. At the system development level, the work will be divided and developed from design to digital modeling, and from digital modeling to physical prototypes. In the initial phase, the integration of generative AI into the 3D modeling software environment (Rhinoceros and Grasshopper) will be investigated, with the objective of generating 3D models that can be directly utilized and modified. In the second phase, a prototyping system will be developed, where the 3D modeling software will communicate directly with the digital fabrication equipment (i.e., robotic arms) to seamlessly and expeditiously produce 3D models into physical models. Subsequently, the integration of these systems in both directions will be undertaken, ensuring a seamless workflow, mitigating technical complexity, and enhancing the interface's ease of use. Conclusively, the system will undergo user testing to evaluate its performance. Scales and data will be utilized to measure the system's progress in terms of cognitive load reduction and prototyping efficiency enhancements.

4.2 Initial Stage Survey

4.2.1 Questionnaire Design

To comprehensively understand designers' opinions, needs, and expectations regarding prototyping and AI-assisted systems in the early design stages before developing the system, an initial survey was conducted. A structured questionnaire was developed, which consisted of 15 key questions (see Appendix I for the full questionnaire) covering several essential areas:

1. **Respondents' backgrounds:** The questionnaire identified respondents' design discipline backgrounds, with participants selecting their primary field from six categories including architecture/landscape design, interaction design, product/industrial design, graphic/visual design, fashion design, or other specialized areas (Question 1); respondents' professional experience was also investigated and categorized into five groups: students or 0 -1 year, 1-3 years, 3-6 years, 6-10 years, and over 10 years (Question 2);
2. **Prototyping Frequency and Digital Fabrication Tool Usage:** Respondents were surveyed on how often they made physical prototypes during the design process, ranging from “never” to “almost every time” (Question 3); in addition, the frequency of use of various types of digital fabrication tools in prototyping was surveyed, ranging from “never” to “almost always” (Question 3); the frequency of use of digital fabrication tools in prototyping was also surveyed. In addition, the frequency of use of various digital fabrication tools in prototyping was investigated, with respondents rating the frequency of 3D printing, laser cutting, CNC machining, and desktop robotic arms from “never used” to “very frequently used” (Question 4).
3. **Key Decision Factors and Main Challenges:** This section investigated the key decision factors and pain points of the respondents in the process of making physical prototypes. Respondents rated the importance of five factors in their prototyping process: time cost, financial cost, accuracy/quality, ease of use, and repeatability(Question 5); and listed a number of common barriers that limit prototyping, including hardware and software

functionality limitations, skill level, high cost, poor accuracy/quality, and so on, for respondents to choose from (Question 6).

4. **Software Usage and Workflow:** This step investigated the respondents' usage of the software ecosystem, firstly investigating the design software commonly used by the respondents (Question 7), and further asking the respondents to rate the software ecosystem from “very smooth” to “very unsmooth” (Question 8).
5. **Attitudes and Expectations for AI Interaction:** Respondents were first surveyed about their knowledge and use of AI (Question 9); they were then asked about their attitudes towards generative AI in the prototyping process and what they expected from the functionality it could provide (Question 10, Question 11).

   Potential benefits were also discussed at this stage, and respondents rated the importance of the direction of improvement of the AI collaboration system according to their expectations, which included increasing the speed of production and iteration, lowering the threshold of operation, and reducing repetitive tasks, etc. (Question 12);

   In addition, the survey asked respondents about potential concerns and reservations about AI collaboration, such as concerns about accuracy, execution stability, precision, cost, and learning curve (Question 13); respondents were also asked to identify areas of interest that they would like to learn more about, such as cost, compatibility, operational security, and data privacy, among other key issues (Question 14).

6. **Open-ended questions:** The last question was an optional open-ended question intended to gather more personal profiles and innovative ideas from the respondents about the use of AI and prototyping in design.

4.2.2 Questionnaire Distribution

The questionnaire was distributed through both online and offline channels to ensure a diverse respondent pool, including design professionals and students from various regions and backgrounds. The online survey was shared via industry forums, social media, and university

design communities, while offline data collection involved QR code scanning at design-related schools and seminar events. The distribution began on January 6, 2025, and by February 3, 2025, a total of 98 responses were collected.

4.2.3 Data Collection and Analysis

Over the distribution period, the survey received a total of 98 responses, of which 81 were valid, resulting in an effective response rate of approximately 82.7%. After data cleaning and preprocessing, the responses were analyzed quantitatively, while open-ended responses were examined qualitatively through thematic analysis. The key findings are summarized as follows:

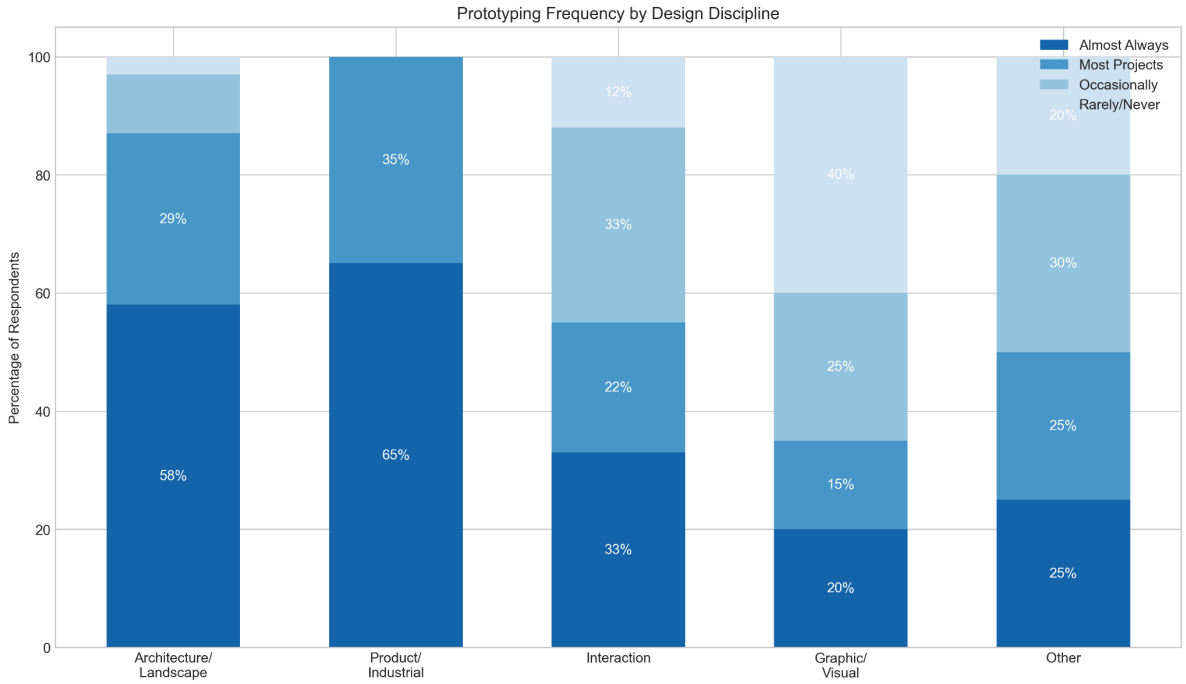
1. **Respondent Background**

- Design Discipline or Professional Background: Among the 81 valid responses, the majority of participants (41 individuals, 50.6%) came from architecture/landscape design, followed by 15 (18.5%) from product/industrial design, 9 (11.1%) from interaction design, 7 (8.6%) from graphic/visual design, and 4 (4.9%) from fashion design. An additional 5 participants (6.2%) identified with other disciplines, such as environmental art and game design.
- Work Experience: In terms of professional experience, 51 respondents (63.0%) were students or had less than one year of work experience, 26 (32.1%) had 1–3 years of experience, 3 (3.7%) had 3–6 years, and 1 (1.2%) had 6–10 years. No respondents reported having more than 10 years of experience.

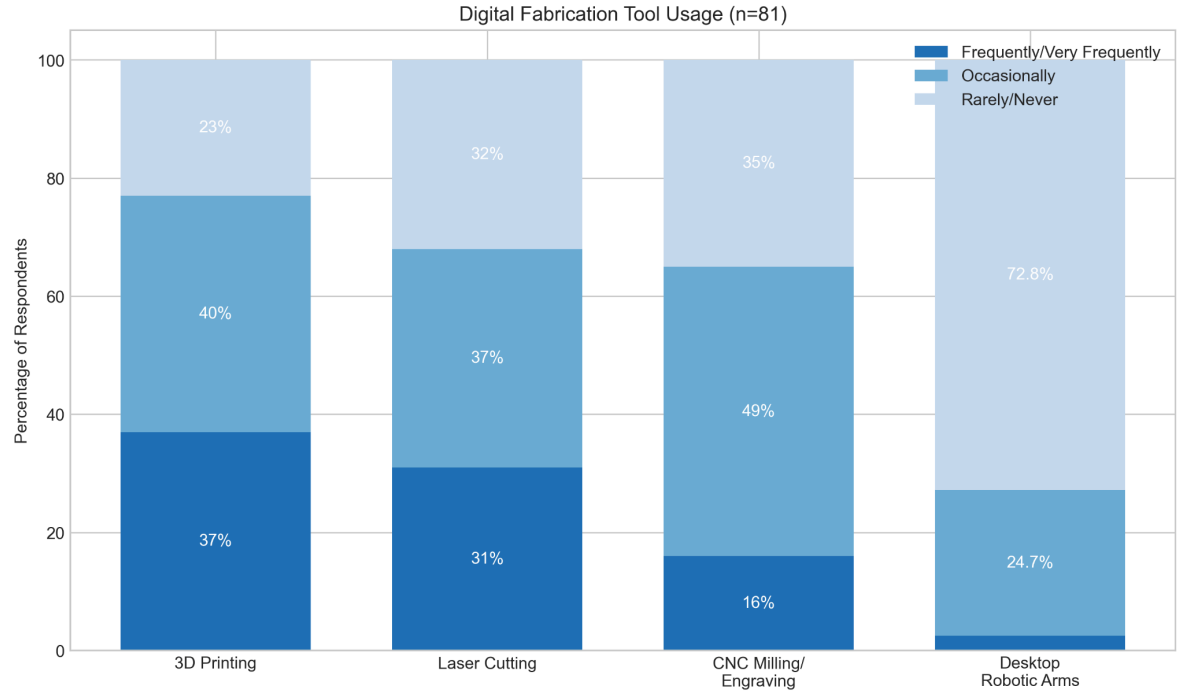
2. **Prototyping Frequency and Use of Digital Fabrication Tools**

- Prototyping Frequency: In response to the question, “How often do you create physical prototypes in your design work?” 35 participants (43%) reported “almost always,” 21 (26%) indicated “most projects,” 14 (17%) stated “occasionally,” 8 (10%) reported “rarely,” and 3 (4%) said they “never” create physical prototypes. Further analysis showed that professionals in architecture/landscape and product/industrial design

exhibited higher rates of prototyping, whereas those in graphic/visual design had a higher proportion of "rarely" or "never" responses.



(a) Prototying Frequency by Design Discipline



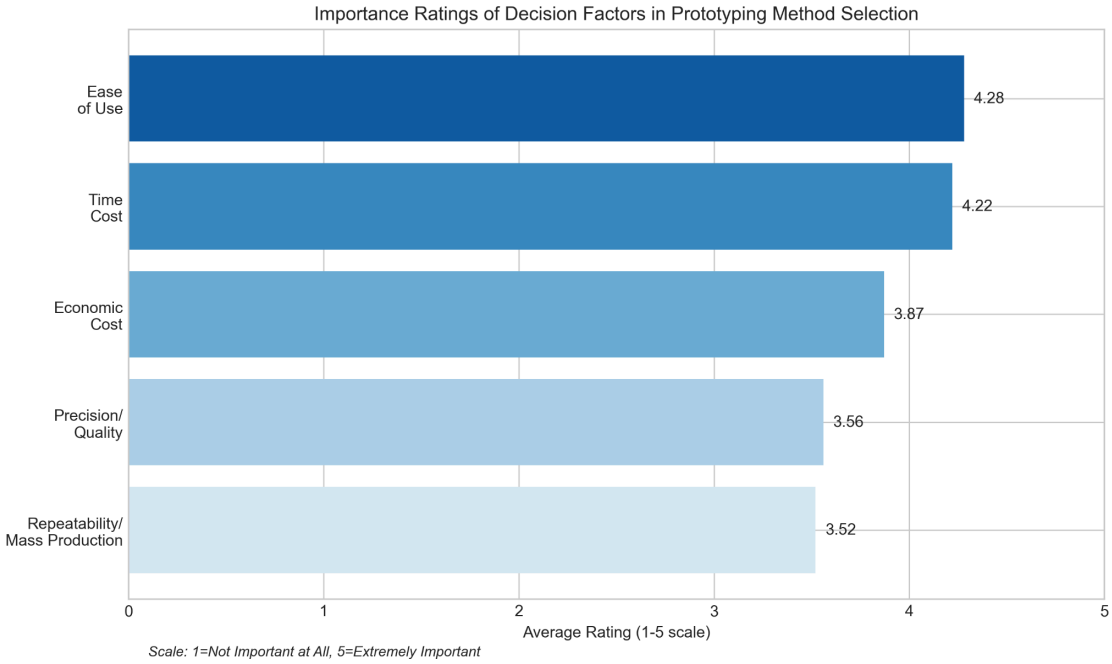
(b) Fabrication Tool Usage Distribution

Figure 4.1 Prototyping Frequency and Digital Fabrication Tool Usage

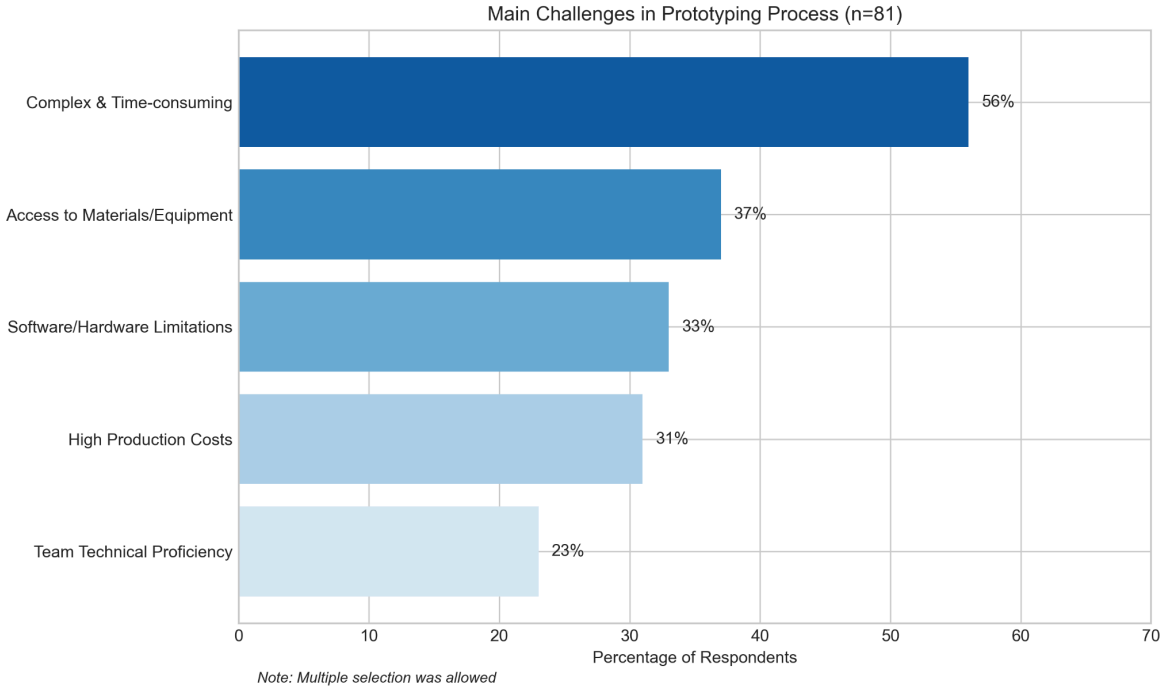
- Usage of Digital Fabrication Tools:
    - 3D Printing: 30 participants (37%) reported using it “frequently” or “very frequently,” 32 (40%) used it “occasionally,” and 19 (23%) used it “rarely” or “never.”
    - Laser Cutting: 25 participants (31%) used it “frequently” or “very frequently,” 30 (37%) “occasionally,” and 26 (32%) “rarely” or “never.”
    - CNC Milling/Engraving: 13 participants (16%) used it “frequently” or “very frequently,” 40 (49%) “occasionally,” and 28 (35%) “rarely” or “never.”
    - Desktop Robotic Arms: Only 2 participants (2.5%) reported “frequent” or “very frequent” use, while 20 (24.7%) used it “occasionally,” and the remaining 59 (72.8%) used it “rarely” or “never.”

3. Decision-Making Factors and Key Challenges

- Decision-Making Factors: When evaluating the importance of various factors in selecting prototyping methods (on a five-point scale), respondents rated “precision/quality” (4.28) and “time cost” (4.22) as the most critical considerations. “Economic cost (material and equipment expenses)” followed with a mean score of 3.87, while “ease of use” (3.56) and “repeatability/mass production” (3.52) were rated relatively lower.
- Key Challenges: In response to the multiple-choice question on major challenges in prototyping, 45 respondents (56%) cited “the process is too complex and time-consuming,” 30 (37%) mentioned “difficulty in accessing materials or equipment,” 27 (33%) noted “limitations in software and hardware functionality,” 25 (31%) identified “high production costs,” and 19 (23%) expressed concerns about “team members' technical proficiency.” These findings indicate that workflow complexity and resource accessibility remain primary concerns among designers.



(a) Decision Factors in Prototype Process



(b) Fabrication Tool Usage Distribution

Figure 4.2 Key Decision-making Factors and Main Challenges

4. **Integration with Digital Design Software and Workflow**

- Commonly Used Design Software: The survey identified Rhino/Grasshopper, 3ds Max/Maya, SolidWorks, and Adobe tools (Illustrator, Photoshop, XD) as the most frequently used software across design disciplines. Architecture/landscape and product/industrial designers showed a preference for Rhino/Grasshopper and SolidWorks, whereas graphic/visual and interaction designers predominantly used Adobe tools and Figma/Adobe XD.
- Workflow Integration: When asked, "How well does your digital design software integrate with subsequent prototyping/manufacturing processes?" 13 participants (16%) rated the integration as "very unsmooth", 23 (28%) rated the integration as "Not so smooth", 33 (41%) described it as "average," 10 (12%) rated it as "Quite Smooth", and only 2 (2%) found it "very smooth". Cross-analysis revealed that users who frequently employed 3D printing or laser cutting generally rated integration more positively, whereas professionals working with CNC milling or robotic arms highlighted compatibility issues and challenges related to file format conversion.

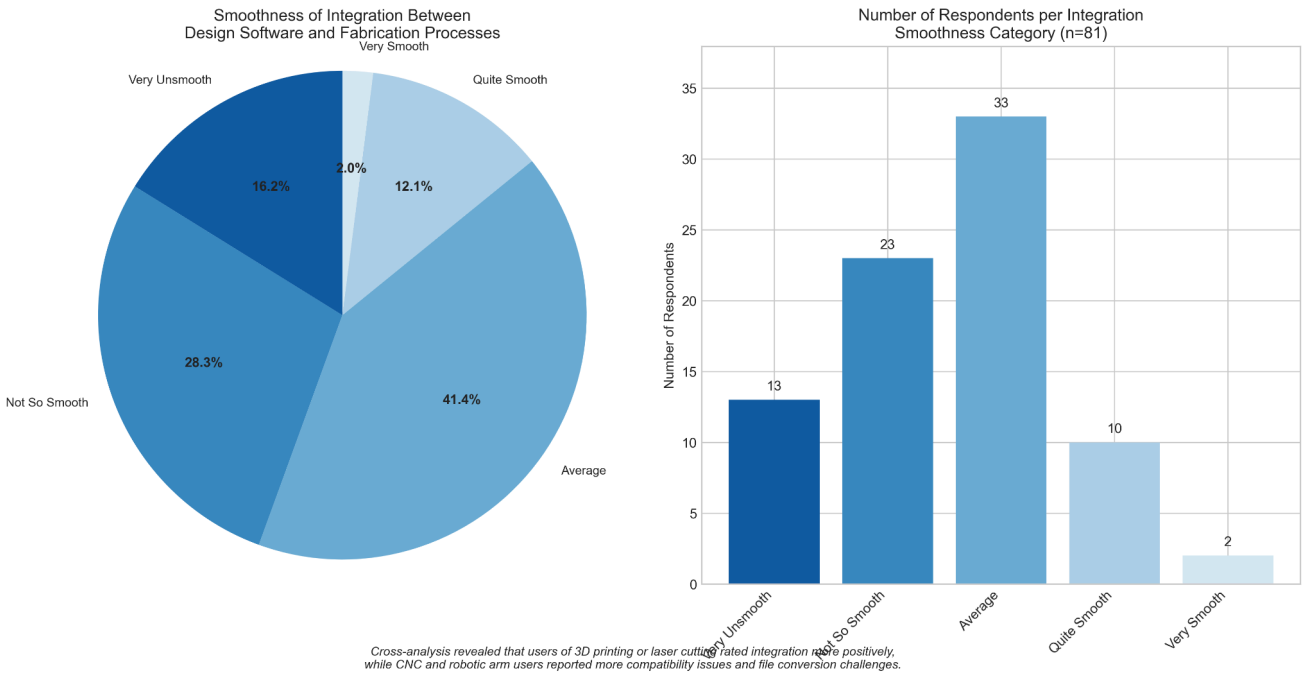
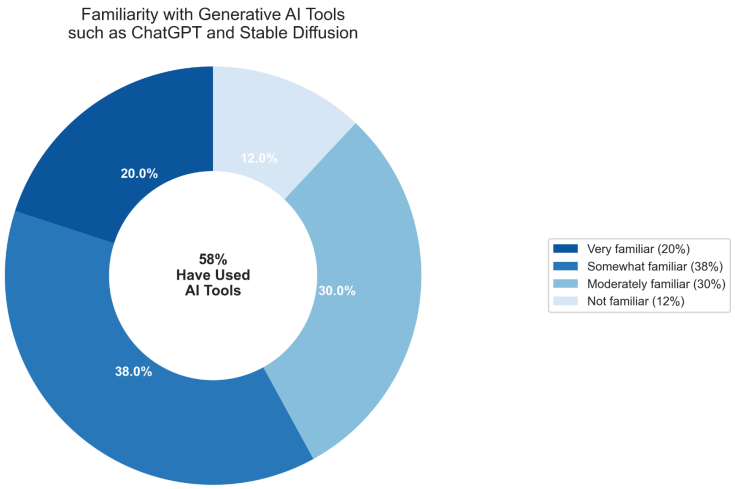


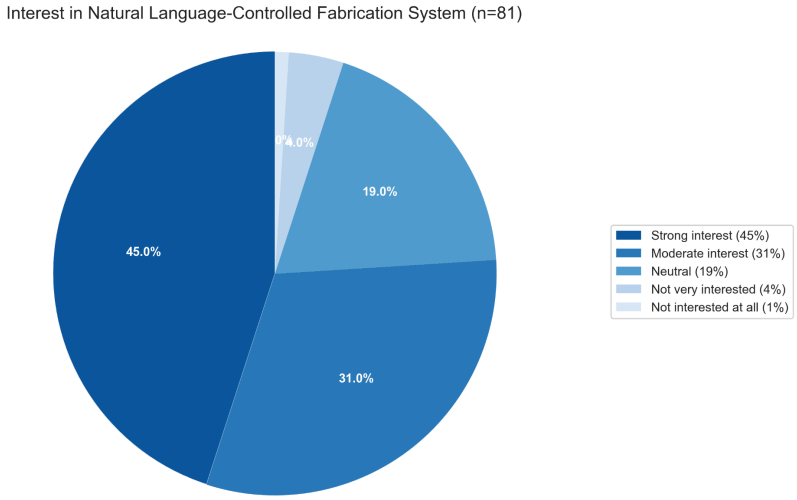
Figure 4.3 Respondents' Attitude towards Current Prototyping Workflows

5. Attitudes Toward AI and Natural Language Control Technologies

- Familiarity with AI Technologies: Regarding familiarity with generative AI tools such as ChatGPT and Stable Diffusion, 47 respondents (58%) reported being "somewhat familiar" or "very familiar," and 33 had experimented with AI for creative sketching, conceptual visualization, or content writing.



(a) Familiarity of Generative AI in Design Process



(b) Interest in the Human-AI-Robot Collaboration System

Figure 4.4 Respondents' Familiarity and Interest in Generative AI

- Interest in Natural Language-Controlled Fabrication: In response to the question, "How interested are you in a system that enables prototyping through simple natural language commands?" 61 respondents (76%) expressed "strong" or "moderate" interest, 16 (19%) were "neutral," and 4 (5%) were "not very interested" or "not interested at all." Many participants indicated that if such a system could seamlessly integrate into existing design workflows, it would have significant potential for adoption.
- Potential Advantages and Concerns:
    - Perceived Advantages: The highest-rated benefits included "lowering the operational threshold" (4.05), "reducing the time from design to prototype" (4.00), and "enabling rapid iteration and modification" (3.93). "Automated error detection and correction" and "seamless integration with existing design software" also received moderate approval (average scores around 3.7).
    - Primary Concerns: 52 respondents (64%) were worried about "whether the system can accurately understand my commands," 42 (52%) cited "high hardware/software costs," and 33 (41%) questioned "the precision and quality of outputs."

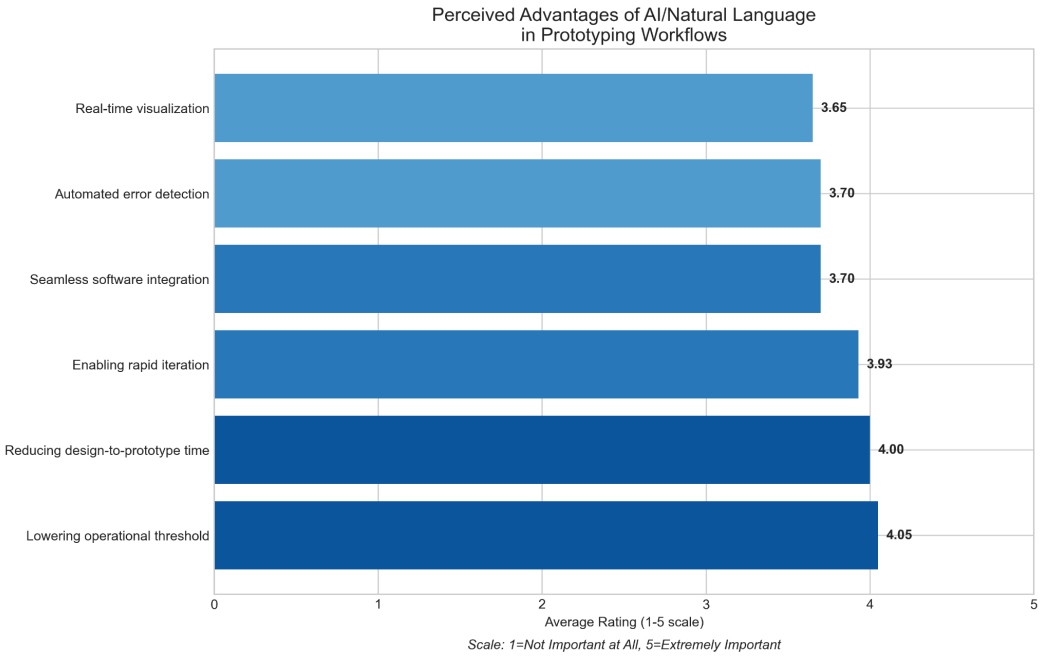


Figure 4.5 Respondents' Rating of the Potential Improvements of the System

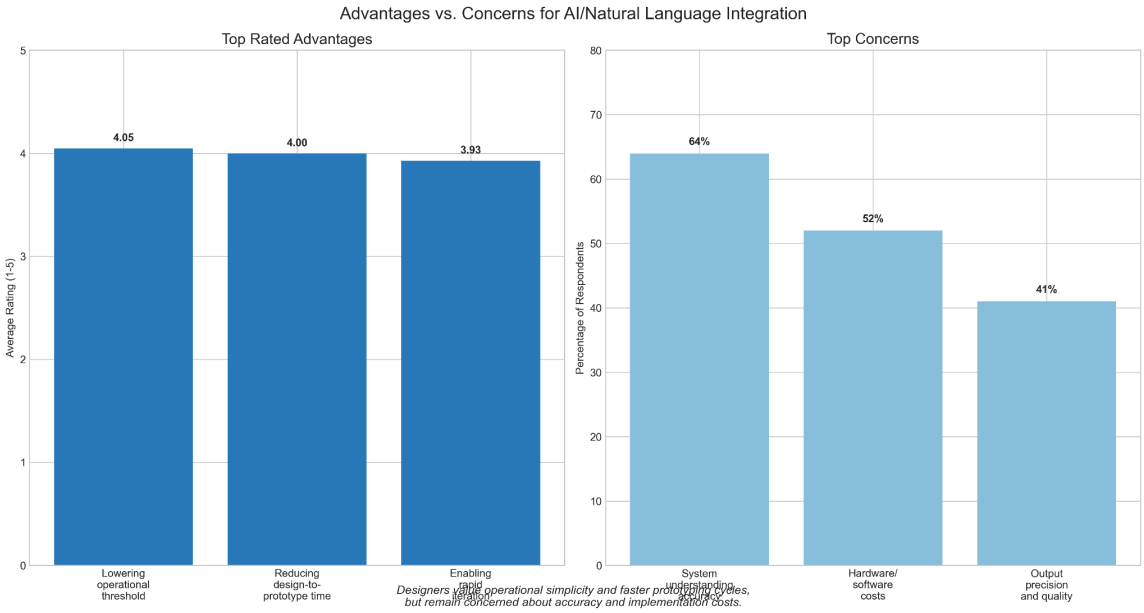


Figure 4.6 Advantages and Concerns for the System

6. Analysis of Open-Ended Responses

- Key Concerns Before Adoption: In response to "What aspects would you like to understand or consider before adopting such a system?" (Question 14), the most common responses included "cost/budget/maintenance requirements" (38 respondents, 47%), "compatibility with specific materials and processes" (31 respondents, 38%), and "operational safety and failure handling" (19 respondents, 23%).
- Additional Suggestions: In the open-ended question (Question 15), some student respondents and startup practitioners emphasized the need for "more free or low-cost introductory training and equipment subsidies." Meanwhile, professionals from established design firms expressed interest in "integrating AI-driven fabrication with parametric modeling workflows and enabling real-time automated validation" to enhance precision prototyping efficiency.

4.2.4 Conclusions

The results of the initial survey reveal a clear need for a more streamlined, low‑barrier prototyping workflow. First, although half of respondents routinely create physical prototypes, nearly one third report that software–hardware integration is only “average” or worse, and over 50 percent find current processes too complex or time‑consuming. Second, while precision and speed remain the top decision factors, “ease of use” ranks substantially lower—indicating that technical complexity still diverts designers’ attention from creative tasks. Third, although most participants are already familiar with generative AI and express strong interest in natural‑language control, they remain concerned about command accuracy, cost, and output quality. Collectively, these findings confirm that any next‑generation system must prioritize seamless integration, robust natural‑language understanding, and perceptible reductions in cognitive load.

Building directly on these insights, the next phase of development will focus on three main directions. **Improving efficiency** by embedding AI‑driven automation for repetitive operations—such as mesh optimization and toolpath generation—will both accelerate iteration cycles and increase the number of design variants achievable within a given timeframe. **Reducing technical complexity** through a unified interface that consolidates modeling, simulation, and fabrication controls will eliminate the need to switch between multiple software environments and minimize configuration hurdles. Finally, **minimizing cognitive load** by providing real‑time feedback (e.g., visual previews of synthesis steps), intelligent error prompts, and adaptive command refinement will enable designers to remain in a creative flow rather than troubleshooting tools.

By explicitly aligning these next steps with the thesis’s overarching objectives—enhancing rapid prototyping efficiency, lowering technical thresholds, and alleviating cognitive load—this initial survey lays the groundwork for the development of integrated human‑AI‑robot collaboration platform that empowers both expert and non‑technical users.

4.3 From Ideation to Digital Environment

4.3.1 Initial Test with Basic Generation

In the early development stages, this research first employed large language models for simple text-to-code-to-model generation experiments to validate the feasibility and scalability of natural language for 3D model generation. The research utilized Rhinoceros and Grasshopper as the 3D modeling platform, given the Grasshopper's strong compatibility with programming and external interfaces, as well as Rhinoceros' widespread use as a 3D design tool across multiple design disciplines.

The initial experiments used GPT-4 as the large language model for processing natural language commands, leveraging its logical reasoning capabilities to invoke Grasshopper and Rhinoceros' built-in components and functions to generate basic geometric shapes. After obtaining the OpenAI API, a Grasshopper plugin was developed in Microsoft Visual Studio that accepts three inputs: the user's natural language commands, the OpenAI API, and an execution switch.

When the first two inputs receive valid data and the execution switch is activated, the component initiates an asynchronous POST request, sending JSON data containing user information and natural language instructions to the specified OpenAI API endpoint. The OpenAI API processes the received natural language instructions and returns a JSON response containing the specific attributes needed to generate the geometric shapes (type, base size, height, radius, etc.). If essential attributes are missing, the component returns an error message prompting the user to modify their instructions. If the returned attributes are all correct, the component uses the RhinoCommon API to generate the corresponding geometric model.

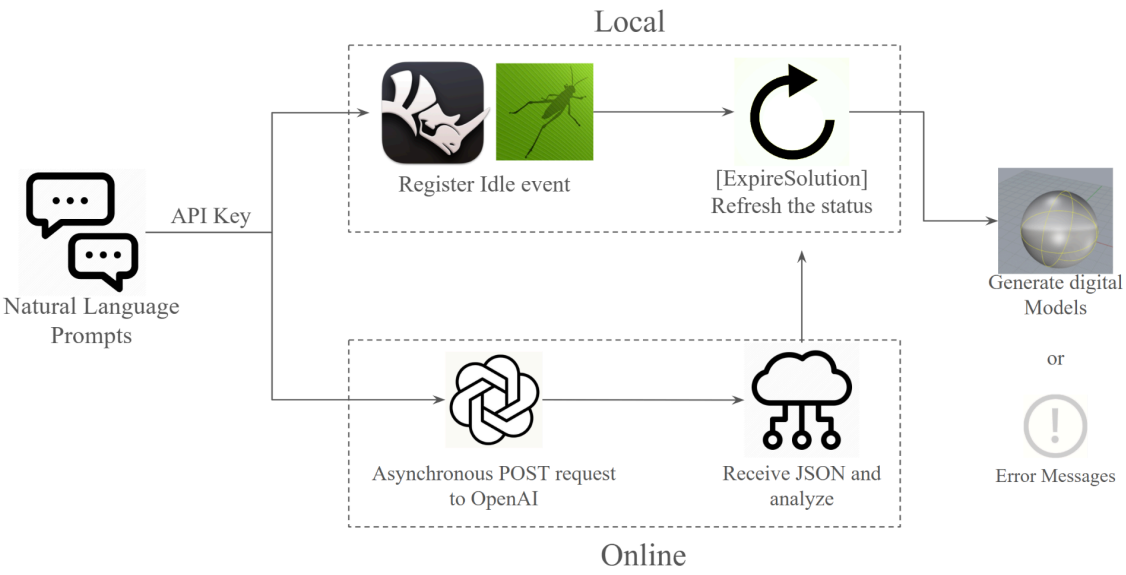
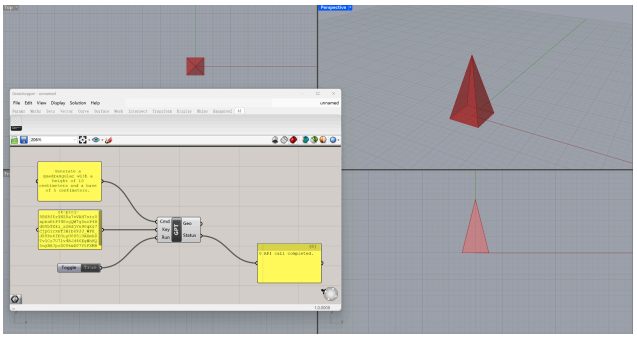
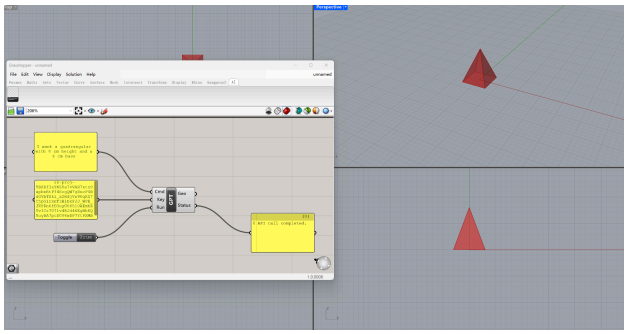


Figure 4.7 Running Process of the GPT in Grasshopper System

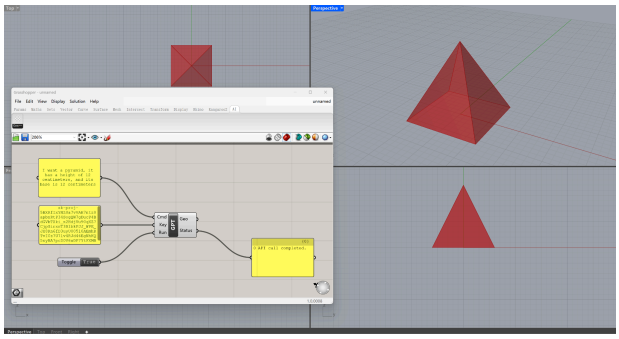
In the first test, the following prompt was provided to the Grasshopper component: “Generate a quadrangular cone with a height of 10 centimeters and a base of 5 centimeters.” The component successfully generated an accurate digital model. In the second test, the parameter values of the quadrangular cone were modified as follows: “Generate a quadrangular cone with a height of 8 centimeters and a base of 15 centimeters.” Again, the component correctly generated the corresponding model.



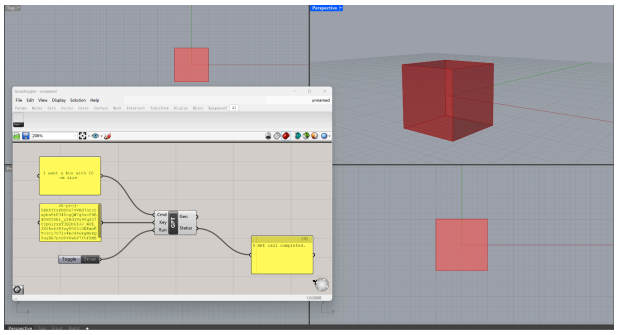
(a) First Test - Prompt: “Generate a quadrangular cone with a height of 10 centimeters and a base of 5 centimeters.”



(b) Second Test - Prompt: “Generate a quadrangular cone with a height of 8 centimeters and a base of 15 centimeters.”



(c) Third Test - Prompt: “I want a quadrangular cone. It has a height of 12 centimeters, and its base is 12 centimeters, too.”



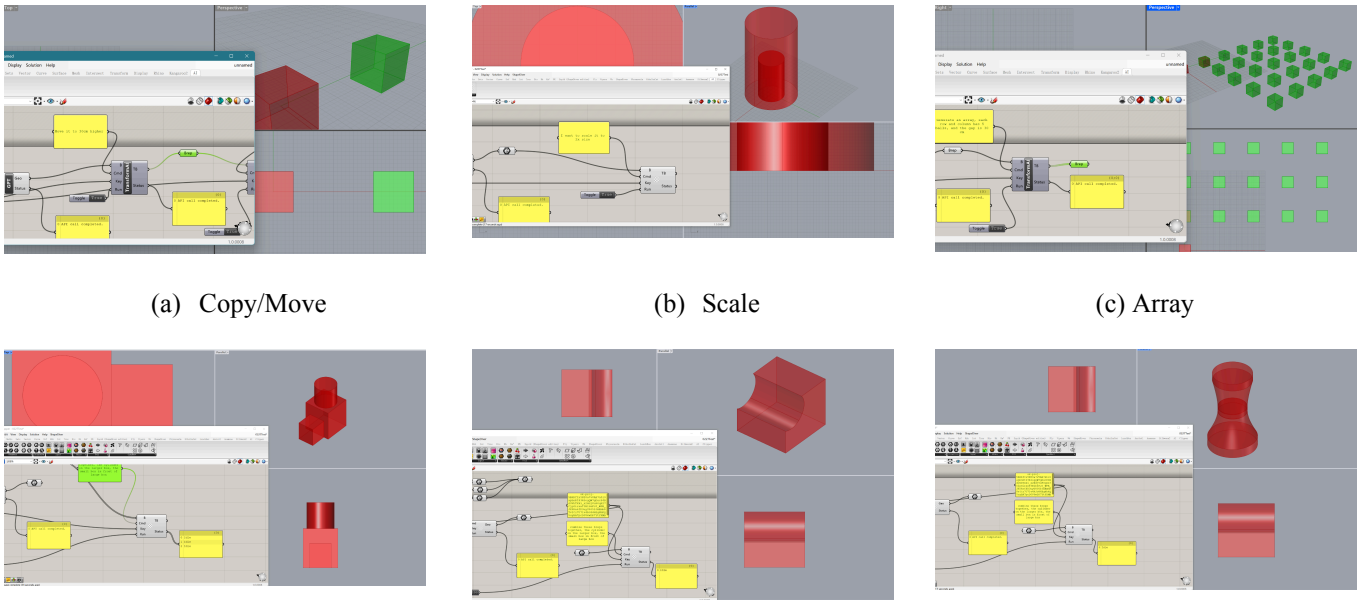
(d) Fourth Test - Prompt: “I want a box with 10 cm size”

Figure 4.7 Initial Test with GPT-4 to Generate Basic Geometric Shapes

In the third test, a more oral expression was used: “I want a quadrangular cone. It has a height of 12 centimeters, and its base is 12 centimeters, too.” Despite the informal phrasing, the component still produced an accurate model. And in the fourth test, the ability to generate other basic geometric shapes is tested. By inputting the prompt: “I want a box with 10 cm size”, the These tests demonstrate the effectiveness of the preliminary implementation and confirm the feasibility of integrating ChatGPT into Grasshopper for digital model generation.

Based on the initial tests, the plug-in is further developed to enhances the plugin’s capabilities in assisting designers with modeling tasks. Several additional functionalities have been integrated

to support more advanced and robust model generation and modification. At this stage, the plugin leverages GPT-4 to interpret natural language commands, enabling users to modify existing models using various transformation operations, including translation, rotation, scaling, array generation, lofting, and Boolean operations. Furthermore, to extend its functionality, the plugin incorporates an automated Python code generation module. This module translates transformation commands into syntactically correct Python scripts that can be successfully executed within Grasshopper.



(a) Copy/Move (b) Scale (c) Array

(d) Combine (e) Subtract (f) Loft

Figure 4.8 Editing and Modifying Operations with LLMs

In summary, the initial experiment above has preliminarily demonstrated that the generative AI prompting with natural language commands has the ability to integrate with 3D design platform, as well a considerable potential for expansion. With the initial developed version of the Grasshopper plug-in, it is possible to generate basic geometric shapes and modify/edit them using simple natural language commands. However, the capability of the large language models (e.g. GPT-4) demonstrated in the preliminary experiments is limited. They could generate basic geometric shapes and conduct simple operations like rotating, scaling and other modifications, or

combination, subtraction and other editions, however, the capabilities stopped here. For more complex 3D models commonly required in design works, large language models are poorly able to generate the required models by generating codes or calling Grasshopper's built-in functions effectively. Therefore, to enhance the practicality of the system developed in this research and expand its functionality, a more performant generative AI-driven approach to generate 3D model is urgently required.

4.3.2 Preliminary Study of Diffusion Models

In the literature review section, the latest research progress in text-to-3D generative AI was reviewed, which mentioned that diffusion models have been the main direction for current text-to-3D and image-to-3D generation research. Therefore, as the preliminary experiments have proved that the large language models have limitations in functionality and scalability, this research will further explore methods of deploying diffusion models to generate 3D models in human-AI collaborative systems.

To explore specific models for the system development, the first step is to study and compare various models that have been published, analyzing their respective advantages and limitations. Current main generative AI models show obvious trade-offs in generation quality, computing speed and hardware requirements, etc. In this stage, 5 distinctive and representative models are selected for further study and comparison: Point-E, Shap-E, DreamFusion, Magic3D, and TRELLIS.

Point-E was proposed by the OpenAI team (Nichol et al., 2022), uses diffusion models to generate 3D points cloud. Its most outstanding advantages are the minimum requirement of hardware and the high speed of computing. However, the generated models lack clear and detailed structure, reducing its capability for subsequent use and modification. Shap-E, also proposed by the OpenAI team (Jun & Nichol, 2023), enhances Point-E by refining the computational methodology to directly synthesize 3D meshes while maintaining computational efficiency. While suitable for rapid prototyping applications, its outputs occasionally demonstrate

divergence from textual prompts and possess moderate precision. DreamFusion (Poole et al., 2022) represents an iterative optimization method that integrates diffusion models with Neural Radiance Fields (NeRF), employing multi-view consistency to progressively refine models. It produces relatively fine results but requires longer iteration times. NVIDIA's Magic3D (Lin et al., 2022) implements a high-resolution multi-view diffusion strategy, resulting in enhanced precision and detail in generated 3D models. However, it requires extremely high hardware configuration and has limited open-source accessibility. TRELLIS (Xiang et al., 2024), recent released by Microsoft research team, combines diffusion models with NeRF technology to generate high-fidelity 3D assets from text or image inputs, supporting multiple output formats while maintaining the ability to deploy on moderate hardware configurations.

The table summarizes the above-mentioned models' features:

Models	**Computing Speed**	**Generation Quality**	**Hardware Requirement**	**Applicable Scenarios**
Point-E	Very Fast	Poor (Points Clouds)	Low (Available on CPU)	Quick sketching, early shape exploration, data augmentation
Shap-E	Very Fast	Moderate (Rough Mesh)	Moderately Low (Normal GPU)	Fast modeling, lightweight AR/VR applications
DreamFusion	Extremely Slow	High (High-quality Mesh)	Relatively High (High GPU)	High-quality visualization, render-grade outputs, artistic creation
Magic 3D	Moderately Slow	Very High (Rendering Class Mesh)	Very High (High GPU, e.g. NVIDIA A100)	Game asset creation, visual content generation, film pre-visualization
TRELLIS	Moderately Fast	High (Well-structured Mesh)	Moderate High (GPU with 8GB above memory)	Conceptual 3D modeling, Fast generation of models for rapid prototyping

Table 4.1 Comparison between Multiple Main Text-to-3D Generative AI Models.

In the initial survey in section 4.2, it is identified that the primary obstacles users face in the design-digital-physical prototype process are iteration speed, technical complexity, and process integration. Therefore, the selected model should focus on these factors, prioritizing faster generation speed, lower deployment difficulty, reduced hardware requirements, and more universally applicable scenarios.

Based on these considerations, the next stage of research will initially utilize the Shap-E model for initial development and experimentation due to its fast generation speed and low technical complexity. Once the feasibility and effectiveness of the human-AI collaborative process have been verified, we will proceed to implement more complex models to enhance the system's capability to handle more sophisticated tasks and improve collaborative capabilities.

4.3.3 Deploying Shap-E in Grasshopper

The Shap-E model is a text-guided diffusion model whose core includes two key modules:

1. Text-guided Diffusion Model: Achieves gradual sampling of three-dimensional implicit representations through a diffusion process (Gaussian Diffusion) with conditional guidance from text prompts.
2. Neural Implicit Decoder: Responsible for decoding the latent representations produced by the diffusion model into explicit three-dimensional meshes, thus completing the transformation from abstract representation to concrete geometry.

In Shap-E's inference process, it first generates a latent space representation of an implicit field based on text prompts, then decodes it through a transmitter, and uses algorithms like Marching Cubes to convert the implicit field into a three-dimensional mesh, resulting in the final usable 3D model. The Shap-E model has fast computation speed and relatively low system configuration requirements, making it suitable for this research's initial diffusion model deployment development.

During development, since Grasshopper plugins are developed in Visual Studio based on the .NET framework, while diffusion models including Shap-E primarily rely on Python and GPU computing environments, the system adopts a cross-language, cross-process calling method. First, Anaconda was used to configure the environment and install all libraries required for running Shap-E, and a script was constructed in Python for the inference interface to run Shap-E. This script can receive text prompts and related parameters, call the pre-trained Shap-E model, complete diffusion sampling, and generate 3D mesh files in OBJ format, which are stored locally.

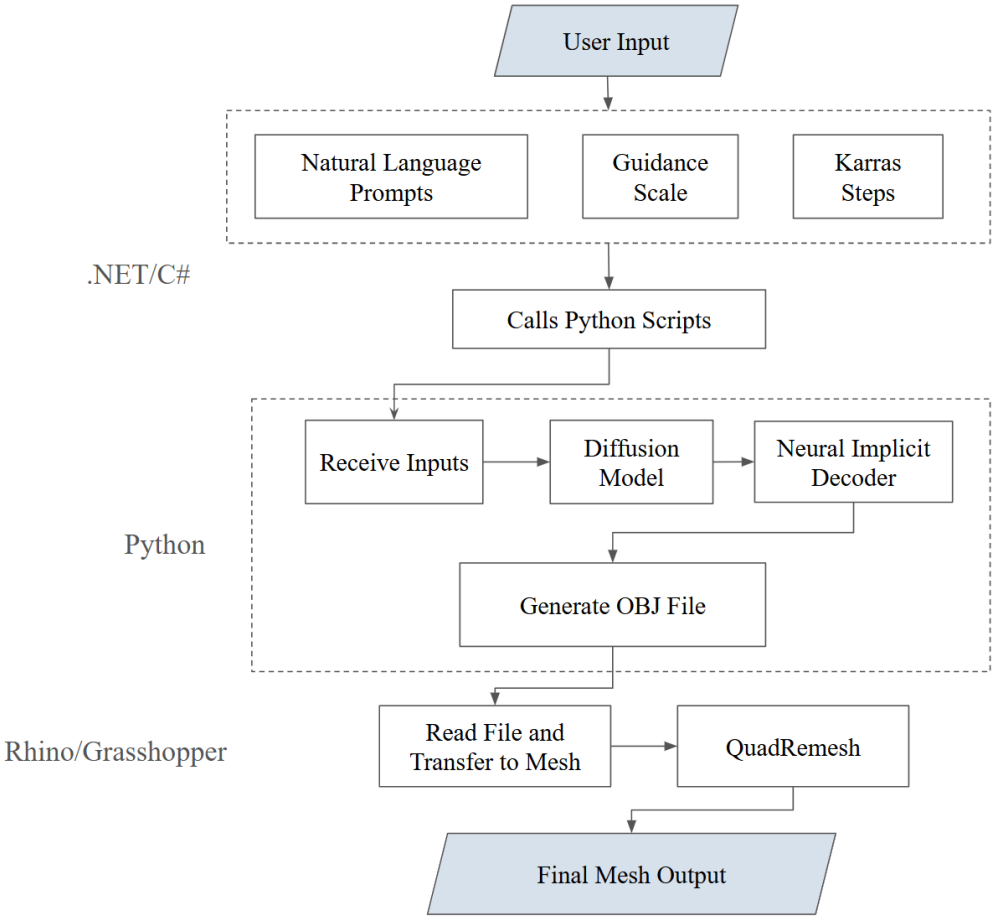


Figure 4.9 Overall System Architecture and Execution Processes of Deploying Shap-E in Grasshopper

Subsequently, a corresponding custom Grasshopper plugin was developed in the C# environment in Visual Studio. This plugin uses the RhinoCommon API and defines input and output ports, where inputs include user-input natural language prompts, Guidance Scale, and diffusion steps, while outputs are the generated Mesh and console output logs from the inference process. Internally, the code uses .NET's System.Diagnostics.Process to call the Anaconda environment and Python script, enabling the Shap-E model to be called within Grasshopper. After the Shap-E model generates the 3D model, the C# plugin automatically reads the model and imports it into the Grasshopper environment.

In Addition, since the models generated by Shap-E have issues when imported into Grasshopper, including excessive face amount, irregularity, and damage problems that brings obstacles for subsequent use, the component further called the QuadRemesh function from RhinoCommon after mesh generation. It automatically performs mesh reconstruction to generate higher quality meshes with fewer faces, enhancing the usability of the models in practical applications.



(a) Generated Model Directly Imported into Grasshopper

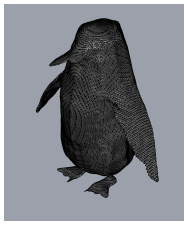
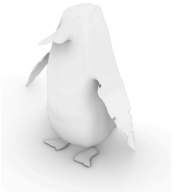
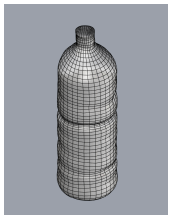
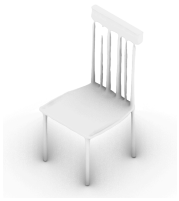
(b) Fewer Facet Mesh after QuadRemesh

Figure 4.10 Model Generated by the Shap-E Grasshopper Plug-in

After completing system development, a series of generation tests were conducted to evaluate the plugin's performance and applicability. The testing was divided into three parts: the first part used simple descriptive prompts to generate common objects from daily life, the second part used a series of common design-related prompts to generate design models, and the third part used unusual or fantasy-oriented prompts to generate exploratory models with imaginative qualities.

For each prompt, the system was configured with consistent diffusion parameters: Guidance Scale of 12.0, Karras Steps of 64, and all output models underwent QuadRemesh processing. The running environment consisted of Python version 3.10, Pytorch version 2.5.1, CUDA version 12.8, an NVIDIA RTX 4080 GPU, and with system environment being Windows 10.

The test process and results are shown in the table below:

Test Group	Prompts	Generated Mesh	Rendering
Group 1 Descriptive Everyday Objects	"A penguin"		
	"A water bottle"		
	"A dinning chair"		

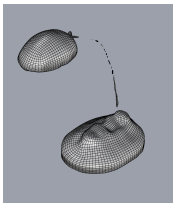
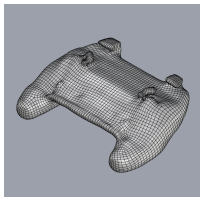
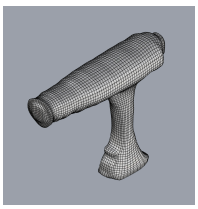
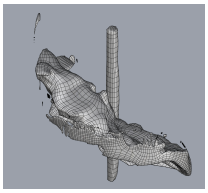
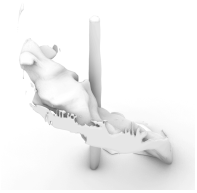
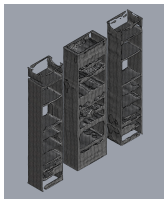
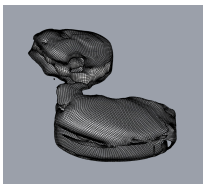
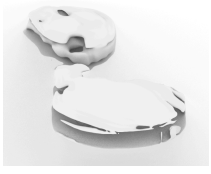
Test Group	Prompts	Generated Mesh	Rendering
Group 2 Design-Oriented Concepts	"A minimalist office lamp"		
	"An ergonomic handheld controller"		
	"A Dyson-style Hairdryer"		
Group 3 Complex Architectural Design Intentions and Ideas	"A vertical library with spiral ramps connecting reading pods at different heights"		
	"A modular housing system with assembled units that can expand vertically and horizontally"		
	"A transit hub with commercial retail and public event spaces"		

Table 4.2 Generation Test of the Shap-E in Grasshopper Plugin

From the test results shown in the table above, we can observe significant deficiencies in the consistency between prompts and generated results in the Shap-E model. When prompts were limited to simple everyday objects, Shap-E could generate 3D models with relatively complete structures, distinct features, and reasonable proximity to the prompt descriptions. However, when design-related terms were introduced and descriptive modifiers were added, although the Shap-E model could identify the noun subjects in the prompts and generate relatively similar objects, the descriptive words were poorly reflected in the generated results. This indicates that Shap-E cannot adequately meet designers' needs. Furthermore, when using more unconventional and imaginative prompts, Shap-E was almost incapable of generating structurally complete objects with distinct features, demonstrating its fundamental inability to expand designers' thinking. Additionally, when processing generation tasks with slightly complex shapes, the Shap-E model frequently exhibited serious issues such as model damage and disorganized forms, making it nearly impossible to use for subsequent modifications. While mesh reconstruction could optimize some models in these situations, many cases remained irreparable.

In summary, at this stage, we successfully developed a simple Human-AI collaborative system for generating 3D models by deploying Shap-E and integrating it with Grasshopper, enabling the direct generation of optimized meshes through simple language commands. This success demonstrated the feasibility and enormous potential of deploying diffusion models in the system developed for this research. However, simultaneously, the test results indicated that the Shap-E model still has serious limitations and struggles to meet designers' needs for quickly and efficiently transforming ideas into digital models during the design process. Therefore, this research will further explore deploying higher-performance models to improve the system's generation quality, interactive capabilities, and expansion potential.

4.3.4 Deploying TRELLIS in Grasshopper

In the previous step, we validated the feasibility and potential of deploying diffusion models into Grasshopper, successfully developing a preliminary system that integrated the Shap-E model. However, due to the inherent limitations of the Shap-E model, the research will further explore models with superior generative performance while seeking balance in factors such as generation time and system configuration requirements.

Upon reviewing the comparison of multiple text-to-3D diffusion models in Table 4.1, it becomes evident that other models present disadvantages including long generation time, high hardware requirements, and incomplete open-source availability. After comprehensive research and comparative analysis, the research has selected the TRELLIS model for the next step of development.

TRELLIS(Xiang et al., 2024) is a recently released generative AI model by Microsoft research team. The system enables the creation of high-quality 3D assets from text descriptions or image inputs, producing diverse 3D representations with intricate shape and texture details. What distinguishes TRELLIS from previous approaches is its unified Structured LATent (SLAT) representation, which serves as the cornerstone of its architecture and allows for versatile output formats. The model operates through a two-stage generation process:

1. Sparse Structure Generation: Initially processes the input prompt (text or image) to generate a sparse structure latent representation at 16^3 resolution with 8 channels.
2. Structured Latent (SLAT) Generation: Transforms the sparse structure into a higher-resolution SLAT representation at 64^3 resolution, maintaining 8 channels but with greater spatial detail.

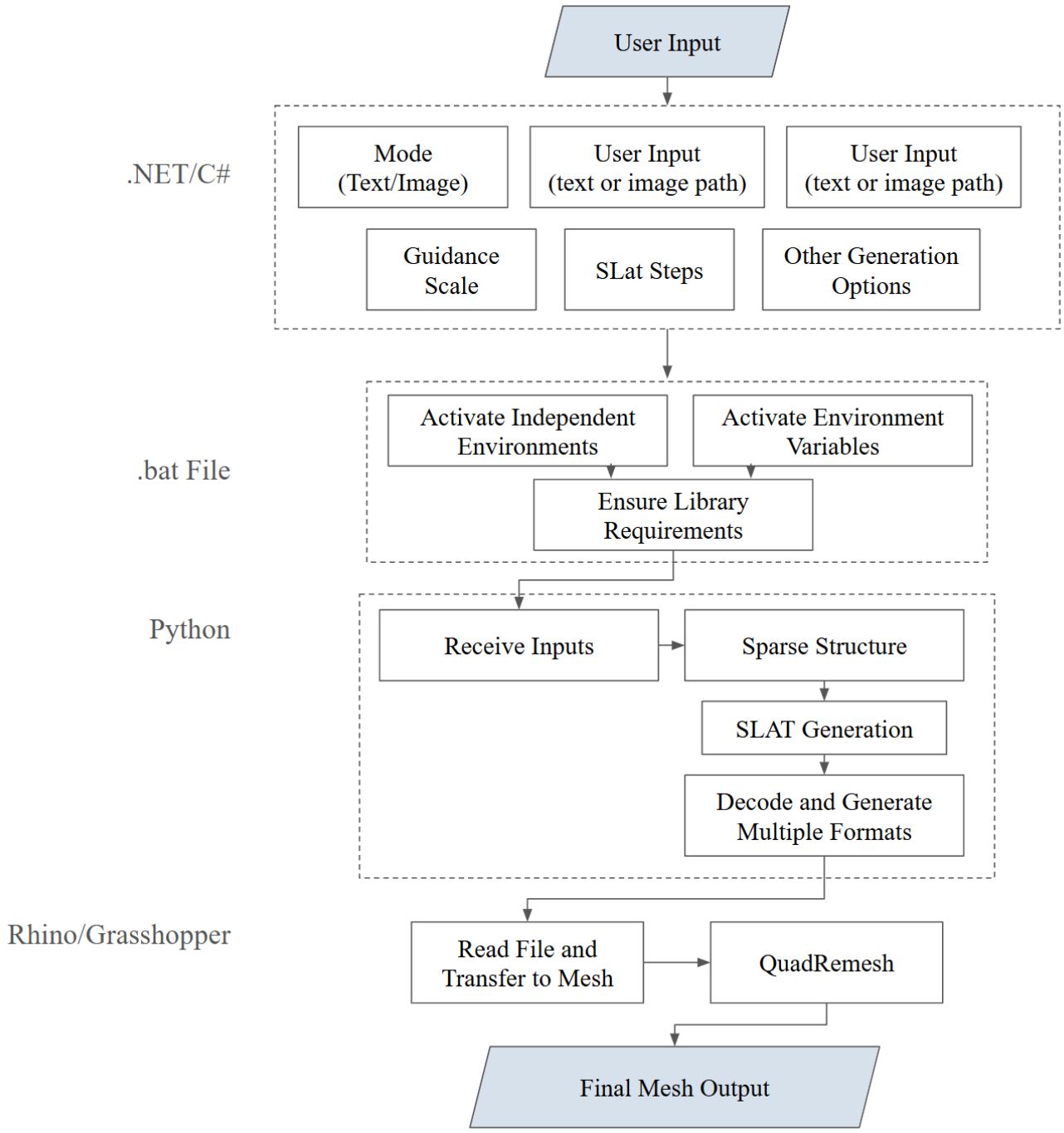


Figure 4.11 Technical Framework of TRELLIS for Grasshopper plug-in

Integrating TRELLIS into Grasshopper presented multiple challenges during the development process. First, similar to the Shap-E model deployment, there exists a fundamental difference between Grasshopper's C#/.NET-based development environment and the Python framework that diffusion models depend on. Second, the officially released model was developed and tested in Linux environments, which requiring reconfiguration to integrate it into Rhino and Grasshopper in Windows environments. Additionally, the increased technical complexity resulting from TRELLIS model's performance improvements led to more complex system environment dependencies, requiring stricter environment management and process isolation. To solve these issues, the system developed a three-layer structure:

1. Interface Layer: A custom Grasshopper component developed with Visual Studio and RhinoCommon API, used to receive user interactions, manage parameters, and output data.
2. Bridge Layer: A batch script to initialize and configure the environment, ensuring proper activation of environments between Grasshopper and Python, correct installation of necessary libraries, and process isolation.
3. Execution Layer: Python scripts directly calling the TRELLIS model to execute calculations and generation, processing inputs, and managing outputs.

The development process began with writing custom components in Grasshopper using Visual Studio, receiving several parameters at the input: prompt type (text or image), prompt content, Guidance Scale, Computing Steps, Seeds, and output path. A batch script was then implemented to properly activate the Anaconda environment containing all necessary dependencies, ensuring the Python environment had full access to GPU resources and CUDA libraries. This intermediary layer resolved environment isolation issues caused by directly calling Python from Grasshopper. Next, the batch file ran a Python script designed to handle direct interaction with the TRELLIS model. This script accepted command line arguments for text or image input, guidance parameters, and output specifications. It managed model loading, the inference process, and exported the generated 3D assets in various formats including OBJ, GLB, and PLY files. Finally, the generated models were read by the component and imported into Rhino/Grasshopper. Similar

to the Shap-E system, the component internally also called the QuadRemesh functionality from RhinoCommon API to optimize mesh face count while preserving important geometric details.

The completed component can receive text or image inputs and generate higher quality digital models with more distinctive features. It maintains reasonable operating speeds, with generation times of approximately 60 to 100 seconds in test environments with different hardware and GPUs. Compared to models like DreamFusion with generation times of tens of minutes, this system better balances generation quality and computing time, while maintaining accessibility for common consumer computers or designer workstations.

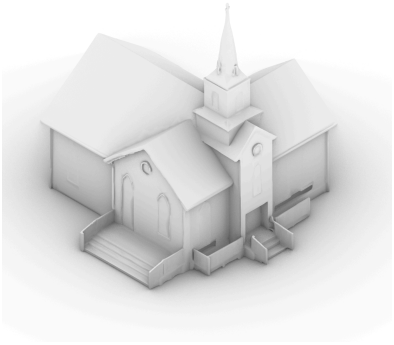
	Input Prompts	**Output Meshes**
Text Input	"A small community church"	
	"A Zaha-Hadid Style Architectural Sculpture"	

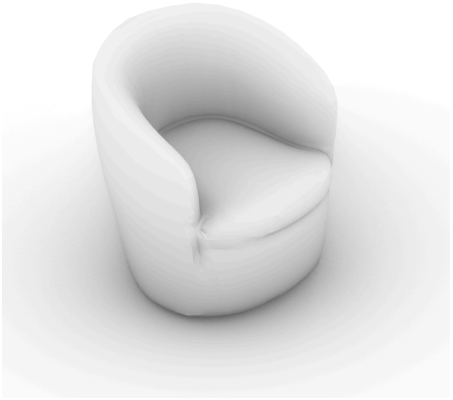
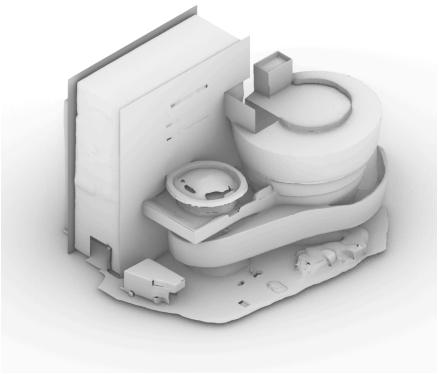
Image Input		
		

Table 4.3 Generation Test with TRELLIS for Grasshopper

The generation test results indicate that the TRELLIS model significantly outperforms the Shap-E model in 3D model generation. Specifically, when using text descriptions as input prompts, TRELLIS generates models that more accurately conform to user specifications than Shap-E while almost entirely avoiding issues of geometric damage and structural disorganization. When images function as input, TRELLIS effectively captures and reproduces the essential characteristics of the input image while successfully supplementing details from perspectives not visible in the original image, ultimately producing models with distinct features that correspond to the source imagery. These test results demonstrate that integrating the TRELLIS model into the Grasshopper environment offers considerable practical value, effectively enhancing the efficiency of three-dimensional model generation while reducing the complexity of technical implementation.

4.3.5 Optimization and Refinement

During generation testing, although good results were obtained after receiving image inputs, when only text instructions were used as generation prompts, the generated results often did not fully match the descriptions in the prompts. To optimize the generation effects of text prompts, we will explore how to improve the current generation process.

Since the TRELLIS research team has not released the training method of the current model, it is not possible to fine-tune the model used for text-to-3D conversion. The research therefore turned to another direction, exploring improvements to the current text-to-3D generation process. The research found that the TRELLIS model produces better generation results in the image-to-3D process. Therefore, the research will use text to first generate images, then use those images as input for 3D generation, thereby transforming the text-to-3D generation process into a text-to-image-to-3D generation process.

As Open AI API was used in the earlier initial research process in 4.3.1, and the Open AI API can access the image generation model DALL-E, the research will use DALL-E as the model for generating intermediary images, without needing to locally deploy other models or call other APIs.

The method of calling DALL-E in Grasshopper is similar to the method of calling the GPT model described in 4.3.1. Specifically, the Grasshopper component first receives users' text input and related parameters (image size, quality, style, etc.), then serializes these parameters into JSON format data conforming to the OpenAI API specification, and sends requests to the OpenAI server asynchronously. After remote inference is completed and a JSON response is returned, the plugin script is responsible for parsing and decoding the response data, converting the image data from Base64 format to Bitmap format, and storing it to a local temporary path.

After development was completed, a series of comparative generation experiments were conducted. These experiments used the same prompts to generate models under both TRELLIS's native text-to-3D workflow and the text-to-image-to-3D workflow with DALL-E-generated images as intermediaries.

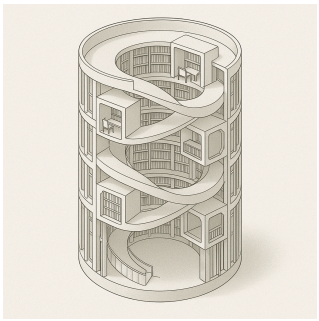
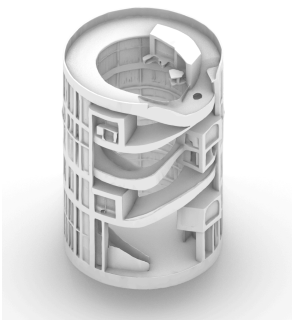
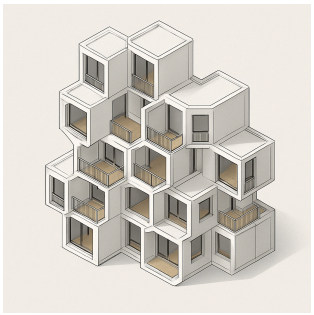
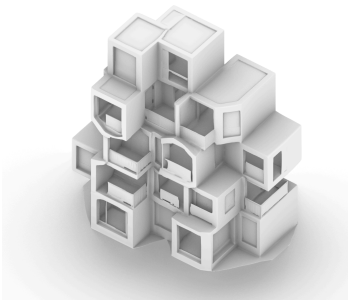
Input Prompts	Intermediary Images	Output Meshes
“An ergonomic handheld game controller”		
“A minimalist office lamp”		
“A vertical library with spiral ramps connecting reading pods at different heights”		
“A modular housing system with assembled units that can expand vertically and horizontally”		

Table 4.4 Generation Test with Optimized Text-to-Image-to-3D Workflow

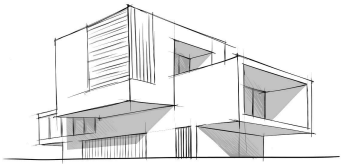
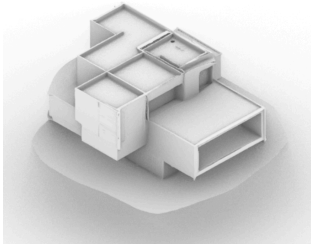
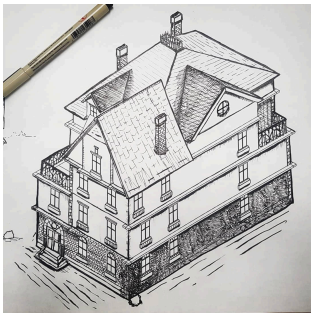
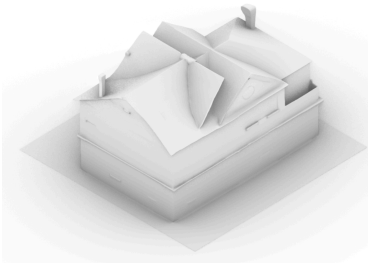
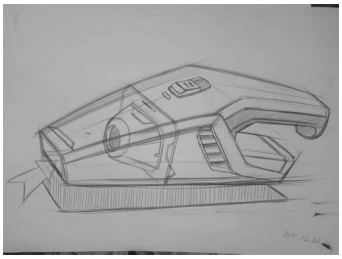
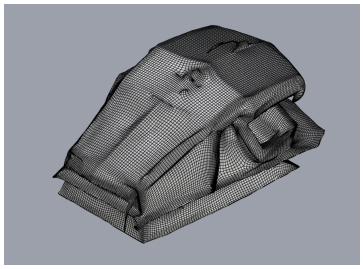
Input Catagories	Image Input	Output Meshes
A Rough Architectural Design Sketch		
A More Detailed Architectural Drawing		
A Simple Industrial Design Sketch		

Table 4.5 Generation Test with Sketches Commonly Used in the Design Process

The findings demonstrate that using DALL-E as an intermediary in the text-to-image-to-3D generation pipeline yields significantly improved outcomes compared to utilizing the TRELLIS model independently. The generated results not only better align with the descriptions in the prompts but also display enhanced morphological richness compared to TRELLIS's native output. Furthermore, since DALL-E generates images considerably faster (approximately 10 seconds) than TRELLIS produces 3D models (60-90 seconds), users can rapidly generate multiple images and select the most effective result as input for 3D generation. This approach substantially reduces the time cost of repeated generation attempts and dramatically accelerates the iteration process.

4.3.6 Summary of Ideation to Digital Environment Stage

In conclusion, the 4.3 section describes a progressive exploration of integrating generative artificial intelligence with three-dimensional modeling workflows, advancing from preliminary feasibility testing using large language models to the deployment of diffusion models within Grasshopper, and ultimately to workflow optimization and integration.

Initial experiments demonstrated that large language models could effectively interpret simple natural language commands, enabling basic shape generation and direct modification. However, limitations emerged when generating complex, detailed, and imaginative models common in design tasks. Subsequently, the research explored diffusion models due to their greater potential for generating complex models with distinctive features. The deployment of Shap-E achieved preliminary success, validating the feasibility of diffusion models while also highlighting significant constraints, including insufficient representation precision, limited receptivity to complex prompts, and frequent structural defects in the generated meshes.

To address these issues, the research progressed to deploying TRELLIS, a more capable model that balances high-quality generation, moderate hardware requirements, and practical integration complexity. TRELLIS significantly outperformed Shap-E, consistently producing accurate, structurally coherent models closely aligned with textual or visual inputs. Despite these

advancements, limitations persisted when using pure text prompts, prompting further optimization through a novel text-image-3D pipeline that leveraged DALL-E for intermediate image generation. This hybrid approach substantially improved the accuracy, morphological richness, and efficiency of model generation, greatly simplifying the iterative design process.

These iterative explorations confirm the immense potential and practical advantages of combining generative artificial intelligence with digital modeling platforms, dramatically enhancing designers' ability to rapidly transition from conceptualization to high-quality digital prototypes.

4.4 From Digital Environment to Fabrication

In the previous research stage, the involvement of generative AI was explored in the process from concept to digital model, and developed a Human-AI collaborative system featuring multimodal input, low technical complexity, and support for rapid iteration. In this stage, the research will focus on discussing the Human-AI-Robot collaborative system from digital model to physical prototype, exploring how to improve prototype manufacturing efficiency and reduce technical complexity.

4.4.1 Mesh Simplification and Wireframe Structure Generation

Inspired by the research of Mueller, et al. (2014) and Untzelmann & Kobbelt (2018), the thesis explores a methodology by converting the generated 3D model into a wireframe structure that can be used for 3D printing. The method attempts to create a geometry processing pipeline for converting surface meshes into wireframe structures, trying to achieve a balance between geometric feature fidelity and fabrication efficiency gains.

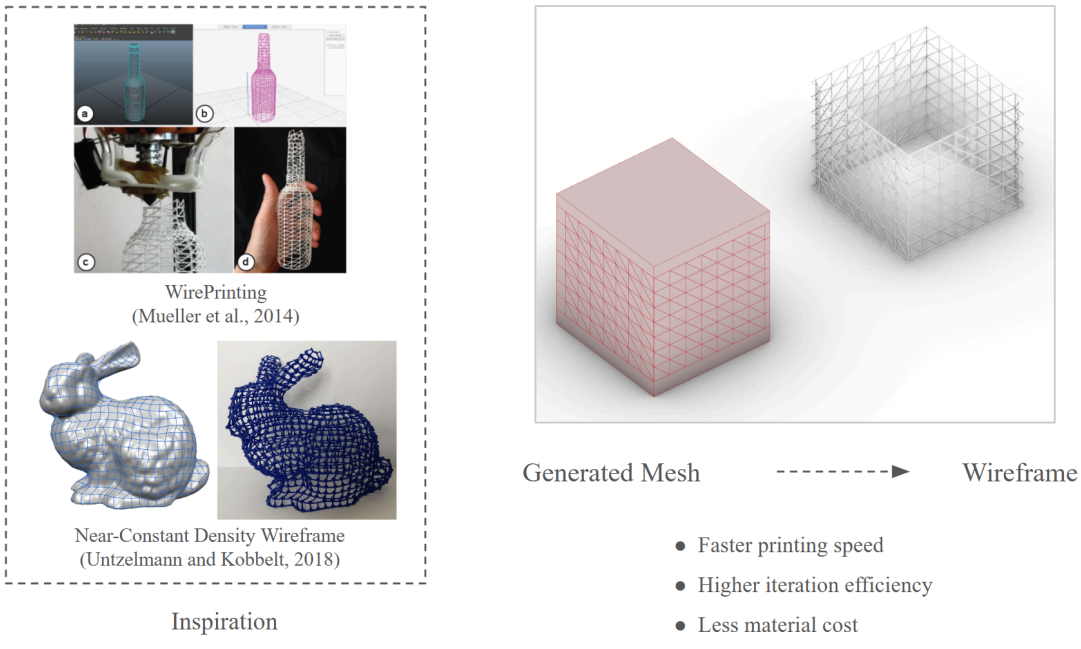


Figure 4.12: Inspiration from Precedent Research Wireframe Printing

Traditional planar height-based slicing methods produce irregular contour spacing on non-horizontal surfaces, resulting in undesirable wireframe structures. To address this limitation, this study uses a scalar field-based approach for wireframe structure generation. The advantage of this approach is that it not only considers the height characteristics of the model, but also integrates the surface normals and geometric topology information, which enables the generation of wireframe structures with more uniform spatial density. For the input triangular mesh $M=(V,E,F)$, where **V** is the set of vertices, **E** is the set of edges, and **F** is the set of faces, a scalar field from vertices to the real domain of the mesh is defined $f:V\rightarrow R$. This scalar field incorporates the surface normal vector information, which allows for the subsequent acquisition of the outer contour lines to produce a uniform outer contour line on surfaces of different orientations.

The method is developed in Visual Studio based on .NET and RhinoCommon, and its complete process consists of four key steps as follows:

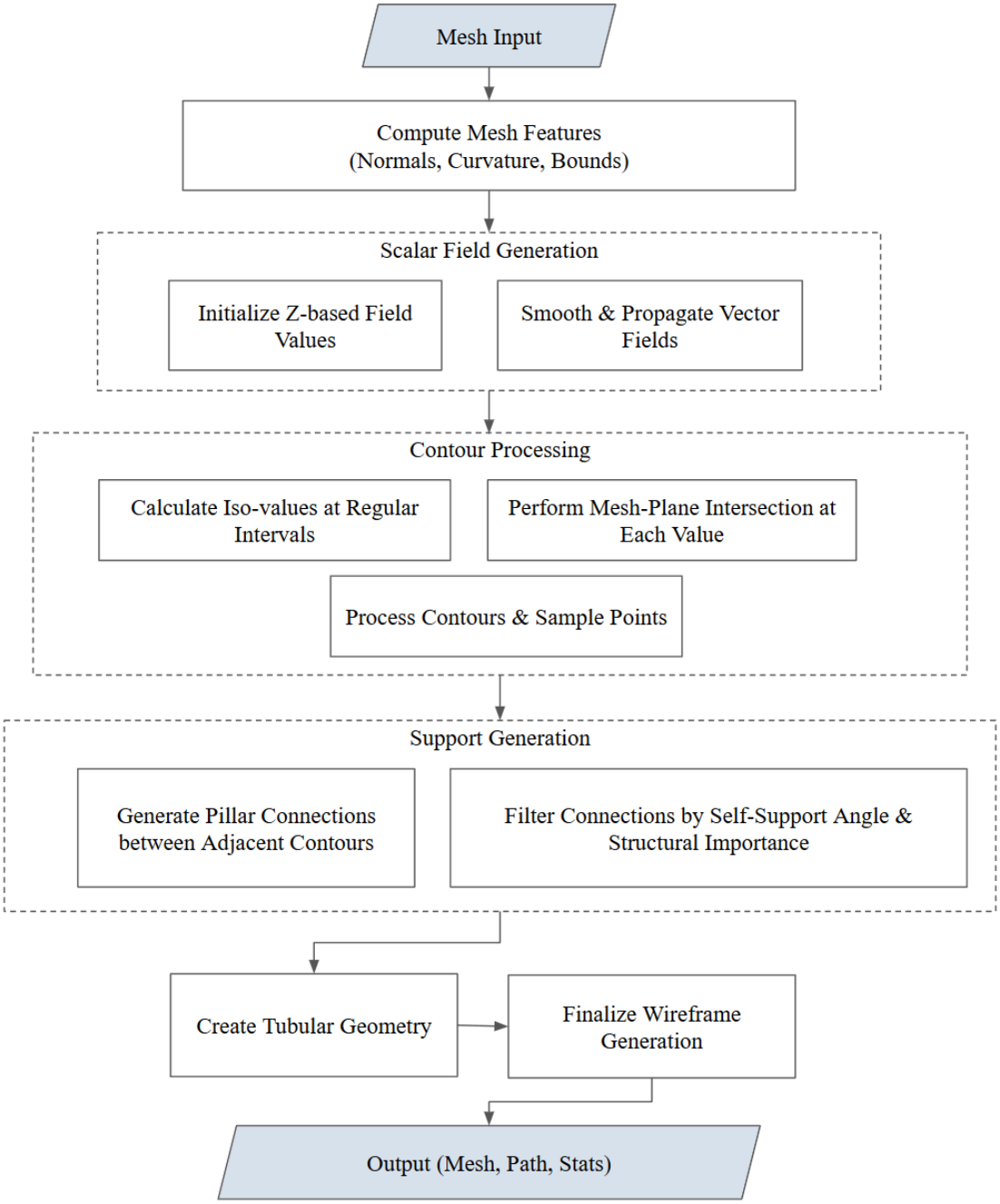


Figure 4.13: Technical Framework and Process of Wireframe Structure Generation

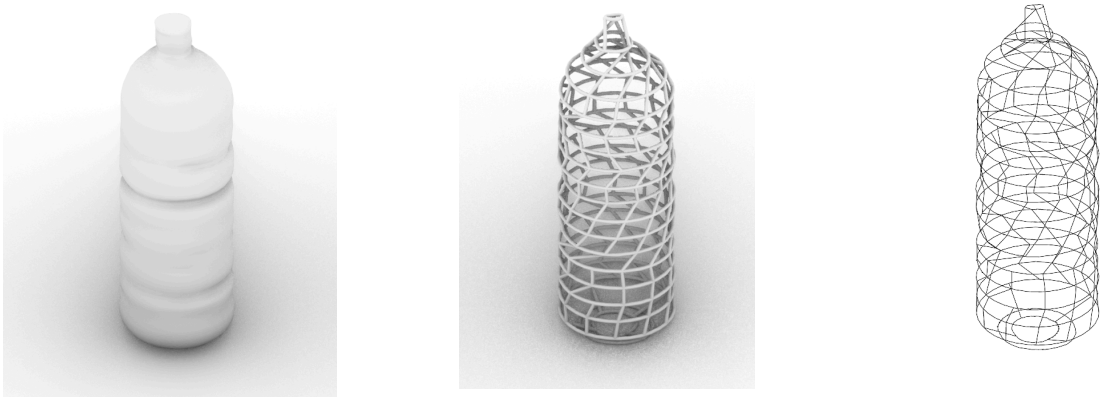
1. **Generate scalar fields for uniform contour distribution:** For the input mesh, it is first triangularly meshed to facilitate subsequent analytical calculations. The scalar field is generated by an iterative optimization process on the triangular mesh. The initial field is built based on the z-coordinates of the vertices and is subsequently continuously optimized through a smoothing operation and a normal vector oriented propagation process. The process incorporates Dirichlet boundary conditions for the mesh to ensure numerical stability and improves convergence through relaxation iterations.

2. **Contour line extraction:** after generating a scalar field, contour lines are extracted at fixed intervals within that field. The algorithm traverses the list of edges of the mesh to find the edges that cross a particular scalar value threshold. For each intersecting edge, linear interpolation determines the exact intersection coordinates. These intersections are then connected to form a continuous folded contour. The algorithm maintains topological integrity by keeping track of edge adjacencies and ensuring correct contour connections. Special cases, such as contours forming closed loops or branching structures, can be handled by a graph traversal algorithm that correctly orders the intersections into coherent curves. For boundary regions where mesh surfaces terminate, additional logic extracts bare edges and processes them separately to ensure complete wireframe coverage. This includes identifying mesh edges that belong to only one face and integrating them into the contour generation process.

3. **Contour Line Simplification**: Extracted contours often contain too many vertices, burdening the computation and manufacturing process. Therefore, after the contour lines are extracted, they are simplified to facilitate the subsequent generation of supports and to reduce manufacturing complexity. The contour lines are reconstructed to reduce the number of segments and vertices while maintaining the features. In general, vertices on straight line segments or vertices with low curvature are the main targets for

optimization, while points with high curvature often characterize important features and are retained to ensure that the contour lines reflect the main features of the original mesh.

4. **Generating Vertical Supports:** Vertical connections between contours are created using a graph-based approach in which each contour layer is a network of nodes. This approach treats potential strut connections as weighted edges in a bi-directional graph, the cost of which is determined by factors such as connection length, print angle compatibility and structural importance. The system is based on a traditional minimum spanning tree algorithm that enforces practical constraints including joint vertex restrictions and overall network connectivity. The selection process inherently favors self-supporting geometries, prioritizing vertical connections or connections within 45 degrees of the build direction. In areas where structural integrity needs to be enhanced, the local optimization routines dynamically adjust the connection patterns to include diagonal bracing or triangular frames as needed.



Input Surface Mesh Wireframed Mesh Path Curves

Figure 4.14: Translating Process from AI-Generated Mesh to Wireframe Structures

These steps successfully convert surface meshes generated from text-to-3D models into wireframe structures, with additional optimizations specifically targeting digital fabrication (e.g. 3D printing). This methodology effectively addresses the limitations of traditional slicing techniques, achieving a successful balance between geometric feature fidelity and manufacturing efficiency through the integration of surface normals and topological information. Also, it provides a crucial foundation for subsequent physical fabrication processes.

4.4.2 AI-Assisted Printing Path Generation

After obtaining the optimized frame structure, the next step is to transform the structure into a format that can be read and printed by 3D printing equipments. At this stage, the research proposes a collaborative AI approach with large language model to assist in generating and optimizing G-Code, which in turn reduces the technical complexity and cognitive load of switching between different software environments. This method will use the previously used OpenAI API to invoke the GPT-4 model as the large language model for assisting G-Code generation, which concludes of the following key steps:

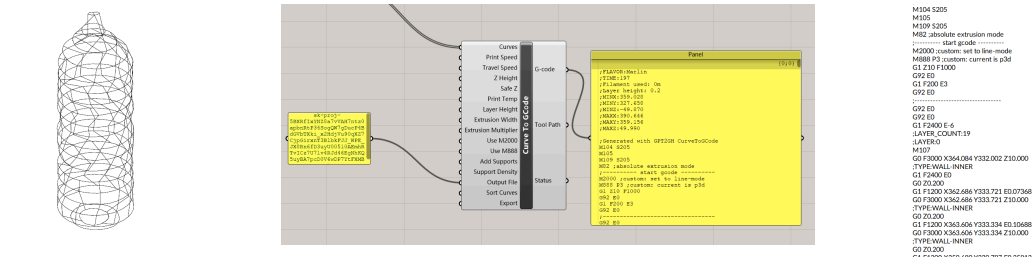
1. **AI-Generated Header Codes:** When the user specifies the printer configuration (including the model number, nozzle size, material type, and temperature setting), the OpenAI API will generate the corresponding header codes. This automated approach handles printer-specific initialization commands such as print bed heating, nozzle calibration, and axis adjusting. The AI adjusts the Header content based on whether the printer is using Cartesian, delta, or CoreXY kinematics, eliminating the need to manually adjust configurations in slicing software or other software environments, reducing technical complexity, and increasing process integration.

2. **Wireframe-to-Coordinate Translation:** The frame structure generated in the 4.4.1 section is used as the curve input to transform the wireframe curve to spatial coordinates by sampling along the start and contour of each curve. The algorithm determines the

sampling density based on the complexity of the curve, placing more points on sharp curves and using fewer points on straight segments. In this way, the coordinate data from the wireframe curve is transformed into the body of the G-code.

3. **AI-Generated Footer Commands:** Using the same printer configuration data as in the first step, the AI can generate appropriate end commands to control shutdown. This includes a gradual cool down, a retraction sequence to prevent stringing, a bed cleanup action, and a safe parking position for the printhead and bed. Footer commands are generated to accommodate different material requirements and printer specific shutdown procedures.

4. **G-code Assembly and Output:** The Header, Ender, and Body codes generated in the above steps are combined in this step into a complete, executable G-code file. Since the printer configuration has been completely set up, no additional operations are required to send it directly to the printing device for manufacturing



Wireframe Curves AI-assisted Grasshopper Component Generated G-Code

Figure 4.15 AI-assisted G-Code Generation Pipeline

In summary, this section validates the potential and effectiveness of big language modeling in assisting digital manufacturing. It has been demonstrated that the Big Language Model can be

involved in G-Code generation and optimization, including the automatic generation of startup and shutdown commands for the print device, the conversion of the optimized wireframe structure into spatial coordinates and the optimization of the sampling density, and the final combination of the parts into a complete G-Code file. This approach significantly reduces technical complexity and cognitive load, and improves the efficiency and ease of use of the manufacturing process.

4.4.3 Selection and Study on Fabrication Equipment

In this thesis, robotic arm 3D printing will be the main fabrication method and research object in the fabrication workflow of physical prototypes. There are several key factors for choosing robotic arm 3D printing as follows:

First, most of the desktop robotic arms, whether custom-built or consumer-grade desktop robotic arms, use standardized control protocols and programming interfaces, which allows for a high degree of integration with parametric modeling or programming environments such as Grasshopper. The ability to communicate directly with the programming environment through customized components and scripts avoids the intermediate conversions typically required in traditional manufacturing equipment, greatly reducing the technical complexity of the workflow and potential points of error in data conversion.

Second, robotic arms can expand the possibilities of more processing methods. Unlike specialized manufacturing equipment that is limited to a specific production method, desktop robotic arms can be quickly reconfigured to perform multiple manufacturing processes by simply changing their end effector. From simple drawing, to slightly more complex cutting or engraving, to more complex 3D printing or laser cutting, the arm can perform them all by changing its end effector. This versatility allows it to adapt to different scenarios and varying prototyping needs, enhancing expandability and functionality without the need to switch between various specialized machines.

Additionally, desktop robotic arms typically offer plenty of flexibility and accessibility. A typical desktop robot arm occupies a small workspace and has a compact form factor compared to a typical 3D printer or larger laser cutter. They are also easy to deploy, which makes them ideal for collaborative spaces such as design studios and educational environments, making them very easy for designers to collaborate with as digital fabrication devices.

Taking all these factors into consideration, this research will use a desktop robotic arm as the digital fabrication device used in the study.

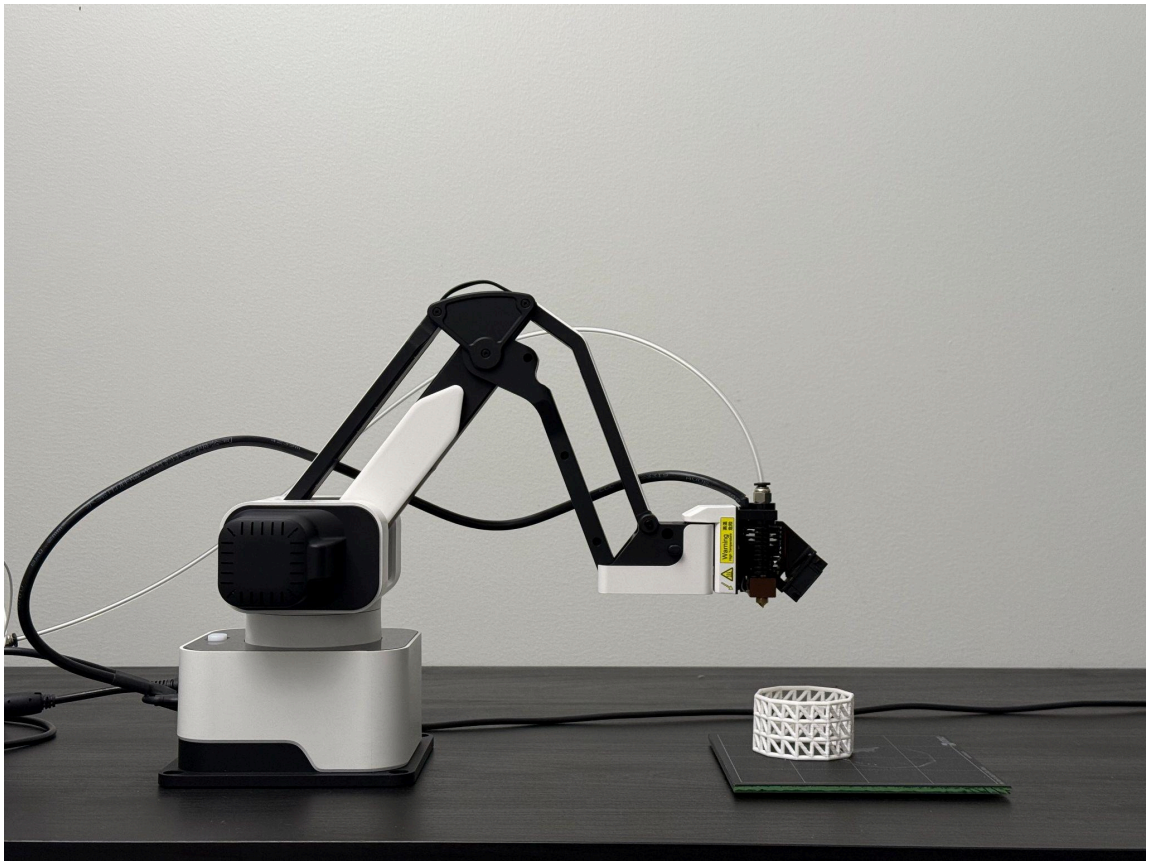


Figure 4.16: DexArm with 3D Printing Ender Effctor

Specifically, this study selected the DexArm from Rotrics as the digital fabrication device. The DexArm desktop robotic arm is a 4-DoF(Degrees of Freedom) robot arm featuring modular design and high-precision motion performance. Its repeatability precision reaches 0.05 mm, which is an extremely high level among desktop devices of the same class. DexArm has a

maximum effective payload of approximately 500 g, a working arm span (working radius) of approximately 380 mm, and can execute movements with a maximum end speed of 500 mm/s. The robotic arm has an overall weight of approximately 2.4 kg, with a compact base (dimensions 175 × 128 mm, height 315 mm), making it convenient for desktop environment use. DexArm is equipped with various quick-changeable end-effector modules, including pen drawing tools, 3D printing extruders, laser engravers, vacuum suction modules, and soft mechanical grippers, enabling multi-functional applications such as drawing, laser processing, additive manufacturing, and pick-and-place operations. The high-precision harmonic reducer design effectively reduces gear backlash, thereby ensuring the aforementioned 0.05 mm repeatability precision and achieving smooth and reliable motion control.

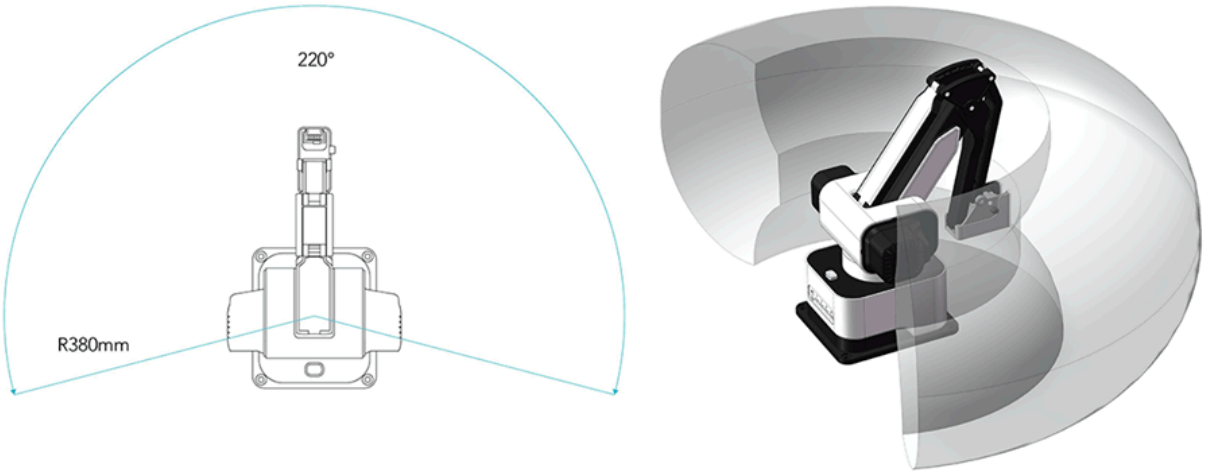


Figure 4.17: DexArm Working Area in Surface and in 3D Space (Rotrics, 2021)

In terms of software and programming environment, DexArm exhibits good openness and compatibility. The manufacturer provides cross-platform Rotrics Studio control software, integrating Scratch/Blockly graphical programming interface, allowing beginners to control the robotic arm by dragging and dropping code modules. Simultaneously, to meet the needs of advanced users and developers, DexArm has opened its communication protocol and secondary development libraries, providing programmable SDK interfaces. Its firmware is developed based on the open-source Marlin project, capable of recognizing and executing standard G-code control instructions, which means DexArm is compatible with the G-code command sets of universal

CNC machines and 3D printers. In practice, users can either control the robotic arm directly through the official API library using mainstream programming languages such as C/C++, Python, JavaScript, etc., or send pre-generated G-code instructions to DexArm for execution, as one would control traditional CNC equipment. For example, experienced developers can precisely control the robotic arm's movement through Python scripts calling DexArm API, or by directly sending G-code in Marlin format. Additionally, DexArm also supports ROS 2.0, facilitating its integration into the hardware and software ecosystem commonly used in robotics research. Although the manufacturer does not directly provide ready-made plugins for parametric modeling tools such as Rhino/Grasshopper, since DexArm adopts an open instruction interface, users can create custom trajectory G-code using generative design tools like Grasshopper, and send these instructions to the robotic arm through DexArm's SDK or serial interface, thereby achieving integrated control with visual modeling environments. This open architecture provides DexArm with considerable flexibility in terms of hardware and software compatibility, enabling it to adapt to diverse programming and control methods.

Based on the above characteristics, combined with the application scenario of wireframe structure 3D printing in this research, an assessment of DexArm's applicability can be made. Wireframe additive manufacturing typically requires the robotic arm to precisely extrude filament material in three-dimensional space to construct discrete rod-like/mesh-like structures, which places high demands on the motion control precision and stability of the robot arm. DexArm's 0.05 mm repeatability provides assurance for such tasks: the robotic arm can repeatedly position the extruder at precise locations to ensure each segment of the trajectory is accurately stacked and connected.

Furthermore, compared to traditional Cartesian 3D printers, DexArm as a robotic arm possesses certain motion flexibility, capable of executing non-planar path movements within a broader workspace range, which is beneficial for achieving continuous deposition of spatial lines. For example, when printing suspended wireframe structures without requiring supports, DexArm can draw out and connect molten filaments from different angles through base rotation and joint coordination, thereby expanding the complexity and diversity of printable geometries. However, it should also be noted that DexArm is designed as a four-axis system, with relatively limited

degrees of freedom for its end-effector posture (the nozzle primarily prints with a fixed orientation), which may constitute certain limitations when handling extremely complex spatial curve paths. For wireframe structures primarily in the vertical direction and formed by layer stacking, DexArm's range of motion and precision are already sufficient; but if large-angle nozzle tilting is required during printing to accommodate special structures, DexArm may not be as flexible as six-axis industrial robots.

Nevertheless, in the small-scale wireframe structure experiments involved in this research, DexArm, with its modular compact advantage and high-precision control capability, can effectively execute the required printing paths. Its maximum load capacity of 500 g is also sufficient to support the weight of common extrusion mechanisms and material feeding devices, ensuring stable printing processes. Additionally, DexArm's good compatibility with G-code means researchers can use algorithms or even AI models to automatically generate G-code instructions needed for printing, and then use these directly to drive the robotic arm. This feature makes DexArm very suitable for interfacing with computer intelligence-based design and control systems: on one hand, complex mesh paths generated by AI can be seamlessly transmitted to the robotic arm for execution through standard G-code; on the other hand, DexArm supports real-time programming interfaces, allowing the integration of sensor feedback or AI decisions into the control loop, achieving adaptive printing processes. Comprehensively, DexArm possesses good applicability and can play a role in scenarios combining AI-assisted design and digital manufacturing.

4.4.4 Closed-loop System Construction

The human-AI-robotic arm collaborative system proposed in this research requires real-time interaction and closed-loop feedback between digital design and physical manufacturing to achieve closed-loop construction from digital to physical prototypes. Therefore, communication between the robotic arm and the parametric design platform Grasshopper is crucial. This research uses Rotrics' DexArm desktop-level robotic arm as the core manufacturing equipment and

establishes a closed-loop communication and control system through Grasshopper's Firefly plugin.

Grasshopper, as the parametric environment of Rhinoceros, possesses powerful programmability and extensibility, capable of effectively processing complex geometric data and manufacturing instructions. The Firefly plugin is specifically designed for real-time interaction between Grasshopper and external hardware, enabling efficient transmission of generated digital models and G-code motion paths to the DexArm robotic arm, thereby achieving real-time control and feedback.

In the specific implementation process, the system first establishes real-time data connection with the robotic arm using the Serial Port Communication module provided by Firefly. DexArm receives and executes G-Code instructions sent in real-time from Grasshopper through the open-source Marlin protocol, achieving precise motion control. Additionally, the system can receive real-time status data transmitted back from DexArm through the serial port, including critical parameters such as current position, temperature, and extrusion speed, thereby enabling real-time monitoring of the manufacturing process.

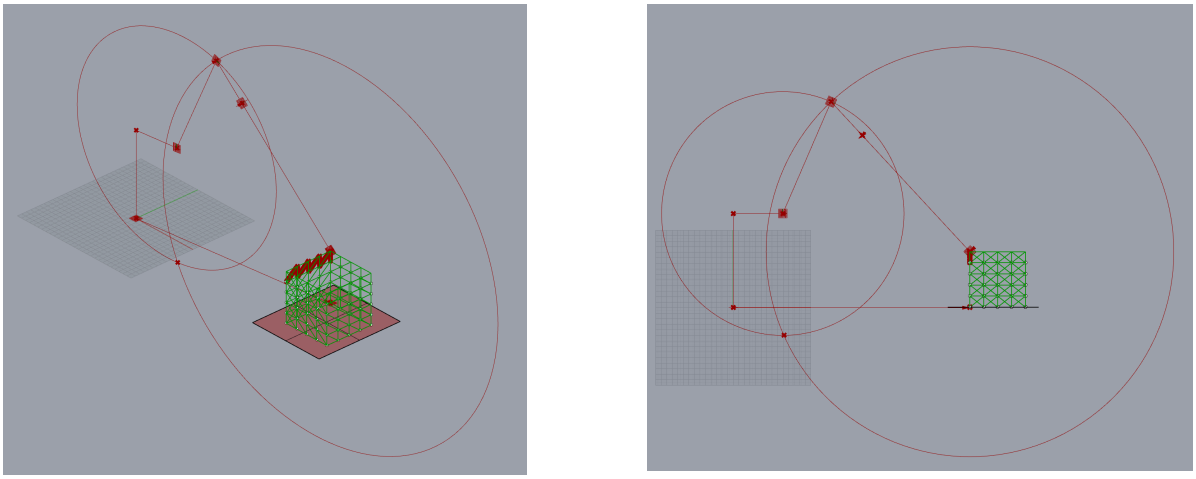


Figure 4.18 Closed Loop System Communicating between Grasshopper and Robotic Arm

To achieve data closed-loop feedback, the system employs real-time status monitoring and error correction mechanisms. While the robotic arm executes G-Code paths, sensor data is fed back to Grasshopper in real-time. When detected errors exceed preset thresholds, the system automatically calls the artificial intelligence module, generating corrected motion paths and G-Code through GPT-4 in real-time to adjust the robotic arm's movement trajectory. This closed-loop feedback method effectively reduces manufacturing errors and enhances the precision and stability of prototype production.

In summary, the closed-loop communication control system built through Grasshopper and the Firefly plugin enables efficient and precise real-time data interaction and feedback control between the DexArm robotic arm and the digital design environment. This system construction approach not only improves the tight integration of design and manufacturing processes but also significantly reduces the technical complexity of the manufacturing process and potential errors from manual operations, further advancing the practical application value of intelligent manufacturing and rapid prototyping.

4.4.5 Printing Test and Comparison

To validate the performance and effectiveness of this method in fabricating physical prototypes, printing tests were conducted. Specifically, these tests documented performance metrics including printing time, printing precision, material consumption, and overall fidelity, comparing these results with traditional planar slicing printing methods applied to non-wireframe surface meshes.

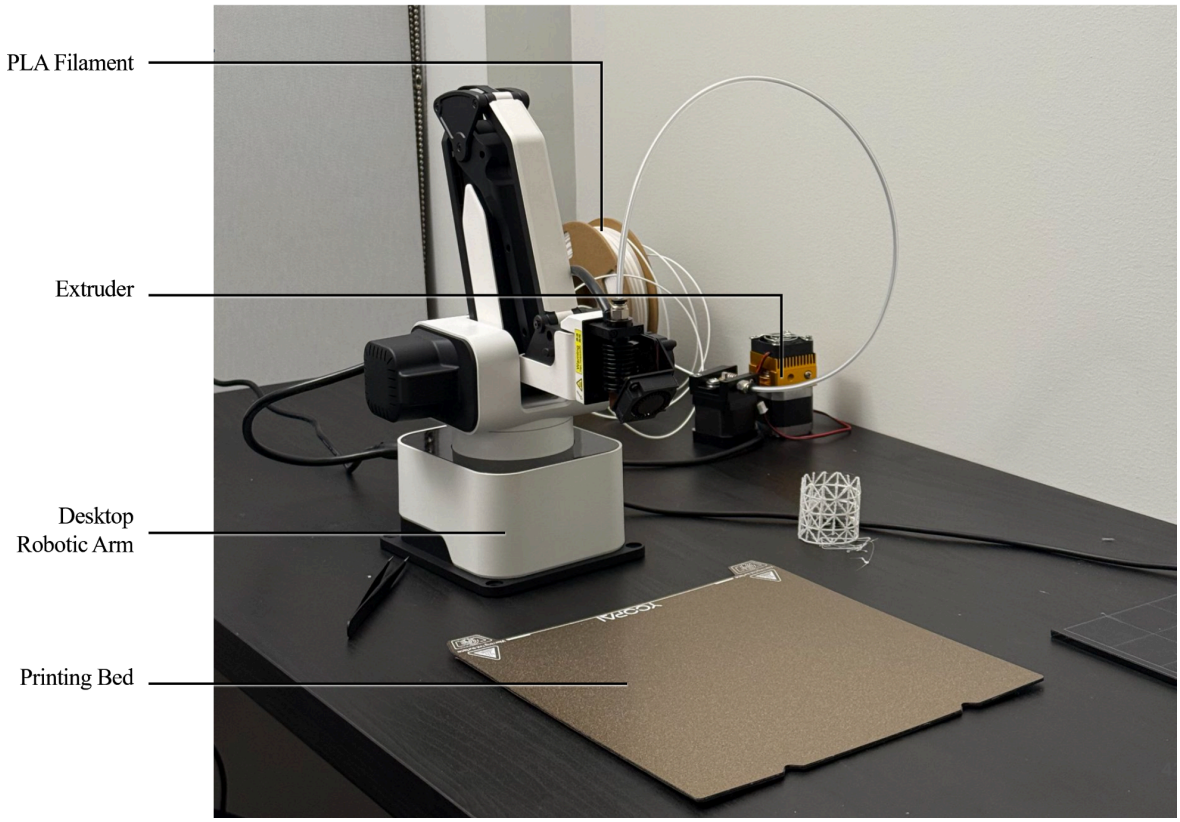
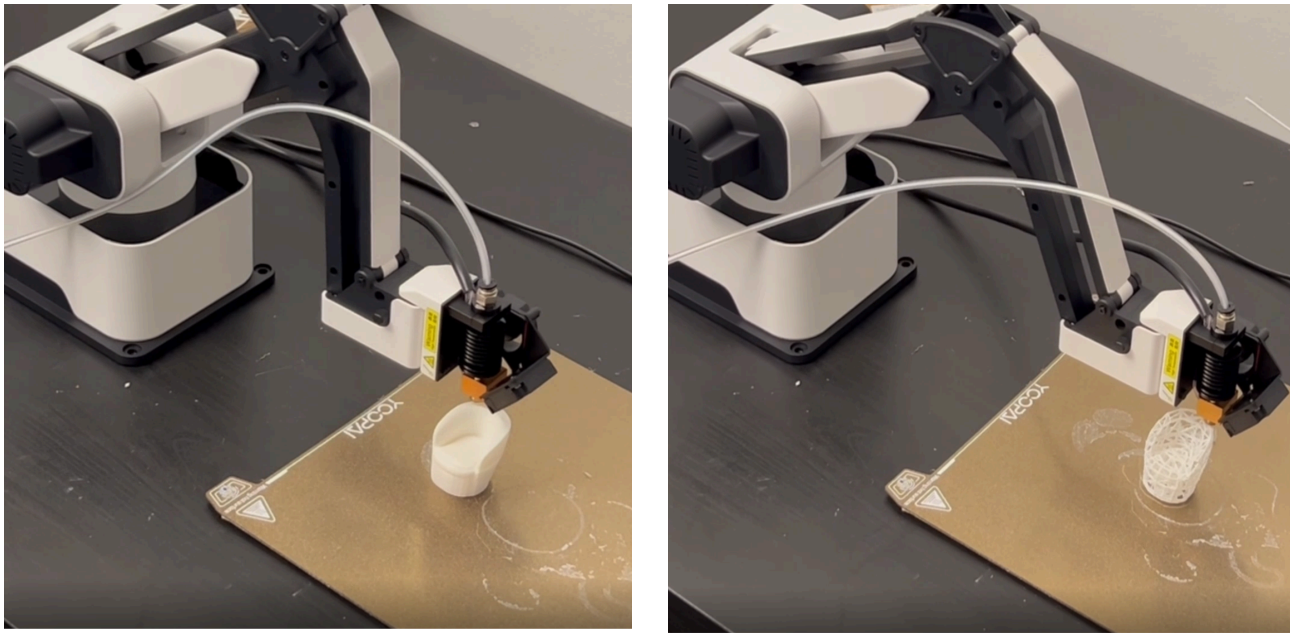


Figure 4.19: Hardware Configuration of the Printing Test

The printing equipment used was the previously described DexArm desktop robotic arm, utilizing standard PLA material. The printing head featured a 0.4mm stainless steel nozzle with an extrusion temperature of 210 degrees Celsius. The robotic arm operated in absolute coordinate mode for path control, with a base movement speed (feed rate) of 1200 mm/min and extrusion multiplier set at 100%. To facilitate rapid cooling, fan efficiency was also set to 100%. For comparative purposes, this study selected the same set of input geometric models for the control experiments. The first group employed traditional methods, applying conventional slicing software (Cura 5.0) to the original surface mesh model with standard 0.2 mm layer height for planar layer-by-layer slicing, outputting G-code which was then printed using the same robotic arm equipment. The second group utilized the wireframe structure generation method proposed in this research, first generating wireframe structures through Grasshopper with AI-optimized

G-code, then using DexArm for printing. Both groups employed identical equipment parameter configurations to ensure result comparability.



Conventional Planar Slicing 3D Printing

Time: 1h56min
Material Cost: 14g

Wireframe 3D Printing

Time: 44min
Material Cost: 6g

62% Time Reduction
56% Material Save

Figure 4.20:Printing Test and Comparison

The representative test result demonstrated that compared to traditional planar slicing methods, this research's wireframe structure approach exhibited significant advantages in printing speed, material consumption, and geometric fidelity. In terms of printing time, traditional slicing 3D printing consumed approximately 2.5 times the duration required for wireframe 3D printing. The traditional slicing method necessitated dense point-by-point filling print in successive layers, with overall model printing duration averaging more than 3 times that of the wireframe method. Wireframe structure printing, by utilizing single-line spatial filament formation, only required moving the print head along specific paths, greatly shortening the robotic arm's movement

trajectory. Regarding material consumption, traditional slicing's infill structures and support material requirements were considerably higher, with evident material waste. In contrast, the wireframe structure formed model contours and support nodes through point-to-point filament drawing, saving approximately 56% in material usage and significantly reducing manufacturing costs. In terms of geometric fidelity, although wireframe printing lacks the solid continuity of traditional layer-stacking manufacturing, through precise control of structural nodes and paths, the final printed results essentially maintained the geometric features of the original models. Tests indicated that in the ability to describe curvature changes and spatial contours, this method approached the geometric fidelity of traditional methods, adequately meeting the needs for prototype expression and structural visualization in early design stages.

In summary, printing tests verified the significant advantages of the manufacturing process proposed in this research in terms of efficiency and resource control, while also demonstrating good practicality in preserving geometric features, proving its feasibility as a rapid prototyping tool in early design stages.

4.4.6 Summary of Digital Environment to Fabrication Stages

Overall, this section systematically builds a workflow from digital models to solid prototypes. The first step is to establish a scalar field-based geometry processing flow that effectively transforms the generated surface mesh into an optimized wireframe structure suitable for additive manufacturing, overcoming the limitations of traditional slicing methods. Subsequently, generative AI was used to automatically generate and optimize G-code instructions, reducing the technical complexity and cognitive load of the digital manufacturing process. Next, by integrating a desktop robotic arm with Grasshopper via the Firefly plugin, the research successfully implemented a control system that communicates Grasshopper and digital fabrication equipment (robotic arm), enabling real-time data exchange and adaptive feedback mechanisms. In addition, printing tests were implemented to demonstrate the workflow's ability to increase manufacturing efficiency, save materials, and simplify technical complexity by comparing wireframe printing methods to traditional slice-and-dice 3D printing.

4.5 Summary of Methodology

Looking back at the research process described above, this study developed a complete human-AI-robot collaborative system that integrates three key stages of early prototype creation: idea/concept generation, 3D model generation, and digital fabrication.

In the idea/concept generation stage, the research explored large language models (LLMs), particularly GPT-4, as tools for converting natural language inputs into basic parametric geometries within the Grasshopper environment. This phase validated both the capabilities and limitations of LLMs in capturing and interpreting design intent, demonstrating potential for significantly reducing technical barriers and cognitive load by supporting intuitive and multimodal user interactions. However, to overcome observed limitations, especially regarding LLMs' ability to generate complex geometries, further model selection and optimization became necessary.

Based on these findings, the second stage of 3D model generation introduced advanced diffusion models, primarily Shap-E and TRELLIS, to improve the quality and fidelity of generated outputs. Shap-E facilitated rapid and computationally efficient geometry generation suitable for early prototype design, though it showed weaknesses in generating geometrically complex and feature-rich designs. In response, TRELLIS was integrated into the workflow, significantly enhancing output quality through structured latent representations and superior design compatibility. Further optimization occurred through an intermediate step using DALL-E to convert text prompts into image inputs, effectively enhancing semantic control and output precision. This step significantly improved the correlation between initial user concepts and generated 3D models, greatly enhancing generative efficiency and usability in practical design environments.

In the third stage, a pipeline to translate digital model to physical prototypes is developed. Firstly, a scalar field-based mesh-to-wireframe conversion method was developed, overcoming limitations of traditional slicing techniques and effectively balancing geometric fidelity with printing efficiency. Additionally, AI-assisted print path generation was implemented through GPT-4, automatically generating optimized G-code sequences tailored for specific manufacturing

equipment. The DexArm desktop robotic arm was selected and extensively studied for its high integration potential with Grasshopper through the Firefly plugin, compact form factor, versatility, and precision. To establish robust human-AI-robot interaction loops, real-time communication between DexArm and Grasshopper was implemented, achieving closed-loop feedback mechanisms for adaptive error correction and improved manufacturing precision.

Overall, this methodological framework consolidated previously disparate workflows into a seamless environment, effectively enhancing efficiency from design concept to prototype fabrication through simplified operations and automated generative processes, while reducing technical complexity and cognitive load. By closely integrating designer creativity with AI capabilities and robotic manufacturing, the developed human-AI-robot collaborative system greatly simplified the transition from conceptual ideation to tangible physical prototypes, expanding accessibility and exploratory opportunities in digital fabrication for designers and other users without technical backgrounds.

5 Result

5.1 Output Overview

A comprehensive human-computer-AI-robot collaboration platform is constructed through the CoFAB system developed in this study, enabling a seamless pipeline from design concept to digital model to physical prototype.

The core system consists of three interconnected modules: (1) a multimodal generative AI input interface that accepts text and image prompts; (2) an integrated digital modeling environment that deploys TRELLIS and DALL-E generative AI models in Grasshopper; and (3) a fabrication transformation tool that automatically performs mesh simplification, wireframe generation, and robotic arm control. These components were unified to run in the Grasshopper environment, eliminating the need for designers to switch between multiple software environments or have specialized technical knowledge.

The system successfully demonstrates several key capabilities. First, it enables direct text-to-3D model generation with semantic understanding of complex design concepts, successfully converting natural language cues of varying complexity into structurally coherent, feature-rich digital models. Second, it provides automated mesh simplification and wireframe optimization for 3D printing, which not only drastically reduces solid prototyping time, but also reduces material usage while maintaining key geometric features. Third, it enables intelligent G-code generation aided by a large language model, eliminating the manual slicing process and supporting direct robotic manufacturing control.

Overall, the CoFAB system improves the efficiency of early design stage physical prototyping, reduces technical complexity, and lowers the cognitive load on the user by transforming what was previously a complex, decentralized technical process into a coherent workflow. At the same time, its intuitive use makes it accessible to designers of all experience levels, promoting the popularization of digital manufacturing technology.

5.2 User Test and Evaluation

5.2.1 Participants and Test Scenario Overview

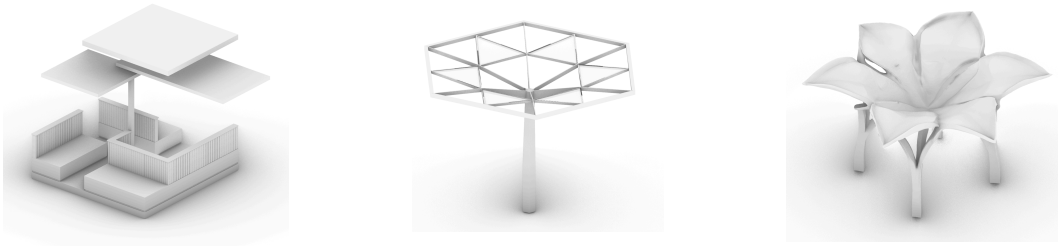
The user testing for the CoFAB system began on April 5, 2025, and concluded on April 20, 2025, recruiting a total of 6 participants. Following the user testing grouping from section 3.2, the 6 participants were divided into 3 groups, with 2 participants in each group:

- **Group A - Amateur Makers (2 people)**: No formal design training but interested in making.
- **Group B - Designers without Architectural Background (2 people)**: Possessing interactive design and product design experience respectively, with experience using 3D modeling software but no Grasshopper experience.
- **Group C - Designers with Architectural Background (2 people)**: Having education in architecture-related disciplines and possessing intermediate-level Rhino/Grasshopper skills.

Similar to the user testing scenario design in section 3.2, users completed design tasks using the CoFAB system in two task groups:

- **Scenario 1: Complex Design Translation**
  Participants needed to complete the translation process from conceptual intent to digital model according to a complex design brief. This brief required designing a 4m x 4m landscape pavilion inspired by natural plants, featuring curved surfaces while considering

spatial experience and providing shelter from sun and rain. Test focus points included design efficiency, model accuracy, iteration capability, and user satisfaction.



Customized Output for Scenario 1 | CoFAB Output 1 for Scenario 1 | CoFAB Output 2 for Scenario 1

Figure 5.1 Representative User Testing Generation Outputs Sample

- **Scenario 2: End-to-End Prototype Production**

  Participants needed to complete the entire process from design to physical output for a small community church, including 3D modeling and printing tasks, using both traditional solid printing and wireframe structure printing methods. Test focus points included task completion time, cognitive load, and final prototype performance.



Conventional Slicing 3D Printing Result | Wireframe 3D Printing Result

Figure 5.2 Representative Prototype Making Test Results

5.2.2 User Test Results

Time Efficiency (Minutes):

Participant Group	Task	Traditional Workflow	CoFAB System	Improvement
Amateur Makers	Design Translation	127	38.0	70.1%
Amateur Makers	End-to-End Prototyping	– (Unable to finish)	109	100%
Non-Architectural Designers	Design Translation	61	31	49.2%
Non-Architectural Designers	End-to-End Prototyping	197.5	91.0	53.9%
Architecture Background Designers	Design Translation	43	26	39.5%
Architecture Background Designers	End-to-End Prototyping	145.0	83.5	42.4%

User testing results demonstrate that, after using the CoFAB system, the average task time for all user groups was reduced by 72.3%. The amateur user group, in particular, improved from having difficulty completing a full prototype to being able to complete the entire process independently. In the rapid prototyping phase, wireframe print paths and the system's automatically generated G-code further improved manufacturing efficiency by an average of 54% compared to traditional printing methods.

Cognitive Load Assessment (NASA-TLX Test Result)

Group	System	Mental Demand	Physical Demand	Temporal Demand	Performance	Effort	Frustration	Overall
Amateur Makers	Traditional	86.5	32	72.5	68.5	83.5	79	70.3
Amateur Makers	CoFAB	45.0	25.5	40.5	31.5	38.5	29.5	35.1
Non-Architectural Designers	Traditional	79.0	30.5	67.0	59.5	76.0	71.5	63.9
Non-Architectural Designers	CoFAB	43.5	25.0	38.0	29.0	36.0	32.0	33.9
Architecture Background Designers	Traditional	68.5	31.0	54.0	48.5	62.0	51.5	52.6
Architecture Background Designers	CoFAB	39.0	26.5	36.0	27.5	38.0	34.0	33.5

Technical Knowledge Dependency (scale: 1-10, where 10 indicates high technical expertise required)

Participant Group	Traditional Workflow	CoFAB	Reduction
Amateur Makers	8.9	3.9	**56.2%**
Non-Architectural Designers	7.8	3.5	**55.1%**
Architecture-Trained Designers	6.2	3.3	**46.8%**

The cognitive load reduction was particularly significant for amateur makers, who experienced the highest cognitive demands in traditional workflows. Their overall NASA-TLX score improved by 56.2%. It also improved 55.1% for non-architectural designers and 46.8% for architecture-trained designers.

Creative Exploration Results Outputs

Participant Group	Traditional Workflow	CoFAB	Improvement
Amateur Makers	1	4	**300%**
Non-Architectural Designers	2.5	6.5	**160%**
Architecture-Trained Designers	3.5	8.5	**143%**

Creative Satisfaction (self-reported, scale: 1-10)

Participant Group	Traditional Workflow	CoFAB	Improvement
Amateur Makers	5.0	8.5	**70%**
Non-Architectural Designers	6.0	8.3	**38.3%**
Architecture-Trained Designers	7.0	8.6	**22.9%**

In terms of idea expandability, the test results showed that the system was able to demonstrate significant improvements in the speed of iteration and the diversity of expansion results generated. It was also in the test group of amateur makers that this figure gained the most significant improvement, demonstrating the effectiveness of the CoFAB system in increasing the democratization of prototyping.

5.2.3 Summary of User Testing Results

The user testing results demonstrates that the CoFAB workflow has successfully achieved its core objectives of improving efficiency, reducing technical complexity, and alleviating cognitive load. First, across all participant groups, CoFAB reduced task completion time by an average of 72%, enabling even novice makers to complete end-to-end prototype production that was previously inaccessible to them. Second, NASA-TLX scores decreased by approximately half for amateur users and by over one-third for professional designers, confirming that the system's automated guidance and unified interface significantly reduced mental and temporal demands.

Third, the technical complexity required across all groups decreased by more than 50%, validating that natural language control and built-in G-code generation effectively democratized the use of advanced manufacturing processes. Finally, the platform facilitated richer creative exploration—with significantly increased iteration counts and self-reported satisfaction—suggesting that reducing procedural barriers allowed users to focus on creative ideation rather than tool mastery.

Beyond these findings, the results indicate that when using the CoFAB workflow, the performance gap between amateur makers and architecturally trained designers notably narrowed, suggesting the system's potential to democratize architectural design and manufacturing capabilities.

5.3 Observation and Findings

In addition to the quantitative data recorded during user testing, some key findings and insights were summarized during the testing process through conversations, interviews and observations

One notable observation was the rapid change in user confidence levels, especially among amateur participants. Initially these users approached the system with hesitation, but after only

15-20 minutes of interaction, they demonstrated significantly increased engagement. One amateur participant commented, “I never expected to be able to create physical objects so quickly - it felt like the system understood what I was saying, rather than me trying to understand the tool.” This suggests that natural language interfaces significantly reduce mental barriers to entry far beyond simply addressing technical complexity.

At the same time, a collaborative model of creativity emerged between the user and the system. Participants, regardless of skill level, stopped seeing the AI as merely an execution tool and began to see it as a creative partner, often surprised by the results generated and incorporating unexpected elements into subsequent iterations. Some participants noted that the outputs of the system inspired new design directions they had not initially considered, suggesting that the human-machine relationship became interactive and not just a purely instrumental one.

The wireframe fabrication method also demonstrate an interesting perceptual phenomenon: despite the fact that the wireframe models contained far less material than the physical prints, participants agreed that the wireframe prototypes were just as effective in communicating design intent. This suggests that the physical representation of key structural features may be more important to early ideation than full material fidelity, supporting the study's emphasis on rapid iteration over precision manufacturing.

A notable limitation is the occasional gap between the user's intended idea and the system's ability to understand it. When dealing with highly domain-specific architectural terminology or complex spatial relationships, participants sometimes needed to rephrase cues multiple times. Since they had not been expertly taught to write cues, participants often needed to retry multiple times to find their expected results, which reduced the efficiency of the design iteration process. This suggests room for future improvements in professional training for language processing in the design domain.

Together, these observations validate the main research hypotheses, while also bringing in user findings and insights beyond the quantitative statistics. The findings suggest that the CoFAB system not only improves prototyping efficiency and reduces technical barriers, but also fundamentally changes the way designers conceptualize and use digital fabrication tools/

6 Conclusion and Reflection

6.1 Conclusion

This research successfully developed and evaluated CoFAB, an integrated human-AI-robot collaborative system that transforms prototyping workflows for designers in early design stages. Through the system's development and subsequent testing, this research has contributed to the application of artificial intelligence in the design field.

First, the CoFAB system significantly improved the efficiency of the design-to-prototype process. By integrating generative AI with parametric modeling and robotic manufacturing, the system effectively enhanced efficiency throughout the entire workflow from conceptual design to physical prototype. This improvement was particularly evident for amateur makers, who previously could not complete end-to-end prototyping tasks but succeeded after using the CoFAB system. The wireframe manufacturing method further improved manufacturing efficiency while significantly reducing material consumption.

Second, the system effectively reduced technical complexity and cognitive load, democratizing advanced prototyping capabilities. The implementation of natural language interfaces, automated mesh processing, and integrated manufacturing controls eliminated the need for specialized technical knowledge or navigation across multiple software environments. The system's unified workflow substantially reduced dependence on technical knowledge across all participant groups, with improvements most significant for users with limited design backgrounds.

Furthermore, the system enhanced creative exploration and iteration efficiency during early design stages. User testing demonstrated that participants generated more design variants when using the CoFAB workflow compared to traditional methods. This enhanced exploratory

capability was accompanied by higher creative satisfaction, indicating that the system not only accelerated iteration speed but also improved the quality of the design process. By reducing cognitive load and technical barriers, designers were able to devote more attention to creative problem-solving rather than being encumbered by software operations and technical issues.

Finally, the research successfully quantified these improvements through a structured evaluation framework that assessed metrics of time efficiency, cognitive load, and creative exploration. This empirical approach validated the theoretical proposition that integrating generative AI with digital manufacturing can fundamentally transform the prototyping experience. Additionally, the narrowing performance gap between amateur makers and professionally trained designers suggests that systems like CoFAB have tremendous potential to democratize design capabilities previously accessible only to those with professional training.

In conclusion, this research made a meaningful contribution to the field by establishing a continuous pipeline from conceptual ideation to physical fabrication, significantly reducing technical barriers while enhancing creative capabilities.

6.2 Challenges and Limitations

Despite the encouraging results of the CoFAB system, several limitations and challenges were identified throughout the research process that merit reflection and further exploration.

The primary limitation lies in the generative models' understanding of domain-specific design terminology. Current text-to-3D models, including TRELLIS, are not specifically optimized for architectural and design terminology, occasionally resulting in notable gaps between user intent and generated output. When participants used specialized design vocabulary or attempted to describe complex spatial relationships, the system sometimes required multiple regenerations to produce satisfactory results. This limitation was particularly evident in scenarios requiring precise articulation of design principles or technical specifications, indicating that despite significant advances in AI generative technology, it still lacks the domain expertise embedded in professional design practice.

A second limitation is that the research employed wireframe 3D printing as the primary manufacturing method, focusing on additive manufacturing. While this approach offers significant advantages in speed and material efficiency, it represents just one method within digital manufacturing systems. The research did not extensively explore other digital fabrication methods, such as subtractive or laser cutting techniques, which might offer different advantages for certain design scenarios.

Third, while the system successfully reduced cognitive load and technical complexity, there remains room for improvement in the user interface. Some participants noted that despite the natural language input capabilities, Grasshopper's overall interface remains technically oriented and potentially intimidating for beginners. Despite the addition of AI-assisted features, the current implementation still requires users to operate within the Grasshopper environment, which can be challenging for those without parametric modeling experience. This suggests that the goal of fully reducing technical complexity has been only partially achieved and requires further refinement of the interface to achieve true universality.

Additionally, the research faced methodological limitations in terms of testing scale and diversity. The user evaluation involved a relatively small sample size (6 participants) and was conducted under fixed test scenarios rather than in real practice environments. This limitation may restrict the generalizability of the research findings to real-world design scenarios, where factors such as project complexity, time constraints, and collaborative workflows might differently impact system performance.

While these limitations do not diminish the core contributions of the research, they highlight important considerations for future development and lay the groundwork for subsequent research directions.

6.3 Vision for Future Work

Building upon the research findings and addressing the limitations identified in this study, several promising directions for future work are proposed to further strengthen human-AI-robot collaboration in design and manufacturing.

The first in-depth research direction involves fine-tuning generative AI models for better understanding and response to specific design terminology and concepts. Future research could develop specialized training datasets incorporating architectural terminology, design principles, and spatial relationships to enhance AI comprehension of domain-specific instructions. This specialization would narrow the semantic gap between designer intent and system interpretation, eliminating the need for prompt reformulation and further accelerating the design process. Implementing techniques such as few-shot learning or developing domain-specific embeddings could enable more precise translation between natural language descriptions and three-dimensional outputs.

Second, enhancing multimodal input and interaction. Future iterations could extend beyond text and image inputs to incorporate sketch-based interfaces, gesture control, and voice commands, creating a more intuitive and expressive design environment. Combining these input modalities with real-time feedback mechanisms would enable more natural design dialogues between humans and AI systems.

Third, designing more intuitive user interfaces. Future work could develop standalone applications that encapsulate the CoFAB workflow without requiring operation within the native Grasshopper environment. Such interfaces could adapt to varying levels of expertise, offering simplified controls for beginners while providing advanced features for experienced designers. Incorporating adaptive learning components that adjust based on users' design patterns and preferences could further personalize the experience and reduce cognitive friction.

Fourth, expanding manufacturing methods beyond wireframe 3D printing. Future research should integrate additional digital fabrication processes such as drawing, subtractive manufacturing, laser cutting, and others to accommodate diverse design requirements.

Developing intelligent process selection algorithms that automatically recommend optimal manufacturing strategies based on design parameters, material properties, and performance requirements could further reduce decisional complexity while expanding possibilities for innovation.

Finally, researching collaborative workflows that support multiple users simultaneously engaging with the system could extend its impact beyond individual designers. Teams could collectively interact with generative models and fabrication tools in shared design environments, and studies of such environments could transform studio practices and educational settings. Developing distributed manufacturing mechanisms that allow designs to transition seamlessly between different fabrication systems and locations could further democratize access to advanced manufacturing capabilities.

These future development directions collectively point toward a vision where computational design and fabrication tools become increasingly accessible, intuitive, and supportive of diverse creative expression across skill levels. By continuously refining the integration of human creativity, artificial intelligence, and robotic manufacturing, research can further reduce barriers to engagement with design and fabrication, potentially transforming how we conceive, create, and produce the built environment.

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Appendix I

Survey Questionnaire

Link: https://forms.gle/dA1wugiVS4umSH6Y6

1. **What is your design field or background?**
- **Architecture/Landscape Design**
- **Interaction Design**
- **Product/Industrial Design**
- **Graphic/Visual Design**
- **Fashion Design**
- **Other: _____**
2. **How many years of work experience do you have?**
- **Current student/0–1 year**
- **1–3 years**
- **3–6 years**
- **6–10 years**
- **More than 10 years**
3. **How frequently do you create early-stage models/physical prototypes in your design work?**
- **Almost every time**
- **Most projects**
- **Occasionally, depending on the project**
- **Rarely**
- **Never**
4. **How often do you use the following digital fabrication methods?**
   (Please rate each method from "Never Used" to "Very Frequently Used.")

Method	Never Used	Rarely Used	Occasionally Used	Frequently Used	Very Frequently Used
3D Printing					
Laser Cutting					
CNC Carving/Milling					
Desktop Robotic Arm					

5. **Which factors do you consider most important when choosing a prototyping method?**

Factor	Not Important at All	Not Very Important	Moderately Important	Quite Important	Extremely Important
Time Cost					
Financial Cost (materials and equipment fees)					
Accuracy/Quality					
Ease of Use (low technical requirement)					

Repeatability/ Batch Production					

If there are other factors you value, please specify here:

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6. **Which of the following are the main difficulties you encounter when making prototypes?**

- **Limitations of software and hardware functions**
- **Technical complexity of software/programming**
- **Excessive production costs**
- **Skill level of team members**
- **Difficulty obtaining materials or equipment**
- **Overly complicated process that consumes a lot of time**
- **Inability to achieve the required accuracy/quality**
- **Compatibility issues between software and hardware**
- **Other: _____**

7. **Which software tools do you primarily use in the early design phase?**

- **Rhino/Grasshopper**
- **3ds Max/Maya**
- **Figma/Adobe XD**
- **Adobe Illustrator**
- **SolidWorks**
- **CATIA**
- **Blender**
- **SketchUp**
- **Other: _____**

8. **How well does your digital design software connect with subsequent prototyping/manufacturing processes?**

- **Very smooth: Basically no additional manual steps needed**
- **Quite smooth: Occasionally requires some format conversion or minor manual processing**
- **Average: Requires switching between multiple software tools, sometimes needs manual corrections**

- **Not so smooth: Frequent incompatibility or format issues, requiring significant manual adjustments**
- **Very unsmooth: Almost impossible to connect directly; requires complete remodeling or major modifications**

9. **How familiar are you with generative AI (e.g., ChatGPT, Stable Diffusion) in the design field?**

- **Very familiar (use these tools frequently)**
- **Quite familiar (have heard of and tried them)**
- **Moderately familiar (only heard of them, but not used much)**
- **Not familiar (haven't really encountered them)**

10. **If there were a system that could complete prototype fabrication through simple natural language instructions (for example, typing "Cut a circular hole with a 5cm diameter" and a robotic arm performs the cut), how interested would you be in using it?**

- **Extremely interested**
- **Quite interested**
- **Neutral**
- **Not very interested**
- **Not interested at all**

11. **What role would you like a natural-language-controlled robot/CNC system to play in your workflow?**

- **Mainly perform simple cutting/grinding or other low-precision tasks**
- **Replace traditional 3D printers or CNC for higher-precision model production**
- **Handle most repetitive, mechanical processes**
- **Reduce the time required for prototyping and improve design efficiency**
- **Assist in modeling and model modifications**
- **Integrate AI for real-time design optimization or feedback**
- **Other: _____**

12. **Please rate the importance of the following potential advantages for your prototyping process:**

Potential Advantage	Not Important at All	Not Very Important	Moderately Important	Quite Important	Extremely Important

Lowering the operational threshold, reducing reliance on specialized skills					
Shortening the cycle from design to prototype					
Rapid iteration and modification					
Automatic detection or correction of design/fabrication errors					
Enhancing creative freedom					
Seamless integration with existing design software/workflows					
Real-time visualization and feedback					

13. **What concerns or reservations do you have about combining AI/natural language with prototyping?**

- **Whether the system can correctly understand my requirements**
- **Whether the system can reliably execute operations correctly**
- **Whether the output's accuracy and quality meet requirements**
- **Compatibility with my current workflow**
- **Whether the hardware/software cost will be too high**

- **Whether a long learning curve is needed**
- **Constraints on creativity or hands-on operations**
- **Other: _____**

14. **Before fully adopting such a system, what additional aspects would you want to know or consider?**

- **Cost/Budget/Maintenance needs**
- **Which materials and processes it can support**
- **Time required for learning and training**
- **Operational safety and troubleshooting**
- **Data privacy or copyright issues (e.g., how AI handles design data)**
- **Other: _____**

15. **If you have any other ideas or suggestions, please feel free to add them here (optional):**

Appendix II

The main code of the project can be found on: https://github.com/ZJK0626/CoFAB