EINDHOVEN UNIVERSITY OF TECHNOLOGY

Text-to-3D Generation in Participatory Urban Design

Using a text-to-3D digital participation tool to support participant engagement and urban planners' decision-making in participatory urban design.

Master Thesis

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Table of Contents

Summary 5
Samenvatting 7
Abstract 9
List of Abbreviations 10
List of Figures 11
List of Tables 13
1. Introduction to the Research Problem and Methodological Approach 15
1.1 Problem Definition and Contextual Background of Digital Participatory Design 15
1.2 Research Scope 18
1.3 Research Questions 19
1.4 Research Design 20
1.5 Reading Guide 21
2. Exploration of Design Requirements for a Text-to-3D Participatory Design Tool 23
2.1 Digital Participation in Urban Planning and Design Processes 23
2.2 Generative AI in Participatory Urban Design 25
2.3 Stakeholder Mapping in Citizen Participation 31
2.4 Empirical Insights from Semi-Structured Interviews 40
2.5 List of Requirements for a Text-to-3D Participatory Design Tool 42
3. Methodology for the Design and Evaluation of a Text-to-3D Participatory Design Tool 47
3.1 Development of the Text-to-3D Participatory Design Tool 47
3.2 Case Description: Maaspark Redevelopment Area 58
3.3 Testing the Text-to-3D Approach Through a Participation Experiment 61
4. Participation Experiment Results 67
4.1 Participant Demographics and Contextual Background 67
4.2 Data Cleaning 67
4.3 Scale Reliability and Validity 68
4.4 Participation Experiment Outcomes 70
5. Conclusion 77
5.1 Answers to the Research Questions 77
5.2 Contributions to Science and Society 78
5.3 Contextual and Methodological Limitations 79
5.4 Recommendations for Future Research 82
References 85
Appendices 93

Summary

This master's thesis investigates how the use of a digital text-to-3D participatory design tool can enhance participant engagement and urban planners' decision-making in the design process of public space. The motivation stems from the increasing need to make participation processes more accessible and effective, as required by the Dutch Environmental Act. Traditional forms of participation are often inadequate, particularly because non-expert participants struggle to translate their ideas into spatial designs. This research therefore develops a tool that directly converts natural language into 3D designs. The tool serves as a means to test the potential benefits of a text-to-3D approach within participation processes.

Based on literature and semi-structured interviews with experts, both functional and non-functional requirements were defined for the tool's development. The needs of key stakeholders: citizens, municipalities, and developers, were used to formulate concrete design principles for a text-to-3D participatory design tool. The main requirements include the ability to translate user-inputted natural language prompts into corresponding 3D public space designs, intuitive usability for non-experts, and the restriction of component placement based on predefined urban planning and design frameworks. A prototype was then developed using Rhino and Grasshopper, integrated with a GPT-4o mini Large Language Model (LLM). The tool enables participants to add and modify elements in a 3D model through text input, establishing a direct feedback loop between the user and the generated 3D design. To overcome the limited spatial awareness of LLMs, the tool uses a structured prompt format and a coordinate-based spatial framework.

The tool was tested in a field experiment at Maaspark in Vlaardingen, a public park undergoing redevelopment as part of Rivierzone area development. Local residents were invited to design their own proposals for the park on site using the text-to-3D tool. Their experience was assessed through the User Experience Questionnaire (UEQ) and seven additional statements grounded in the Technology Acceptance Model (TAM). The results indicate that the text-to-3D approach was evaluated positively in terms of attractiveness, stimulation, and innovation. Text input was appreciated as an accessible and intuitive form of interaction, especially for participants unfamiliar with 3D design. However, practical usability received lower scores. The most significant limitations included a mismatch between user expectations and the LLM's design output, as well as generation times of 10–20 seconds per iteration, which sometimes disrupted interaction flow.

Participants typically followed an iterative design process, submitting multiple prompts and refining their ideas based on the visual feedback. While most users valued the tool's simplicity, some needed assistance with prompt formulation. This underlines the importance of guided interaction, structured prompt templates, and fallback mechanisms by the system for handling unsupported input. In some cases, participants expressed a preference for voice-based interaction, suggesting that speech-to-text integration could further reduce barriers and enhance accessibility. Additionally, while users could not modify the routing of paths or fine-tune object dimensions, most did not perceive this as a limitation, focusing instead on the placement of greenery and urban elements.

In addition, the tool's effect on decision-making by urban planners was evaluated. The designs generated by participants quickly revealed their preferences in terms of physical component

types and spatial placement. Urban planners valued the clarity and structure of the outputs, which offered a strong foundation for analysis within the tool's digital parametric environment. However, meaningful impact on decision-making requires that these outputs can also be efficiently assessed. As this analytical layer was not fully developed, future research is needed to explore how participant-generated designs can be effectively integrated into urban planning and design workflows. This includes embedding contextual data, such as spatial conditions and regulatory constraints, to ensure feasible outputs with predefined design principles. Yet, care must be taken to balance participants' creative freedom with practical constraints, avoiding both excessive restriction and overly unrestricted input.

This study demonstrates that real-time natural language translation into 3D models can enrich participatory processes. It stimulates participant engagement while providing urban planners with structured insights into citizen preferences. By visualizing public input spatially, the tool helps bridge the gap between abstract participant needs and actionable design outcomes. While current limitations, such as LLM spatial reasoning, response time, and restricted design libraries, still constrain full alignment between user intent and output, the tool presents a novel and promising direction in participatory urban design.

Future research should examine how structured dialogue systems and voice-controlled interaction can further improve user experience and accessibility. In addition, broader experimentation across different demographic groups and planning scales is recommended to evaluate generalizability. Further development is also needed to embed the tool within urban planners' workflows, including the integration of real-time analysis tools and evaluation frameworks. Ultimately, this study positions the text-to-3D approach as a promising step toward transforming participation into a more inclusive and design-informed dialogue between citizens and professionals.

Samenvatting

Deze masterthesis onderzoekt hoe het gebruik van een digitale tekst-naar-3D participatietool de betrokkenheid van participanten en de besluitvorming van stedelijke ontwerpers kan versterken in het ontwerpproces van de openbare ruimte. De aanleiding hiervoor ligt in de toenemende noodzaak om participatieprocessen toegankelijker en effectiever te maken, zoals vereist door de Omgevingswet. Traditionele vormen van participatie schieten vaak tekort, met name omdat niet-deskundige participanten moeite hebben om hun ideeën ruimtelijk te verbeelden. Dit onderzoek ontwikkelt daarom een tool die natuurlijke taal direct omzet in 3D-ontwerpen. De tool dient als middel om de potentiële meerwaarde van een tekst-naar-3D-benadering binnen participatieprocessen te toetsen.

Op basis van literatuuronderzoek en semigestructureerde interviews met experts zijn zowel functionele als niet-functionele eisen opgesteld voor de ontwikkeling van de tool. De behoeften van belangrijke stakeholders: burgers, gemeenten en ontwikkelaars, werden gebruikt om concrete ontwerpprincipes te formuleren voor een tekst-naar-3D participatietool. De belangrijkste eisen omvatten het kunnen vertalen van natuurlijke taal naar bijbehorende 3D-ontwerpen van de openbare ruimte, intuïtieve bruikbaarheid voor niet-experts, en de beperking van componenten plaatsing op basis van vooraf gedefinieerde stedenbouwkundige en ontwerptechnische randvoorwaarden. Vervolgens werd een prototype ontwikkeld in Rhino en Grasshopper, gekoppeld aan een GPT-4o mini Large Language Model (LLM). De tool stelt participanten in staat om via tekstinvoer elementen toe te voegen of aan te passen in een 3D-model, waarmee een directe feedbacklus ontstaat tussen gebruiker en ontwerp. Om de beperkte ruimtelijke interpretatiecapaciteit van LLM's te ondervangen, is gebruikgemaakt van een gestructureerde prompt opbouw en een coördinatengebaseerd ruimtelijk raamwerk.

De tool is getest in een praktijkexperiment in het Maaspark te Vlaardingen, een stadspark in herontwikkeling als onderdeel van de gebiedsontwikkeling Rivierzone. Lokale bewoners werden ter plaatse uitgenodigd om hun eigen voorstellen voor het park te ontwerpen met behulp van de tekst-naar-3D tool. Hun ervaring werd geëvalueerd aan de hand van de User Experience Questionnaire (UEQ) en zeven aanvullende stellingen gebaseerd op het Technology Acceptance Model (TAM). De resultaten tonen aan dat de tekst-naar-3D benadering positief werd beoordeeld op aspecten als aantrekkelijkheid, stimulatie en innovatie. Tekstinvoer werd gezien als een toegankelijke en intuïtieve manier van interactie, vooral voor deelnemers zonder ervaring met 3D-ontwerpen. De praktische bruikbaarheid kreeg echter lagere scores. De belangrijkste beperkingen betroffen een mismatch tussen gebruikersverwachtingen en de gegenereerde ontwerpen, evenals wachttijden van 10–20 seconden per iteratie, die het interactieproces soms onderbraken.

Deelnemers volgden doorgaans een iteratief ontwerpproces waarbij zij meerdere prompts invoerden en hun ideeën verfijnden op basis van de visuele terugkoppeling. Hoewel de meeste gebruikers de eenvoud van de tool waardeerden, hadden sommigen hulp nodig bij het formuleren van effectieve prompts. Dit onderstreept het belang van begeleide interactie, gestructureerde prompt structuur en fallback-mechanismen in het systeem voor het verwerken van niet-ondersteunde invoer. In sommige gevallen gaven deelnemers de voorkeur aan spraakgestuurde interactie, wat suggereert dat integratie van spraakherkenning de toegankelijkheid kan vergroten. Daarnaast konden gebruikers geen paden aanpassen of

objectafmetingen verfijnen, maar dit werd over het algemeen niet als een beperking ervaren: de nadruk lag op de plaatsing van groenvoorzieningen en stedelijke elementen.

Daarnaast werd het effect van de tool op de besluitvorming van ontwerpers geëvalueerd. De door participanten gegenereerde ontwerpen gaven snel inzicht in voorkeuren met betrekking tot de verschillende element types en hun ruimtelijke positionering. Ontwerpers waardeerden de helderheid en structuur van de output, wat een solide basis vormt voor analyse binnen de digitale parametrische omgeving van de tool. Voor een betekenisvolle bijdrage aan besluitvorming is echter vereist dat deze ontwerpen ook efficiënt kunnen worden beoordeeld. Aangezien deze analytische laag nog onvoldoende was uitgewerkt, is vervolgonderzoek nodig naar hoe participantenoutput effectief kan worden geïntegreerd in stedenbouwkundige processen. Dit omvat het integreren van contextuele gegevens, zoals ontwerpprincipes en ruimtelijke regelgeving, om uitvoerbaarheid van de gegenereerde ontwerpen te garanderen. Tegelijkertijd is het cruciaal om de creatieve vrijheid van participanten in balans te brengen met deze praktische beperkingen, en zo zowel overmatige restricties als een te vrije invulling te vermijden.

Deze studie toont aan dat real-time vertaling van natuurlijke taal naar 3D-modellen participatieprocessen kan verrijken. De aanpak stimuleert participatie en biedt (stedelijke) ontwerpers gestructureerd inzicht in bewonersvoorkeuren. Door publieke input ruimtelijk te visualiseren, slaat de tool een brug tussen abstracte behoeften van de participant en concrete ontwerpresultaten. Hoewel beperkingen zoals beperkte ruimtelijke interpretatie, responstijd en een beperkte bibliotheek de volledige afstemming tussen gebruikersintentie en output nog belemmeren, benadrukt de tool een veelbelovende stap binnen digitale participatieve stedenbouw.

Vervolgonderzoek zou moeten verkennen hoe gestructureerde dialoogscripts en spraakgestuurde interactie de gebruikservaring verder kunnen verbeteren. Daarnaast wordt aanbevolen om de aanpak breder te testen onder verschillende demografische groepen en schaalniveaus. Verdere ontwikkeling is nodig om de tool daadwerkelijk te integreren in stedelijke ontwerp processen, inclusief real-time analysetools en evaluatiekaders. Uiteindelijk positioneert deze studie de tekst-naar-3D benadering als een veelbelovende stap richting een inclusiever en ontwerpgericht participatiedialoog tussen burger en professional.

Abstract

This thesis explores the potential of real-time text-to-3D translation to enhance citizen engagement and inform urban design decisions in participatory public space design. a digital tool was developed that converts natural language input into 3D design proposals. The tool integrates a GPT-4o mini Large Language Model into Rhino + Grasshopper, to enable a direct and iterative feedback loop between participant input and spatial output. Functional and non-functional requirements were derived from literature and expert interviews to guide the tool's development. A field experiment was conducted in Maaspark (Vlaardingen), where local residents used the tool to design public space elements. User experience was evaluated using the User Experience Questionnaire (UEQ) and customized metrics. Results present high ratings in hedonic qualities such as stimulation and novelty, with text input perceived as intuitive and engaging. Although pragmatic aspects like perceived control and processing time scored lower, participants overall reported increased involvement in the design process. Urban planners valued the tool for its ability to reveal participant preferences and spatial intentions. Recommendations for future research include structured prompt frameworks and analytical features to support scalable implementation in urban planning and design workflows.

Keywords

Participatory Urban Design, Citizen Participation, Digital Participation, Text-to-3D Generation

List of Abbreviations

AI	Artificial Intelligence
CDS	Citizen Design Science
GDPR	General Data Protection Regulation
GIS	Geographic Information System
GPT	Generative Pre-trained Transformer
HCI	Human-Computer Interaction
IFC	Industry Foundation Classes
JSON	JavaScript Object Notation
KPI	Key Performance Indicator
LDM	Latent Diffusion Model
LLM	Large Language Model
MVP	Minimal Viable Product
NeRF	Neural Radiance Fields
RAG	Retrieval-Augmented Generation
TAM	Technology Acceptance Model
UI	User Interface
UEQ	User Experience Questionnaire
UX	User Experience

List of Figures

Figure 1: Arnstein's Ladder of Participation illustrates that higher rungs on the ladder correspond to increased levels of citizen involvement in decision-making processes. Based on: (Mueller et al., 2018) 15
Figure 2: Citizen Design Science framework illustrating the interaction between citizens, design, and scientific inquiry. Based on: (Public Twin, 2025b) 16
Figure 3: Design Science Research framework presenting the interaction between the application domain, design process, and knowledge base, based on: (Hevner, 2007) .. 20
Figure 4: Research strategy described in Chapter 2 to identify design requirements for the Text-to-3D participatory design tool. 23
Figure 5: The User Interface of the PublicTwin participation platform presenting an example project. (Public Twin, 2025a) 26
Figure 6: An example of the text-to-image methodology applied in the UrbanistAI participation tool. (UrbanistAI, 2025a) 26
Figure 7: Feedback board from the participation meeting for the Rivierzone redevelopment area, organized by the Municipality of Vlaardingen in February 2025 (source: author's photograph). 39
Figure 8: Design Science methodology framework including research progress highlighted in green. The central component 'Design Science Research' is described in Chapter 3. ... 47
Figure 9: System Architecture of the text-to-3D participatory design tool including the three main components: User Interface, the GPT-based LLM of OpenAI, and the Grasshopper script. 49
Figure 10: User Interface of text-to-3D participation tool displayed in Rhino including the HumanUI window 50
Figure 11: Snippet of System Architecture presenting the four prompt components. 50
Figure 12: Snippet of the System Architecture illustrating the Grasshopper script used for real-time model visualization and spatial component placement. 52
Figure 13: BPMN diagram illustrating the API Request Phase, including associated input files and system components. 53
Figure 14: BPMN diagram illustrating the Data Preparation Phase, including associated input files and system components. 54
Figure 15: LLM output parameters used as input for component placement in Grasshopper. 54
Figure 16: Component representation 55
Figure 17: BPMN diagram illustrating the Data Preparation Phase, including associated input files and system components. 55
Figure 18: Maaspark Project as part of the Rivierzone area development in Vlaardingen. (Inspire Real Estate, n.d.) 59
Figure 19: Final feedback board from the Maaspark participation session, displaying community input collected during the event. (source: author's photograph) 60
Figure 20: Setup of the participation experiment in a community center near Maaspark, showing the moment during which the tool was being explained to participants. (source: author's photograph) 62
Figure 21: An example of a UEQ item about to what extent the product is annoying or enjoyable. 64
Figure 22: Customized-Statements related to the Technology Acceptance Model (Davis, 1989) 65

Figure 23: Example of a participant-generated design during the participation experiment, illustrating how components were placed within the 3D model using the text-to-3D tool. 75
Figure 24: User Interface of the Qua-Kit Tool displaying urban elements placed by participants. (Tomarchio et al., 2019).....93
Figure 25: Methodological steps for replacing one element with another in the UrbanGenAI tool. (Kapsalis, 2024b) 94
Figure 26: Interface of the Urban Architect tool showing elements removed or added through text input. (Lu et al., 2024b) 95
Figure 27: Using a Latent Diffusion Model to generate "a house". (Li et al., 2024) 97

List of Tables

Table 1: The corresponding advantages and disadvantages of digital participation. 25
Table 2: The key stakeholders (grouped by public, private, and community) in participation processes identified by four academic studies. 32
Table 3: Functional requirements for a text-to-3D participatory design tool, derived from literature and semi-structured interviews with key stakeholders, and categorized according to the MoSCoW prioritization method. 42
Table 4: Non-functional requirements for the text-to-3D participatory design tool, derived from literature and semi-structured interviews with key stakeholders, and categorized according to the MoSCoW prioritization method. 44
Table 5: Overview of all functional requirements categorized using the MoSCoW method, including an assessment of whether each requirement was implemented in the text-to-3D participatory design tool. 56
Table 6: Overview of all non-functional requirements categorized using the MoSCoW method, including an assessment of whether each requirement was implemented in the text-to-3D participatory design tool. 57
Table 7: The six categories and their descriptions for the 26 UEQ item clusters. 64
Table 8: Overview of participant demographics, including average age, gender distribution, frequency of park use, average support for the Maaspark redesign, and average familiarity with 3D design tools. The last two items are measured on a 7-point Likert scale, where higher scores indicate greater support or familiarity. 67
Table 9: Cronbach's Alpha scores for the UEQ scales. Values range from 0 to 1, with scores above 0.70 indicating strong internal consistency within each category. 68
Table 10: Cronbach's Alpha scores of statements 1-4 including their interrelated correlations. 69
Table 11: Cronbach's Alpha score of statements 5-7 including their interrelated correlations. 69
Table 12: Mean scores for individual User Experience Questionnaire items. Each color represents one of the six UEQ categories: Attractiveness, Perspicuity, Efficiency, Dependability, Stimulation, and Novelty. 70
Table 13: Mean scores and 95% confidence intervals for the six User Experience Questionnaire scales. 71
Table 14: Mean scores and variances for the six User Experience Questionnaire scales. 72
Table 15: UEQ results grouped by attractiveness, pragmatic quality (perspicuity, efficiency, dependability), and hedonic quality (stimulation, novelty). 72
Table 16: Results of the seven customized-statements evaluating user experience and perceived involvement. 73
Table 17: Means and variances of the seven customized-statements. 74
Table 18: Advantages and disadvantages of using the Drag & Drop functionality according to Tomarchio et al. (2019) 93
Table 19: Advantages and disadvantages of using the Drag & Drop functionality according to Marshall et al. (2024) 94
Table 20: Advantages and disadvantages of using the text-to-image approach in participatory design. (Kapsalis, 2024b) 94
Table 21: Advantages and disadvantages of the text-to-3D approach in the Urban Architect tool. (Lu et al., 2024b) 95

Table 22: Advantages and disadvantages of the text-to-city approach. (J. Zhuang et al., 2024b) 96
Table 23: Advantages and disadvantages of the collaborative 3D GIS platform. (Hu et al., 2015b).....96

1. Introduction to the Research Problem and Methodological Approach

Effective citizen participation is a fundamental component of public space design. With the introduction of the Dutch Environmental Act, participation has evolved into a formalized and integral requirement in urban design processes. Its purpose extends beyond merely generating public support and project approval, it also serves to capture local user knowledge, enabling designs to align closely with local needs and preferences. Digital participation has emerged as a promising strategy to broaden citizen engagement. However, despite these developments, current participation ecosystems struggle with translating non-expert citizen input into meaningful spatial design proposals. This challenge defines the core focus of the thesis. The introduction elaborates on the problem and outlines the research design developed to explore a potential solution.

1.1 Problem Definition and Contextual Background of Digital Participatory Design

Engaging stakeholders in urban design processes is a key factor in improving project outcomes. Active stakeholder involvement encourages a sense of ownership, improves project acceptance, and in the end, enhances the overall success rate of urban projects (Turyasingura et al., 2023). However, traditional participation methods, such as physical participation meetings where communities are informed about upcoming developments, have their limitations. Such participation meetings require in-person attendance at a specific time and location. They are often structured around one-way communication where residents are informed about plans but are given limited opportunities to influence the decision-making process meaningfully (van der Klauw, 2020). Literature suggests that shifting from one-way communication to interactive methods significantly improves stakeholder involvement and commitment (Martinez-Avila & Olander, 2024a). Additionally, participation often occurs too late in the process, when major design and planning decisions have already been made. As a result, there is little to no opportunity to integrate participant input into the final design. Effective citizen participation should be integrated at the earliest stages of decision-making, rather than serving as a symbolic exercise once policies and plans are already finalized (OECD, 2022a). Another limitation of the participation process is its static nature. Typically, public input is collected at a single point in time, failing to account for the evolving nature of stakeholder values and concerns (Herzog et al., 2022a). These limitations of conventional participation contradict the Dutch Environmental Act (Omgevingswet), which emphasizes co-creation and early collaboration between urban planners and citizens in the urban plan area (Dutch Governance, 2024).

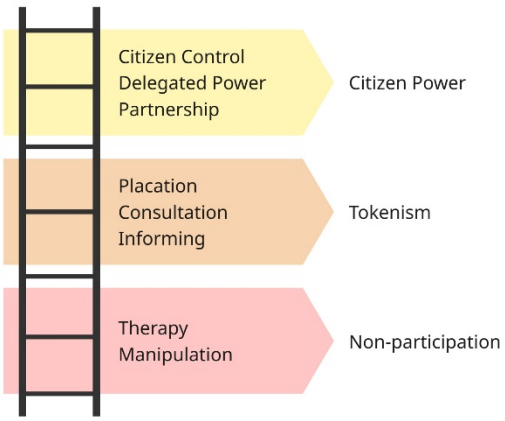


Figure 1: Arnstein's Ladder of Participation illustrates that higher rungs on the ladder correspond to increased levels of citizen involvement in decision-making processes. Based on: (Mueller et al., 2018)

Arnstein's Ladder of Citizen Participation, who coined the concept for the first time in literature, proposes a theoretical framework for measuring the extent to which stakeholders are involved in the participatory process (Figure 1). A key principle of this framework is that meaningful participation requires moving beyond just informing citizens to achieve higher levels of citizen power (Arnstein, 1969).

One approach that aligns with this principle and aims to strengthen citizen involvement is the Citizen Design Science (CDS) methodology (Figure 2). The CDS methodology integrates three key dimensions: citizens, design, and science (Mueller et al., 2018). By linking these components, CDS enables citizens to meaningfully engage in the spatial design process while allowing urban planners to derive actionable insights from participant contributions. As such, CDS forms a conceptual and methodological link between top-down planning systems and bottom-up design engagement.

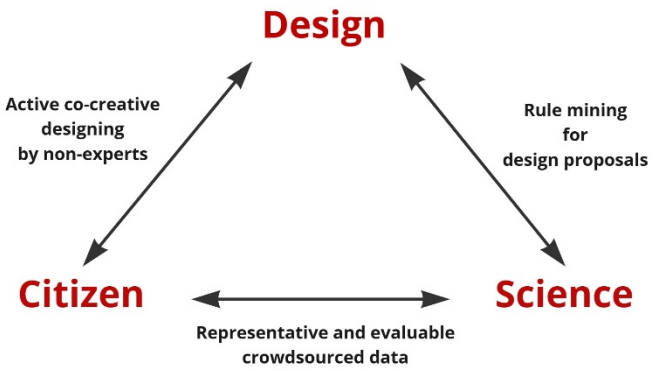


Figure 2: Citizen Design Science framework illustrating the interaction between citizens, design, and scientific inquiry. Based on: (Public Twin, 2025b)

The CDS methodology is strengthened using digital participation (Mueller et al., 2018). Digital participation encompasses a range of information and communication technologies that facilitate citizens involvement in urban design and planning processes. Key characteristics of digital participation include low-threshold accessibility, scalability, asynchronous interaction, and data traceability (Shin et al., 2024a). However, even when leveraging digital participation, still a disconnection exists between citizen-generated input and its integration into feasible urban design outcomes (Herzog et al., 2022b).

Various interactive and iterative methods have been developed to enhance the participatory process, including gamification elements, multi-criteria decision-making tools, and collaborative digital platforms. However, despite these advancements, a direct feedback loop between participant input and the system's output is often still missing (Shin et al., 2024a). Most digital tools excel at collecting input but fall short in providing real-time feedback in the form of concrete design proposals. Consequently, participation processes rely on one-way communication and is characterized by a static nature. Therefore, existing digital participation tools frequently fail to support meaningful engagement (Tappert et al., 2024a). As a result, participation frequently remains symbolic rather than impactful, limiting citizens' actual influence on public space development. The problem is rooted in several systemic issues. Firstly, there is a lack of intuitive design tools that non-experts can use without training (Ivgi et al., 2024). Secondly, there are inadequate mechanisms to translate textual or abstract

citizen input into structured and spatial design proposals (Chassin et al., 2019a). Thirdly, most digital tools are implemented without integration into regulatory frameworks or existing municipal workflows (Barrile et al., 2024).

Recent studies present that generative design offer an innovate approach to participatory urban design. Generative design enables the simulation of various design scenarios in real-time (Hurtado & Gomez, 2021). Real-time refers to immediate generation and visualization of design outputs in response to user input, without noticeable delay. This allows stakeholders to immediately visualize their ideas including active feedback loops (Hurtado & Gomez, 2021). Generative design is driven by advancements in Artificial Intelligence (AI), particularly through the emergence of Generative AI (GenAI). GenAI refers to a class of AI models capable of generating new content, such as text, images, or 3D models, based on patterns learned from existing data (Bommasani et al., 2022). As such, GenAI can interpret user input, while generative design techniques can generate and evaluate spatial solutions based on those inputs. The scalability of GenAI makes it possible to accommodate urban developments of all sizes. Additionally, the data-driven nature of GenAI techniques enables the identification of patterns, communalities, and trends in stakeholder preferences. These insights stimulate the decision-making process from the urban planners' perspective (Delgado et al., 2023). These capabilities suggest that GenAI can empower participants to co-create urban designs and actively influence decision-making processes. However, over-reliance on GenAI as a standalone application in participatory urban design processes is a risk. It may lead to a loss of control not only over the outcome but also over the process itself (Mak, 2023). Therefore, GenAI applications should always be integrated into a broader participatory framework that emphasizes inclusivity, clarity, and responsiveness.

Among the various interaction methods enabled by GenAI techniques, text-based interaction stands out for its accessibility. Text-based interaction lowers technical barriers and enables broader participant inclusion (Ivgi et al., 2024). Research findings indicate that participants preferred to provide input through textual descriptions, regardless of the availability of alternative input methods (Pinkaarts, 2024). This suggests that text input is perceived as an accessible and intuitive way for users to communicate their ideas and feedback on proposed designs.

To maximize the impact of text-based interaction, it is essential to pair it with equally intuitive output formats, such as interactive 3D models. 3D modeling enables stakeholders to experience a project from a more immersive and holistic perspective (Linkola et al., 2025). Integrating 3D models into public participation platforms enhances a better understanding of spatial and design complexities. Additionally, the ability to interact with a model makes the participation process more engaging and enjoyable for users (Hu et al., 2015a). By leveraging 3D representations, stakeholders can understand the implications of design decisions on urban spaces more intuitively compared to traditional 2D plans. This deeper understanding not only enhances the quality of feedback but also bridges the knowledge gap between technical experts and laypersons (Toukola & Ahola, 2022; Tung & Chang, 2024).

Given the accessibility of text-based interaction and the immersive value of 3D visualisation, integrating these two modalities, enabled by GenAI, presents a powerful opportunity for participatory urban design. The text-to-3D approach is a GenAI technique that translates

natural language directly into 3D design outputs (J. Zhuang et al., 2024a). As such, text-to-3D can enable participants to articulate design intentions through natural language, which are then automatically transformed into spatially accurate 3D representations.

In conclusion, effective citizen participation is a fundamental component of inclusive public space design. Digital participation has emerged as a promising strategy to broaden citizen engagement, yet existing participation ecosystems struggle to translate non-expert input into meaningful spatial design proposals. This challenge can be attributed to three main factors: (1) the lack of intuitive design tools that non-experts can use without prior training, (2) inadequate mechanisms for converting citizen input into structured spatial proposals, and (3) the limited integration of participatory methods into existing regulatory and planning and design frameworks. To address this gap, this study develops a text-to-3D participatory design tool that combines natural language input with real-time 3D modeling. This tool serves as a means to investigate how the direct translation of text into spatial 3D models influences participant engagement and urban planners' decision-making.

1.2 Research Scope

This study is scoped to participatory urban design at the project scale, focusing on non-expert citizen involvement in public space design. Within this scope, the study explores a text-to-3D participatory design tool that enable intuitive input and immediate spatial visualization. The selected design directions and domains are outlined in this section.

The study focuses on citizen participation within the broader context of participatory urban design. Citizen participation specifically refers to the involvement of non-expert residents in the planning and design of urban spaces. It is increasingly recognized as a critical component of democratic planning processes and is essential for ensuring that spatial interventions reflect the needs of local communities (Kusi, 2023). Secondly, the focus is on urban planners who play a key role in translating design proposals into practical and policy-compliant urban plans. They navigate within well-defined regulatory frameworks to ensure that projects are feasible and aligned with broader urban strategies (Øystein Førre Erfjord, 2016).

Citizen participation is part of broader urban planning and design processes. Within this process, several spatial scales can be distinguished: the city and regional, the area, and the project level (De Zeeuw, 2023). For the text-to-3D participatory design tool, the participation process should focus on the generation of concrete design proposals. This makes it less suitable for city or regional participation, where the focus is typically on broader policy themes (Nam, 2013). This does not negate the need for GenAI participatory design tools that can be applied at regional and citywide scales. However, this falls outside the scope of the current study and could be addressed in future research. Participatory methods at the area development level place greater emphasis on collecting design ideas (Geekiyanage et al., 2021). At the project development level, participation becomes increasingly design-oriented. In this context, the text-to-3D participatory design tool is well aligned with participation methods that emphasize visualization, co-creation, and iterative design. Therefore, the project level was selected as the appropriate scale for applying the tool. Broader urban scales, such as area-wide or regional planning, and domains requiring highly technical or expert-driven design inputs are beyond the scope of this study.

Within the project level, several domains can be distinguished. The fewer data-driven decisions a design process requires, the more relevant citizen participation becomes (Rovolis & Habibipour, 2024). This is because design choices that rely on values, preferences, and lived experiences benefit significantly from direct input by community members. In this context, public space design offers significant opportunities for participant engagement. Citizens are particularly invested in shaping public spaces, as decisions in this domain directly affect their daily experiences and overall quality of life. Public participation is therefore essential to ensure that these spaces reflect the diverse needs of the community (Norozi & Forouzande, 2021). For this reason, this study focuses specifically on the domain of public space design.

In this study, public space design is categorized into three components: urban elements, greenery, and routing. The infrastructural layout, such as the placement of pathways, is typically regarded as secondary by participants (Özden et al., 2025). The emphasis tends to lie on the presence or absence of an adequate number of paths, rather than their precise alignment or configuration within the space. As a result, the focus during tool development was placed on enabling participants to add and modify urban elements and greenery. Research also indicates that the definition of the built fabric surrounding public space, particularly the design and function of the building plinth, plays a critical role in shaping user experience and perception (Kickert, 2016). Nevertheless, this study deliberately focuses on the design of the public space itself, thereby fixing the surrounding spatial context. Although this limitation narrows the scope of design exploration, incorporating the adjacent building plinth as a variable would be a valuable extension for future participatory design tools.

In conclusion, this study is scoped within the domain of participatory urban design, focusing on the involvement of non-expert citizens in the design of public spaces at the project scale. It explores the use of a text-to-3D GenAI tool to support participation by enabling intuitive expression of design intentions and the immediate visualization of spatial outcomes. The research does not aim to develop novel AI algorithms but instead evaluates the integration and impact of existing text-to-3D methods within a participatory framework.

1.3 Research Questions

The aim of this study is to investigate how a text-to-3D approach can influence participant engagement and urban planners' decision-making in the context of digital participatory urban design. Based on this aim, the following research question has been formulated:
Sub-questions:

> *How can real time natural language translation into 3D design outputs enhance non-expert participant engagement and urban planners' decision-making in digital participatory urban design?*

1. *How can a tool be developed to facilitate the real time translation of natural language into 3D design outputs for participatory urban design?*
2. *How does the implementation of this tool influence participant engagement and urban planners' decision-making in participatory urban design processes?*

The first part of the main research question *(How can real time natural language translation into 3D design outputs)* emphasizes the software-technical aspect of the study, specifically, the development of a text-to-3D tool that translates natural language input into 3D design

representations in real time. Sub-question 1 addresses this component. The objective here is to develop a Minimal Viable Product (MVP) that enables a structured participant experiment. The development process of the MVP is detailed in Section 3.1.

Sub-question 2 focuses on the potential impact of the text-to-3D approach in participatory processes. The sub-question highlights two key aspects: participant engagement and urban planners' decision-making. The engagement dimension investigates how participants interact with the model, focusing on active engagement and perceived value. It aims to assess the extent to which the solution adds real value for this stakeholder group. The engagement aspect ensures the investigation of the participant's involvement and satisfaction level in the process (Z. Zhang & Zurlo, 2020). The second dimension concerns how urban planners interpret and utilize the outputs generated through the tool. Although participant decision-making is also influenced, the primary focus is on how the tool supports urban planners in making more informed, data-driven, and socially grounded design decisions. This distinction is important for understanding how such tools can bridge the gap between public input and professional design processes.

1.4 Research Design

The methodology applied in this research is known as the Design Science methodology. This structured methodology is widely used to develop and evaluate solutions to practical problems (Wieringa, 2014). The methodology ensures that the tool is developed based on stakeholder needs, has a robust technical foundation, and is tested in real-world participatory processes. A core framework of the Design Science methodology is the framework of Hevner (2007), which is visualised in Figure 3.

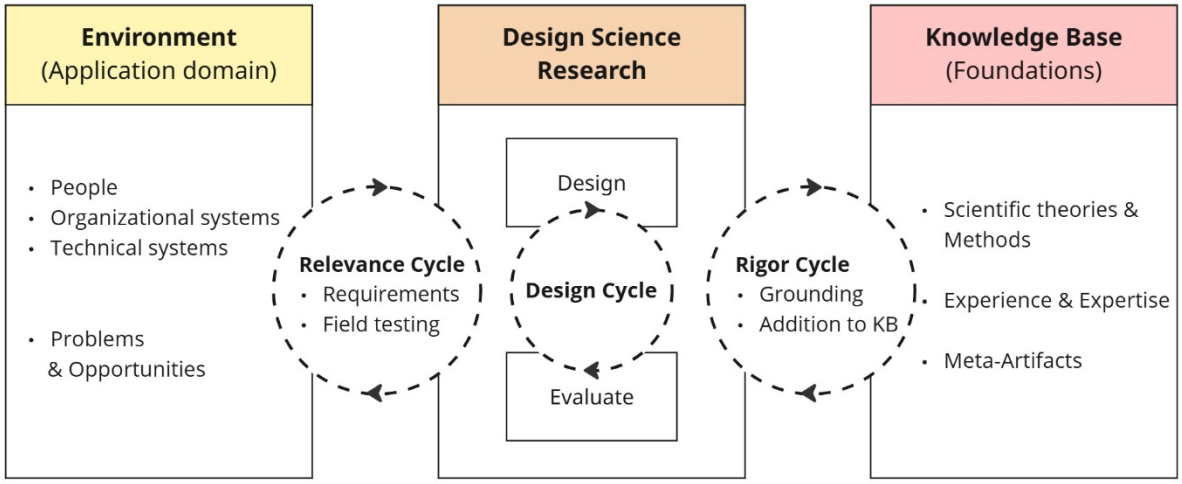


Figure 3: Design Science Research framework presenting the interaction between the application domain, design process, and knowledge base, based on: (Hevner, 2007)

On the left side of the framework, the environment represents the real-world context in which the problem is situated. Problems and opportunities are identified by examining the relevant actors (people), organizational systems, and existing technical infrastructure. The Relevance Cycle connects this environment to the design process by providing critical input such as the requirements, and by enabling field testing of the developed solution. For this study, the description of the environment is based on both a literature review and insights gathered from seven semi-structured interviews with experts.

The study continues with the central component of the Design Science methodology, the Design Cycle. This is an iterative process involving the design and evaluation of the artifact, in this case the text-to-3D participatory design tool. The purpose of this phase is to develop and refine the tool through successive iterations.

Field testing is a critical component of the Design Science Methodology. Following the development of the tool, a participant experiment is conducted in this study as well. This experiment serves to evaluate the impact of the text-to-3D approach on participant engagement and urban planners' decision-making. The experiment is based on a case study, to align the evaluation with real-world conditions and ensure that the findings reflect practical applicability within an actual participatory context.

The Design Cycle is supported by the Knowledge Base, which includes the scientific theories, frameworks, and existing tools that inform the development process. In this study, examples of relevant knowledge elements include evaluation methodologies such as the User Engagement Questionnaire (UEQ) and meta-artifacts used during the tool development. The Rigor Cycle connects this knowledge base to the design process by ensuring the research is theoretically grounded and contributes new insights or artifacts to the academic field.

In conclusion, the Design Science Methodology offers a structured and iterative approach to develop and evaluate the text-to-3D participatory design tool in alignment with the study's aim: to investigate how the text-to-3D approach can influence participant engagement and urban planners' decision-making in digital participatory urban design. By grounding the design in stakeholder needs, academic theory, and real-world testing, the methodology ensures both practical relevance and scientific rigor.

1.5 Reading Guide

This thesis follows the structure of the Design Science Methodology as outlined in Section 1.4. Chapter 2, titled *Exploration of Design Requirements for a Text-to-3D Participatory Design Tool*, elaborates on the problem context in relation to digital participation, participatory GenAI techniques, and the key stakeholders involved in participatory processes. The analysis of these three themes is based on a literature review. The outcomes of this review are subsequently complemented by semi-structured interviews with seven experts. The analysis presented in Chapter 2 results in a list of requirements for the development of the text-to-3D participatory design tool.

The subsequent chapter, Chapter 3 titled *Methodology*, outlines the tool development process, the case study description, and the participation experiment conducted for this research. It begins with a justification of the design choices made in the development of the text-to-3D tool, followed by an introduction to the case study. The final section of the chapter details the experimental setup and protocol used to evaluate the tool with participants.

Chapter 4, titled *Participation Experiment Results*, presents the outcomes of the experiment. The experiment utilized the User Experience Questionnaire alongside seven customized statements based on the Technology Acceptance Model. The chapter begins with a general

description of participant demographics, followed by a data cleaning procedure. Subsequently, the results of the participation experiment are discussed in detail.

Finally, Chapter 5 presents the main conclusions by addressing the research questions. This is followed by an examination of the study's contributions to both science and society. The chapter concludes with a discussion of the study's limitations and offers recommendations for future research and practice.

2. Exploration of Design Requirements for a Text-to-3D Participatory Design Tool

Chapter 2 presents the insights from literature complemented by stakeholder interviews to define the problems in participation practices and establish a list of requirements for the text-to-3D tool. The chapter contains an contextual analysis of digital participation, technological assessment of AI techniques, and stakeholder mapping to identify users needs and translate them into requirements. The described strategy to establish the list of requirements is also presented in Figure 4.

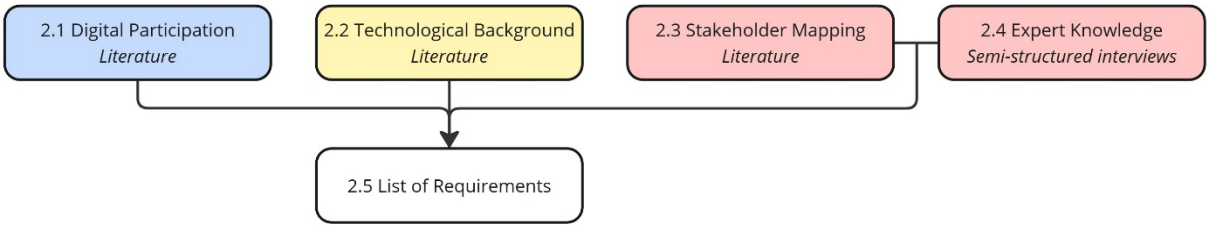


Figure 4: Research strategy described in Chapter 2 to identify design requirements for the Text-to-3D participatory design tool.

Existing literature on participatory urban design and digital tools is first synthesized to establish a foundation for this study in Sections 2.1 and 2.2. This synthesis further informs an initial stakeholder mapping, which identifies key actors and their roles in planning and design processes in Section 2.3. The mapping is grounded in the literature but further contextualized through empirical data. To complement and critically reflect on the literature-based analysis, seven semi-structured interviews were conducted with professionals from diverse backgrounds, including representatives from a municipality, two urban developers, two software developers, an Dutch Environmental Act specialist, and two experts from participation agencies (Section 2.4). These expert interviews serve to deepen the understanding of stakeholder needs and support the formulation of system requirements for the proposed tool described in Section 2.5. By integrating theoretical insights with practitioner perspectives, this chapter aims to align the design approach with both academic discourse and the practical demands of real-world implementation.

2.1 Digital Participation in Urban Planning and Design Processes

With the rise of digital tools, digital participation has become increasingly important in facilitating and enhancing citizen engagement in urban development processes. According to the study of Mariani et al. (2025), digital participation is defined as the integration of Information and Communication Technologies (ICTs) into the participation process to facilitate public engagement. The different digital participation types identified by literature are: crowd-source mapping, interactive surveys, analytical tools, crowdfunding, drafting, online debates, and comprehensive decision-making platforms (Shin et al., 2024b).

2.1.1 Advantages of Digital Participation

One of the key advantages of digital participation is that it widens access to engagement opportunities, particularly for those who may face barriers to physical participation. Citizens who are constrained by time, location, or mobility issues can still contribute to decision-making through online platforms. The low accessibility threshold reduces barriers to participation and enhances inclusivity (Shin et al., 2024b).

Additionally, digital platforms offer greater efficiency in collecting and analysing public input. AI-integration allows for automated data synthesis that provides planners and policymakers with structured insights (Shin et al., 2024b).

Another significant benefit of digital participation is its ability to facilitate real-time feedback. Digital tools, such as discussion platforms, allow citizens to provide instant responses to urban planning and design initiatives. The real-time feedback loop enables urban planners to quickly gauge public sentiment on proposed policies and projects (Gonzalez-Mohino et al., 2023).

Moreover, digital participation increases transparency in decision-making. By making participatory processes more visible and accountable, digital participation platforms strengthen citizen confidence in government institutions (Tappert et al., 2024b). Thereby, digital participation enables more citizen-centered governance. As digital participation platforms promote cooperative and participatory approaches, reinforcing community-driven decision-making and co-creation (Gonzalez-Mohino et al., 2023).

Finally, digital participation plays a crucial role in mobilizing public action and awareness on urban planning and design issues. For example, social media provide accessible platforms to encourage discussions. Thereby, a broader outreach and engagement can be achieved (Tappert et al., 2024b).

2.1.2 Disadvantages of Digital Participation

While digital participation offers numerous benefits, it also presents significant challenges. One of the primary shortcomings of digital participation is the concept of 'pseudo-participation', which means that citizens provide input, but their suggestions are not considered in the decision-making processes. This can create the perception that digital participation is merely symbolic, rather than a meaningful avenue for public influence (Tappert et al., 2024a; Wirtz et al., 2018).

Another challenge associated with digital participation is 'engagement fatigue'. When citizens are repeatedly consulted without seeing concrete outcomes, they may become disengaged from the process. Study highlights the problem of low long-term engagement, where participants lose interest due to a lack of visible outcomes (Shin et al., 2024b).

Moreover, digital participation often skews toward more technological adept groups. So, it potentially excludes older adults, low-income populations, or those with disabilities. Many digital participation initiatives struggle to engage a truly representative portion of the population (Mariani et al., 2025a). In addition, most digital participation initiatives require digital literacy and critical thinking, which not all users possess. The division between digitally skilled participants and those who lack these competencies results in an unequal distribution of influence in public decision-making (Gonzalez-Mohino et al., 2023).

Another risk of digital participation lies in the manipulation of digital platforms. Online tools can be influenced by governance structures, algorithms, or misinformation. Therefore, digital participation is not a guaranteed solution for democratizing urban decision-making. The success depends heavily on the political and governance context in which it is implemented (Tappert et al., 2024b).

A fundamental challenge with digital participation tools is that participation is often a static, one-time event. However, urban projects evolve over time, with changing objectives, constraints, and stakeholder inputs. Literature highlights the challenge of designing a platform that can dynamically adjust to these evolving factors while supporting different levels of participation (rungs on Arnstein's Participation Ladder) (Chassin et al., 2019b).

Finally, data privacy and security concerns remain a major challenge in digital participation. Collecting and managing large-scale citizen input raises issues regarding data protection and cybersecurity (Shin et al., 2024b).

When comparing the advantages and disadvantages of digital participation, it becomes evident that its greatest strengths also present significant challenges. For example, while digital participation enables a broader audience to engage in the decision-making process, it also risks excluding marginalized groups due to technological barriers and digital inequalities.

Table 1: The corresponding advantages and disadvantages of digital participation.

Advantages	Disadvantages
Broad accessibility	Exclusion of marginalized groups
Data-driven decision-making (incl. AI)	Data privacy and security concerns
Citizen-driven governance	Manipulation risks
Transparency in decision-making process	Pseudo-participation
Real-time feedback loop	Engagement fatigue

Table 1 presents a structured overview of the advantages of digital participation and their corresponding challenges. The analysis highlights that while digital participation offers substantial benefits, its effectiveness depends on addressing its limitations to realise the full potential of digital participation.

2.2 Generative AI in Participatory Urban Design

This section presents the technological background, beginning with a review of existing tools discussed in the literature, followed by an exploration of GenAI techniques, especially Large Language Models (LLMs). Sections 2.2.3 and 2.2.4 explore two key challenges associated with the application of LLMs in the context of urban design: limited spatial awareness and the necessity of a structured prompting framework.

2.2.1 Existing Tools for Digital Participatory Design

Numerous digital participation solutions have been proposed in the literature. This section provides an overview of the most relevant existing tools and techniques, highlighting their strengths and limitations.

Participation platforms such as Go Vocal, Bpart, and Consul provide integrated digital environments that enable multiple forms of engagement. These platforms offer functionalities including project status updates, surveys, voting and prioritizing tools, document feedback, budgeting exercises, and discussion forums (Bpart, 2025; Consul, 2025; GoVocal, 2025). Digital platforms significantly increase citizen participation by removing physical and logistical

barriers to engagement. The large-scale participation enabled by digital tools allows for a more inclusive democratic process, reaching marginalized groups who may not traditionally engage in face-to-face deliberations (Arana-Catania et al., 2021a). However, there is a risk that high engagement leads to information overload, making it difficult for both citizens and officials to process the vast amount of input (Davies & Procter, 2020a).

Figure 5: The User Interface of the PublicTwin participation platform presenting an example project. (Public Twin, 2025a)

An example of the innovative approach to digital participation is the PublicTwin platform. This online platform (Figure 5) allows users to explore new area and project developments in a digital environment. However, at this stage, real-time modifications within the model are not yet possible. According to the developers, this functionality would be a valuable addition to further enhance the interactive capabilities of the platform (Public Twin, 2025a). This also highlights the need for a technology that enables real-time modifications, such as a text-to-3D tool.

The UrbanistAI tool serves as a prime example of how AI-driven technologies can transform the participatory design process (UrbanistAI, 2025). It allows users to input textual prompts or drop elements and translate them into 2D urban design images (Figure 6). The tool turns passive observers into active participants and is used in cities all over the world. The *text-to-image* method highlights the challenge that non-expert users must intuitively engage with the tool without extensive training. The first main challenge with the Diffusion Model used in this tool is to accommodate the planning standards. Because the AI generates images through Stable Diffusion, no urban planning rules can be given to the model (Hovi, 2023). The second challenge is that Stable Diffusion offer high-quality visual output but limit user control over the design (Lu et al., 2024a).

Figure 6: An example of the text-to-image methodology applied in the UrbanistAI participation tool. (UrbanistAI, 2025a)

The literature identifies several other GenAI tools used within participatory processes. These tools can be categorized according to their functionality: drag & drop interfaces, text-to-image methods, and text-to-3D applications. Appendix 1 contains a detailed analysis of each tool, including their advantages and disadvantages. This section provides the most important findings in relation to the development of a text-to-3D participatory design tool.

1. Textual input has proven to be an accessible and intuitive method for non-expert users. However, the effectiveness depends on the quality and structure of the prompts (Kapsalis, 2024a), which was also reflected by the study of Marshall et al. (2024), highlighting that participants require structured guidance when using design tools.
2. Tools should move beyond just placement of components. They must enable participant to configure the underlying spatial layout. Additionally, 3D modeling supports spatial understanding an introduces a fun factor that can increase user engagement (Hu et al., 2015a).
3. Computational power is a recurring limitation in many GenAI tools (J. Zhuang et al., 2024a).
4. The use of digital tools is most effective when combined with physical workshops (hybrid approach) (Marshall et al., 2024a).
5. Information overload remains a risk. A short user path and a simplified UI are essential to maintain usability (Özden et al., 2025).

These findings are essential for maintaining a high level of user engagement. Therefore, the findings must be translated into the tool's design requirements to ensure the development of an effective and user-centered participation method.

2.2.2 Large Language Models in Participatory Urban Design

Four different GenAI techniques can be distinguished from the literature: Latent Diffusion Models (LDM), Neural Radiance Fields (NeRF), Large Language Models (LLMs), and Retrieval-Augmented Generation (RAG). The analysis of LDMs and NerFs are included in Appendix 2. The analysis demonstrates that these techniques are not appropriate for establishing a direct feedback loop with participants. Both methods are computationally intensive, which limits their ability to support the interactivity necessary for iterative design processes.

The use of LLMs a GenAI technique is a promising solution for text-to-3D applications in the participatory process. LLMs are advanced AI systems trained on vast amounts of text data to understand, generate, and manipulate natural language. In the context of text-to-3D generation, LLMs serve as the intermediate between human input (text) and 3D model generation (W. X. Zhao et al., 2024). The study of Yang et al. (2024) uses an LLM to generate indoor environments from textual input. The LLplace tool presents that a direct feedback loop is possible, allowing users to add or remove objects without needing extensive computational resources (Y. Yang et al., 2024).

LLMs can also be used in the context of text-to-3D to generate scripts that control 3D modeling in Blender (Sun et al., 2023). The study of Sun et al. (2023) uses the open-source API of OpenAI

which can be integrated into several 3D modeling software applications. The system extracts procedural parameters from enriched text to effortlessly interface with 3D software. Also, the study of Shang et al. (2024) developed an LLM-based tool that translates textual descriptions into structured 3D parameters used for urban modeling. This enables the possibility of incorporating text-to-3D generation in a parametric tool such as Grasshopper. Grasshopper allows users to create models that can be easily adjusted by modifying parameters in real time. Open-source LLMs such as the OpenAI GPT can be integrated by the programming nodes using Python or C#.

Additionally, the study by Rietschel et al. (2024) further illustrates the potential of LLMs in computational design workflows (Rietschel et al., 2024). Their prototype system enables users to generate complete parametric scripts in Grasshopper from natural language prompts by leveraging a multi-agent LLM architecture. This system interprets high-level user intent, translates it into a chain of geometric operations, and maps these operations directly onto the Grasshopper canvas via JSON-based scripting. The study demonstrates how LLMs can serve as mediators between human intuition and algorithmic logic.

There are three limitations associated with the use of LLMs: computational limitations, lack of spatial awareness, and limited creativity. Computational limitations make it challenging to achieve real time translation of text inputs into 3D outputs (K. Zhao & Larsen, 2024). Computational limitations can disrupt the interactive nature that is critical to stimulating participant engagement. For this study, it is important to consider that if the generation time exceeds 10 seconds, users' attention may be disrupted, potentially leading to frustration and reduced engagement. Maintaining a response time within this threshold is therefore essential to ensure a smooth and interactive user experience (Nielson, 1994). Furthermore, LLMs have poor spatial awareness. They lack an understanding of three-dimensional spaces (G. Zhang et al., 2024). However, this is essential for generating urban design proposals that align with real-world spatial constraints. As described in the paragraph above, integrating an LLM into urban modeling software, including spatial constraints imparted to the model is a solution to the poor spatial awareness of an LLM. Lastly, LLMs have limited creativity due to the lack of human consciousness. Their creativity is restricted by their data-driven nature. Therefore, LLMs may struggle to generate outputs that align with user intentions (Franceschelli & Musolesi, 2024). Study presents that, especially in the built environment, the challenge is to find the right balance between automation of the system and human creativity to allow non-expert users to meaningfully contribute to the design processes (Bono, 2024). The question is whether the platform should encourage creativity or whether it would be better already provided by existing methods.

However, with the advantages of enabling real time feedback loops and the integration with existing modeling tools such as Rhino+Grasshopper, LLMs can be highly suitable for application in participatory urban design. Accordingly, the three main challenges: computational limitations, spatial awareness, and limited creativity must be considered. This is further elaborated upon in the technological description of the text-to-3D tool developed for this study, described in Section 3.1.

Additionally, Retrieval-Augmented Generation (RAG) offers a promising solution by combining the strengths of LLMs with real-time access to external knowledge sources (Wang, 2025).

Appendix 2 contains a literature review on RAG. Implementing RAG in the context of text-to-3D generation for participatory urban design has several advantages: (1) improving topic specialization, (2) enabling access to real-time information, (3) reducing hallucinations, and (4) supporting retrieval from diverse data sources (Campo et al., 2025; Wang, 2025). However, the literature review in Appendix 2 also mentioned some disadvantages: (1) reduced accuracy with complex data, (2) dependence on high-quality, structured knowledge base, (3) underperformance in creativity, (4) limited output transparency, and (5) high demands for dataset curation (Campo et al., 2025; Wang, 2025; Zhu et al., 2024). The advantages of RAG demonstrates that the GenAI technique holds potential for future applications in participatory urban design tools. However, because of the implementation complexity, the development and integration of a fully functioning RAG system lies beyond the scope of this study. This is further addressed in Section 2.5.1 at Requirement 1.15.

2.2.3 Solution Spatial Awareness of LLMs

Spatial awareness is one of the three key limitations in applying LLMs within the context of urban design. In the context of this study, it is considered the most critical of these three challenges because the generated design must be spatially feasible. Therefore, the spatial limitation requires the most urgent attention in identifying an effective solution. Various spatial strategy approaches have been proposed to enable LLMs to work effectively with the arrangement, relationships, and structure of elements within a physical design space. This section outlines the most relevant methods for incorporating spatial logic into text-based generative systems.

1. Coordinate System

One of the most fundamental approaches to introducing spatial structure into LLMs is the implementation of a coordinate system (Tehenan et al., 2025). This method involves instructing the LLM to output structured data formats, such as JSON, that define the positions of objects using x, y, and z coordinates. By doing so, the model's textual output can be directly interpreted by 3D modeling environments like Grasshopper. This method is also proposed by the study of Mikami et al. (2024) which presents that LLMs can interpret natural language instructions and generate precise coordinate-level commands for robotic control tasks (Mikami et al., 2024). However, while LLMs can capture certain spatial aspects, their reasoning is often limited without additional contextual information (Yamada et al., 2023). Coordinates lack contextual awareness unless accompanied by semantic rules or spatial hierarchies, which means the tool may still require a spatial logic layer beyond raw XYZ positioning. Furthermore, LLMs do not inherently understand spatial relationships such as adjacency, hierarchy, or enclosure (Yamada et al., 2023). As such, they may place objects in implausible or unintended configurations without additional constraints.

2. Grid System

An alternative spatial strategy is the implementation of a grid system. A grid system introduces spatial structure through a predefined layout, dividing the design area into discrete cells. Each cell can serve as a potential location for placing an object. The grid structure helps decompose complex scenes into manageable spatial segments (J. Yang et al., 2021). The grid can incorporate rules about adjacency, spacing, and alignment. However, the discretized nature of grids may limit the expressive detail of the generated design.

3. Space Syntax

A more advanced spatial strategy for structuring layout logic in a text-to-3D system is the space syntax methodology, which is a spatial framework that models urban form as a network of spatial relationships (Mohamed & van der Laag Yamu, 2024). In computational context, space syntax can be implemented using a topology graph, where spatial elements are nodes, and spatial relationships are edges. This structure allows the LLM to process spatial logic. However, limitations involve the complexity of accurately translating natural language into graph-based representations (Xie & Ding, 2023).

In conclusion, three primary strategies have been identified to address the limited spatial awareness of LLMs in the context of generative urban design: the coordinate system, the grid system, and the space syntax approach. These methods range in complexity from relatively simple implementation (coordinate system) to more advanced spatial reasoning capabilities (space syntax). In Section 3.1, a justified selection will be made regarding which spatial design strategy is adopted for the development of the text-to-3D tool.

2.2.4 LLM Prompt Structure in Participatory Urban Design

Especially for participation purposes, effective prompt design plays a crucial role in text-to-3D generation using LLMs. Textual prompts serve as the communication bridge between users and machine learning algorithms. The clarity of these prompts significantly influences the accuracy of the generated urban models (X. Zhang & Liu, 2024). The four key challenges are: prompts outside data scope, multi-indicator prompts, vague prompts, and managing scale and complexity.

1. Prompts outside Data Scope

Participants may request elements that do not exist in the LLM's dataset, such as 'create a self-sufficient floating neighborhood with zero carbon footprint'. Without mechanisms to detect such requests, AI models may generate irrelevant outputs. Research suggests that fallback behavior is inherent to LLMs (Ivgi et al., 2024). Fallback behavior is a mechanism designed to maintain continuous relevant service when a model fails to respond or encounters an error. Understanding this limitation is crucial for improving the LLM interaction. This means that out-of-distribution prompts are very important to detect (J. Yang et al., 2021). In this case, alternatives that are within the LLM data scope must be suggested by the LLM. So, a fallback mechanism must be implemented where the LLM requests additional user input or provides approximate alternatives.

2. Multi-Indicator Prompts

Participants may combine multiple or even contradictory objectives in a single prompt, such as 'design a high-density area with lots of open space.' Handling such requests requires the LLM to balance competing priorities effectively. Research by Cheng et al. (2023) introduces a framework that decomposes the generation process into a series of local editing steps to refine complex 3D content. This method can handle prompts that describe multiple interacting objects with different attributes (Cheng et al., 2023). Another promising solution is a constraint-based design where users can prioritize design factors. A suggested approach within constraint-based design is to present three main characteristics of the responses and allow users to rate which indicator they prefer over others (J. Yang et al., 2021). In this way, the LLM gets an understanding of user priorities.

3. Vague Prompts

Non-expert participants often use vague or inconsistent terminology. For example, 'create a lively neighborhood' lacks specificity in defining open space layout and infrastructure elements. Also connecting words (e.g. 'painted in the style of') has minimal impact on result quality. Instead, clear and descriptive subject keywords improve LLM effectiveness (Liu & Chilton, 2021). Even though LLMs such as GPT-4 can transfer vague inputs to concrete outputs, a certain structure must be given to the textual prompts (Y. Yang et al., 2023a). A structured prompt template allows users to refine their ideas step by step. For example, this can be done by interactive questioning (e.g. What type of greenery? Trees, parks, or green roofs?').

4. Managing Scale and Level of Detail

The fourth key challenge of handling prompts for urban design generation is that some prompts may be very general (e.g. 'Design a sustainable city'), while others may be overly detailed (e.g. 'Add a bike lane next to the third row of trees.'). LLM models struggle to balance macro and micro-elements. Therefore, implementing a multi-stage generation pipeline enables a progressively refined urban layout (Y. Yang et al., 2023b). By transitioning from a broad concept to specific details, the model maintains coherence across different scales of urban design. This approach is also reflected in the study of Shang et al. (2024), where urban layouts are generated from a general to a detailed context. This structured process presents how AI models can manage both high-level urban planning concepts and detailed design elements through progressive refinement (Shang et al., 2024).

The four key challenges highlight the necessity of a structured prompting approach. Without proper guidance, participants may struggle to provide meaningful input which directly impacts the LLM output.

2.2.5 Conclusion on Generative AI in Participatory Urban Design

From Section 2.2, it can be concluded that integrating a LLM, such as a GPT-based system, into 3D modeling software is a suitable GenAI technique for the development of the participatory tool. This integration also creates opportunities to prepare the system for future implementation of RAG. The success of the text-to-3D application relies on three key aspects: overcoming computational limitations, refining user input structures, and improving spatial awareness. These form the core design requirements that the tool must address to function effectively within a participatory urban design context.

2.3 Stakeholder Mapping in Citizen Participation

Urban development projects involve a wide range of stakeholders, each with distinct and often conflicting interest and priorities. To effectively map the challenges within the citizen participation process, it is essential to gain a clear understanding of the involved stakeholders. This chapter identifies the key stakeholders, outlines their roles within the participation process, and highlights their primary objectives and challenges.

2.3.1 Key Stakeholders in Participation Processes

Urban development involves multiple interests, and participation extends beyond citizens alone (Abd Elrahman & Asaad, 2019a). Table 2 presents the findings of four different studies on stakeholder management in citizen participation (Erfjord, 2016a; Lindenau & Böhler-Baedeker, 2014a; Martinez-Avila & Olander, 2024a; T. Zhuang et al., 2019a). The distinction

between public, private, and community interests is evident. According to Ju et al. (2021), the key stakeholders in citizen participation are therefore: government, developers, and citizens (Ju et al., 2021). These three stakeholder groups are therefore also considered the key stakeholders in the participation process for this study.

Table 2: The key stakeholders (grouped by public, private, and community) in participation processes identified by four academic studies.

Interest	*(Martinez-Avila & Olander, 2024b)*	*(T. Zhuang et al., 2019b)*	*(Erfjord, 2016b)*	*(Lindenau & Böhler-Baedeker, 2014b)*
Public	Municipality	Municipality	Municipality	Municipality
	Politicians		Politicians	
Private	Developer	Developer	Developer	Developer
	Property owners	Consulting parties	Consulting parties	
	Financial institutions	Financial institutions		
Community	General public	General public	General public	General public
	Local communities	Affected residents	Local communities	Local communities
		Local communities		

2.3.2 Key Stakeholder Positions and Objectives

Just as there is no standardized participation method, each participation process may vary depending on the initiating party. This section outlines the most common stakeholder positions and their main concerns.

1. Municipality

Municipalities can adopt three distinct roles in the participation process (Overheid, 2024):

1. *Framework-setting*

   Defining the guidelines and conditions for the participation process.
2. *Supervisory*

   Ensuring that the participation process complies with the established framework.
3. *General public representative*

   Advising on the involvement of stakeholders and/or shaping the process based on knowledge of the local context.

According to Jäntti et al. (2021) the main objectives of municipalities in participation processes is to promote: local democracy, inclusivity, and transparency. Effective participation can reduce political dissatisfaction and prevent conflicts arising from top-down decision-making. One of the core challenges for municipalities is ensuring that all citizens have an equal opportunity to participate (Jäntti & Kurkela, 2021a).

Furthermore, the municipality oversees the formal process of granting permits and evaluates applications. The municipality examines who was involved in the plan, how participation was conducted, and how stakeholder input was incorporated (Overheid, 2024). The outcome of the participation process does not be decisive in municipal decision-making, as the municipality balances the initiator's interests against the broader public interest. In this role, the municipality acts as a mediator between developers and citizens (Mirzaei & Hemati, 2023).

2. Developer

As private entities, developers play a key role in the participation process. With the introduction of the Dutch Environmental Act, the responsibility for organizing participation is increasingly shifting to developers (Verheul et al., 2021). The main objectives of developers are (Kang & Homsy, 2020):

1. Maximizing profitability
2. Minimizing costs and delays
3. Ensuring project approval

In addition to these key objectives, enhancing the marketability and social acceptance of a project is also an important goal for developers. This is often achieved by involving the general public in the design process. As a result, developers frequently take the initiative in organizing participation processes. The main reasons for a developer to take the lead in a participation process are (Verheul et al., 2021):

1. Meeting public frameworks and creating political support
2. Reducing delays and costly legal challenges
3. Gaining market insights and improving plans
4. Improving developer and project reputation
5. Connecting with ambassadors and co-creators

These objectives indicates that the profit-driven approach of developers often conflicts with the objectives of municipalities and participants. As a result, the success of developer-led participation depends on two key factors: the presence of clear municipal guidelines and the willingness of developers to invest in meaningful participation.

3. Citizen

In the context of participatory urban planning and design, citizens refer to individuals and groups who actively engage in planning and design processes by expressing their values, preferences, and concerns (Herzog et al., 2022b). As end users of the built environment, citizens are directly impacted by urban decisions. Therefore, they often engage in participatory processes because they feel connected to their neighborhoods and want to shape them (OECD, 2022b). As a result, their role in participation is essential to ensure that urban development aligns with societal needs. Although citizens participate for various reasons, the primary objective is to have their voices heard and influence decision-making. Citizens aim to ensure that their perspectives are acknowledged and considered (Källström et al., 2021).

It can be concluded that the objectives for participation are relatively consistent from the citizen's perspective, to influence decision-making. However, urban development often involves conflicting priorities among citizens. The study of Herzog et al. (2022) identifies several common types of conflicts between citizens:

1. *Development conflict (equity vs environment)*
   Balancing the need for affordable housing with the preservation of green spaces.
2. *Gentrification conflict (livability vs equity)*
   Addressing rising housing costs while ensuring that local communities remain socially inclusive.
3. *Growth management conflict (economic development vs livability)*
   Promoting business and economic growth without compromising residential quality of life.
4. *Mobility conflict (safety vs accessibility)*
   Enhancing pedestrian-friendly environments while maintaining access for vehicles.

These conflicts highlight the complex role of urban planners, who must integrate competing interests and develop solutions that satisfy as many citizens as possible. To define the position of citizens in the participation process, Arnstein's Ladder has already been introduced. The extent to which citizens influence decision-making depends on their position on Arnstein's Ladder. This position is largely determined by the choice of participation strategy, which is often established by the initiator of the process. As a result, the extent to which citizens can influence decision-making is predominantly shaped by those leading the participatory initiative. However, in some cases, citizens themselves act as initiators of participatory projects. These are usually smaller, community-driven initiatives where plans originate from local residents rather than external stakeholders (De Zeeuw, 2023).

In the context of developing a text-to-3D participatory design tool, this analysis demonstrates that the tool must operate within the boundaries of established urban planning and design frameworks, while still providing sufficient flexibility to accommodate citizen decision-making. Designs generated by participants must therefore continuously balance the often conflicting public and private objectives of municipalities, developers, and the citizens themselves. This balance is essential to ensure that the tool produces outcomes that are both technically and legally feasible within regulatory constraints and representative of community values and priorities.

2.3.3 Key Stakeholder Barriers to Effective Participation

In this section, the challenges associated with current participation processes are identified and categorized according to the key stakeholders. Furthermore, a distinction is made between challenges related to the participation process and those specific to design tools, such as the text-to-3D tool examined in this study.

The text-to-3D participatory design tool utilizes GenAI as a core component of its planning and design functionality. AI-driven design tools introduce a range of risks that are considered independently of any stakeholder group. While AI technologies offer promising capabilities for participatory urban design, they introduce several significant risks:

1. *Algorithmic bias*

   AI-driven participation tools may introduce biases, influencing decision-making in unintended ways (Sanchez et al., 2024).
2. *Lack of transparency ('black box')*

   Many AI models function as "black boxes", making it difficult for urban planners and the public to understand how decisions are made. This lack of explainability undermines trust and raises concerns about unjustified decision-making (Tong & Li, 2024).
3. *Data availability*

   AI-based tools require substantial amounts of data, which may not always be accessible or complete (Amnuaylojaroen, 2025).
4. *Underrepresentation*

   Certain communities may be misrepresented or excluded due to the algorithm bias and data availability problem (Acolin & Kim, 2024).
5. *Data security and privacy risks*

   Poorly regulated AI systems may expose personal and community data to security breaches (X. Ye et al., 2025).

These five factors can affect the effectiveness and acceptance of AI-drive participatory tools. Addressing these challenges is therefore essential to ensure that the digital participation tools are transparent and inclusive.

In the following sections, the challenges faced by developers, municipalities, and citizens are examined. These challenges are systematically divided into two categories: general challenges related to participation processes and those specifically associated with digital participatory design.

2.3.3.1 Developer Challenges related to Participation Processes

As initiators, developers have significant control over which participation methods are used and the position on Arnstein's Ladder of Participation. This means that the level of engagement and influence given to citizens is largely determined by developers themselves. As a result, many urban projects only meet the basic legal standards for consultation, without creating meaningful dialogue (Erfjord, 2016b). This is partly due to the flexible nature of the participation process as defined by the Dutch Environmental Act. Although the Dutch Environmental Act aims to strengthen participation requirements, uncertainty regarding its implementation may lead to inconsistencies.

Another significant challenge is that some developers continue to rely on traditional expert-led decision-making models. These models exclude citizens from the decision-making process. One of the underlying causes is the lack of structured methods for translating citizen input into actionable policies and design proposals (Herzog et al., 2022a). Without clear frameworks, participation remains a symbolic exercise rather than a meaningful process. This highlights the need for a GenAI tool that provides a structured method to translate participant ideas into design proposals.

The lack of resources – in terms of time, funding, and personnel – poses a particular challenge for small-scale projects (Martinez-Avila & Olander, 2024b). As a result, citizen participation is often minimally implemented or entirely absent. Developers, face cost-benefit uncertainties, which discourage them from investing in high-quality participatory processes. This underscores the difficulty of balancing economic interests with the social concerns raised by local communities (Abd Elrahman & Asaad, 2019b).

From the perspective of developers, citizen participation is not always perceived as a positive addition to urban planning and design processes. The study of Jäntti et al. (2021) indicates that participation can introduce negative implication for decision-making, including: increased costs, extended project timelines, and conflicts between planners and participants. Additionally, higher levels of public participation have been found to increase the likelihood of developers issuing threats to relocate or cancel projects in response to opposition (Jäntti & Kurkela, 2021a). Participation can sometimes stimulate negative sentiment among citizens who might not have otherwise been involved. Developers often perceive participation as a risk rather than an opportunity. Particularly when it introduces uncertainty, delays, or additional costs into the approval process (Kang & Homsy, 2020). This contrasts with the study of Turyasingura et al. (2023) which indicates that active stakeholder involvement enhance the overall success rate of urban projects.

Another challenge is the lack of transparency in developer-led participation processes. Developers often fail to present all relevant project details, which undermines trust in the participation process (Kang & Homsy, 2020). Additionally, developers should provide feedback to participants on how their input has influenced decisions, a step that is often insufficiently implemented in the current process (OECD, 2022b).

In conclusion, the participation process challenges related to the developer are: (1) control over participation level, (2) uncertainty in regulations, (3) reliance on expert-led models, (4) resource constraints, (5) cost-benefit concerns, (6) perceived risks of participation, (7) lack of transparency, and (8) value conflict. The analysis reveals that the profit-driven nature of developers often conflicts with the inclusive and democratic objectives of citizen participation. This misalignment creates tensions between developers, municipalities, and citizens.

2.3.3.2 Developer Challenges related to Digital Participatory Design

Developers face several challenges related to digital participatory design. One of the most significant challenges for developers is the ability to process and translate large volumes of raw participatory data into meaningful insights (Davies et al., 2021). According to Arslan et al. (2023), decision-makers often lack the capacity to manually review vast amounts of stakeholder input, making it crucial to develop structured methods for analysing the input.

Another challenge is that implementing advanced participatory tools requires significant technical expertise and resources. Developers often lack the time, funding or personnel to deploy and maintain these tools effectively (Chassin et al., 2019a), and digital participation tools frequently require high initial investments (Jäntti & Kurkela, 2021b). These resource constraints hinder the adoption of advanced participatory design tools within the process.

Moreover, developers often struggle to integrate digital participatory tools with existing urban planning and design software, such as BIM or GIS. The lack of interoperability further complicates the adoption of digital participation methods (Barrile et al., 2024). This highlight the need for a 3D modeling based software solution which can be seamlessly integrated in the current workflow.

In conclusion, the digital participatory design challenges related to the developer are: (1) data processing limitations, (2) lack of technical expertise and resources, (3) high implementation costs, and (4) poor interoperability with existing planning and design software.

2.3.3.3 Municipality Challenges related to Participation Processes

As concluded in Section 2.3.2, governments must ensure transparency and regulatory oversight in participatory processes. However, in practice, municipalities often struggle to balance inclusivity with decision-making efficiency (Jäntti & Kurkela, 2021a).

Since the Dutch Environmental Act does not prescribe a uniform methodology for participation, each municipality has developed its own approach to structuring and evaluating participatory processes. This results in case-specific criteria, meaning that the structure and evaluation of participation can vary significantly depending on the project.

Similar to developers, municipalities face significant challenges related to resource availability. For participation to be effective, local governments must allocate sufficient resources, time, and clear mechanisms (Bobbio, 2019). However, municipalities often operate under tight budgets and limited personnel. These resource constraints make it difficult to conduct detailed analyses of participation outcomes. This issue is particularly relevant for advanced participation methods, which require specialized staff and funding (Kurkela et al., 2024a).

Furthermore, rigid municipal structures make it difficult to integrate advanced participation methods into the process (Kurkela et al., 2024b). The traditional bureaucratic workflows are often slow and resistant to external influence.

In conclusion, the participation process challenges related to the municipality are: (1) balancing inclusivity and efficiency, (2) lack of standardized participation frameworks, (3) resource constraints, and (4) rigid organizational structures.

2.3.3.4 Municipality Challenges related to Digital Participatory Design

Municipalities face many of the same digital participatory design challenges as developers. These challenges primarily relate to data processing, technical expertise, and resource constraints. In particular, municipalities struggle with challenges related to AI and data privacy. The integration of AI-driven tools raises concerns about balancing data-driven decision-making with protecting citizen privacy (Sanchez et al., 2024). Digital participatory tools often require the collection of large datasets, which presents ethical and legal risks that municipalities must carefully navigate.

2.3.3.5 Citizen Challenges related to Participation Processes

According to Jäntti et al. (2021), the challenges citizens face in participation can be categorized into three main groups: societal, personal, and instrumental-processual challenges. These

categories include various sub-challenges which are described below and are identified by the literature, and supported by semi-structured interviews conducted for this research.

Societal challenges
Citizens' willingness to participate is strongly influenced by trust in government institutions. Higher trust levels encourage engagement, while skepticism towards authorities discourages participation. If participation is merely symbolic, it may decrease trust in decision-making (Ataman et al., 2024).

Marginalized groups, such as low-income residents or migrants, often face barriers to participation due to rigid bureaucratic procedures. Those with stronger connections to influential actors, such as community leaders or NGOs, have better access to decision-making authorities. Marginalized citizens lack these networks, which limits their ability to influence urban planning and design (Alhassan, 2025).

Citizens often engage in participation with the expectation of shaping policies. However, some later realize that their influence is limited, as key decisions have already been made before public consultation. This perception discourages further engagement and is also known as tokenism, which refers to participation efforts that are symbolic rather than substantive (Källström et al., 2021). If citizens believe their participation will not lead to tangible changes, they are less likely to engage in decision-making (Källström et al., 2021). Overuse of consultations without real decision-making power discourages further participation. This 'consultation fatigue' occurs when citizens repeatedly provide input but see no tangible outcomes (Lindenau & Böhler-Baedeker, 2014a).

Personal challenges
Because of their perceived lack of competence and confidence, participants may find it challenging to actively engage in the participation process. A common challenge is that participants often struggle to articulate their ideas in a way that suggests concrete design proposals. Their inputs often remain vague or get lost in translation. This communication gap between participants and urban planners often results in outcomes that do not align with the wishes of the participants (R. Zhang et al., 2022). This presents a significant potential for digital participation tools.

According to the study by Jäntti et al. (2021), many residents perceive participation as time-consuming. It may be difficult to engage in participation processes alongside work, studies, family obligations, and other personal commitments.

Community attachment significantly influences a person's willingness to participate in local decision-making processes. A strong sense of belonging to a community encourages engagement, whereas feelings of detachment or rootlessness discourage participation (Jäntti & Kurkela, 2021b).

Instrumental-processual challenges

Current participation methods often rely on complex technical planning language, which makes it difficult for many citizens to engage meaningfully (Erfjord, 2016a). Figure 7 illustrates a participation meeting where maps and designs are presented for public feedback. However, the technical complexity of these drawings makes it difficult for participants to fully understand and assess them. To increase accessibility, initiators should offer a variety of participation methods (eg. town hall meetings, online consultations, social media, et cetera) (OECD, 2022b). Existing methods lack a system to provide continuous feedback to participants. Participants often must wait a certain time for new urban proposals. Accelerating this feedback loop would increase transparency and satisfaction in the participatory process (Tian et al., 2023).

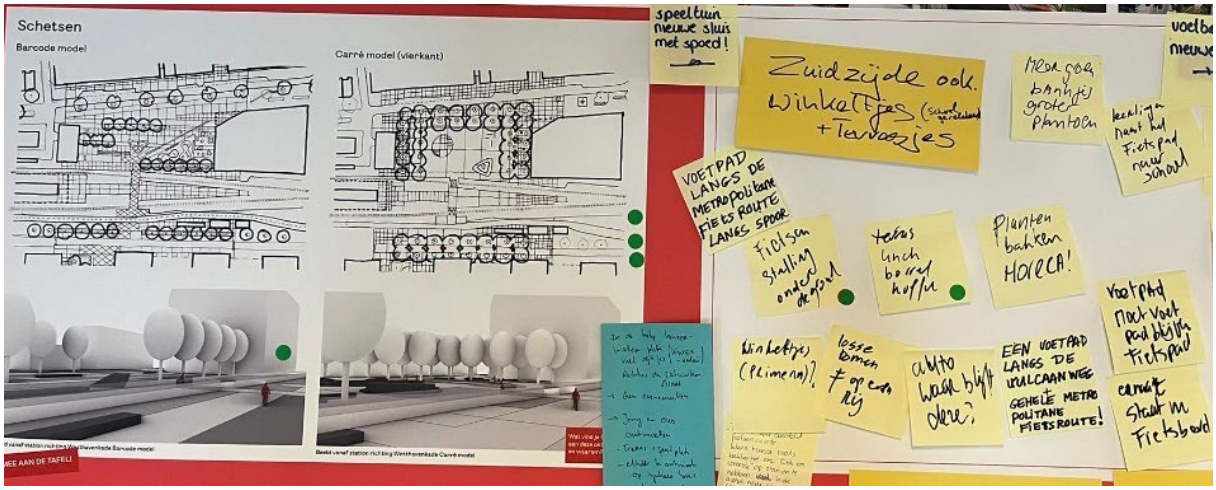


Figure 7: Feedback board from the participation meeting for the Rivierzone redevelopment area, organized by the Municipality of Vlaardingen in February 2025 (source: author's photograph).

In conclusion, the participation process challenges related to citizens include: (1) low trust and tokenism, (2) exclusion of marginalized groups, (3) limited influence and consultation fatigue, (4) perceived lack of competence and articulation skills, (5) time constraints and competing obligations, (6) weak community attachment, (7) complex technical language, and (8) lack of timely feedback mechanisms. These challenges highlight the multitude of factors that can contribute to challenges in citizen participation. While these aspects do not necessarily arise in every case, literature identifies these societal, personal, and instrumental-processual factors as the most significant challenges to consider when designing participatory processes.

2.3.3.6 Citizens Challenges related to Digital Participatory Design

Several planning and design support tools have been developed to facilitate citizen participation, but they are often not user-friendly for non-experts. They require technical skills and knowledge that many participants lack. As a result, participation is limited to a small subset of the community rather than engaging a diverse audience (Mariani et al., 2025b). Furthermore, participants' rates are highly influenced by the usability threshold of these tools. Complex interfaces and excessive navigation steps discourage engagement, which creates a barrier to broader community involvement (Thoneick, 2021). As a result, certain groups (e.g. marginalized communities) may be underrepresented in digital platforms (Herzog et al., 2022b).

While digital tools democratize participation, citizens may distrust automated decision-making if it is perceived as opaque. Transparency in how GenAI tools process, categorize, and prioritize user input is essential to maintain public trust (Davies & Procter, 2020b). Therefore, urban planners must clearly communicate how citizen contributions influence design outcomes. Explanation of design logic can also be incorporated into the tool beforehand. Moreover, users must trust that AI-generated summaries and design recommendations are unbiased and neutral (Arana-Catania et al., 2021b). Establishing a clear, interactive dialogue within the tool can support this transparency.

Spatial perception varies among users. Therefore, different user groups (e.g. citizens, experts, decision-makers) require different navigation and interaction methods (Chassin et al., 2019a). Navigating through a 3D environment can cause disorientation. Including landmarks in the model is helpful, since landmarks act as cognitive anchors that improve orientation in both physical and virtual environments (Yesiltepe et al., 2019).

Traditional participatory design processes rely on face-to-face trust-building and informal interactions, which are difficult to replicate in digital environments. Remote participation can create a sense of detachment, reducing participants' perceived ownership over the design outcomes (Ataman et al., 2024). Anonymous or text-based interactions can sometimes discourage engagement or reduce accountability in discussions (Slingerland et al., 2022).

From this analysis, it can be concluded that user engagement with digital participatory tools is shaped by four interrelated challenges: (1) tool complexity and interface design, (2) transparency in AI reasoning, (3) spatial orientation in 3D environments, and (4) the need for strong guidance in digital settings. These factors must carefully be considered during the development of the participatory tool.

2.4 Empirical Insights from Semi-Structured Interviews

Even though the literature review provided profound insights into stakeholders' perspectives and common practices in digital participation for urban planning and design, this study aimed to complement and reinforce those findings. Semi-structured interviews are a commonly employed method in diverse investigations, addressing topics such as the development of participatory guidelines to enhance citizen engagement (Correia et al., 2023), the exploration of governmental perspectives on public participation (Cao, 2022), and the evaluation of digital participation processes in urban planning and design (Ataman et al., 2025).

The focus of these interviews was to explore the interrelated challenges in digital participatory design from multiple viewpoints. An interview guide was meticulously prepared based on an extensive review of the literature, supplemented by discussions with field experts. These preliminary discussions were discussions were crucial for refining the questions and ensuring their relevance, focus, and effectiveness in eliciting responses aligned with the research objectives. The full list of questions used in the semi-structured interviews is provided in Appendix 3.

Seven semi-structured interviews with experts were conducted in 2025. Each interview lasted approximately 1 hour and was held in Dutch. The transcripts were then analyzed in relation to

the findings from the literature review. Additionally, the interview questions themselves were informed by the review already presented in this section.

Findings from the literature conclude that establishing a clear evaluation mechanism for the information collected during the participation process is essential. Semi-structured interviews with developers confirmed that a robust scoring method for evaluating participatory outputs is essential. However, there is a risk that these Key Performance Indicators (KPIs) are defined solely from the developer's perspective, rather than incorporating the interests of citizens.

Another challenges that is highlighted by the interviews with the developers is the expectation gap that arises when participants engage with digital design tools. Allowing stakeholders to create design proposals or modifications can lead to misconceptions that their contributions will directly influence the final design. The interviews with developers highlighted concerns that citizens may assume their proposed design will be implemented. To prevent this, it is essential to clearly communicate the purpose and scope of the participation tool. This is also confirmed in the literature, which notes that digital participation methods often fail to clarify how user input will influence final decisions, leading to misunderstandings and false expectations (Davies & Procter, 2020b).

From the municipal perspective, the literature highlights that rigid institutional structures hinder the integration of advanced participation methods into existing planning processes (Kurkela et al., 2024b). The traditional bureaucratic workflows are often slow and resistant to external influence, while participation processes require rapid response times to effectively incorporate citizen feedback, as highlighted in the semi-structured interview with the municipality.

Outcomes of the semi-structured interviews with two participation agencies provided insights into the challenges citizens face during participatory processes. Both interviews emphasized that the capabilities of participants are often overestimated, highlighting the need for short and simple user pathways to ensure intuitive use. In addition, the literature concludes that navigating within a 3D model can lead to disorientation among participants. Participants may struggle to interpret information presented at different scales within the same model, as reflected in the semi-structured interviews. Users become overwhelmed when all spatial information is presented simultaneously. The principle of progressive disclosure allows information to be revealed incrementally based on user interaction or zoom level. A strategy within this principle is to let users design the public area step-by-step or by thematic categories (e.g. mobility, greenery, facilities) (Ashmawy et al., 2022).

The semi-structured interview with the Dutch Environmental Act specialist highlights that, although participation under the Dutch Environmental Act is form-free, municipalities have the authority to require it and evaluate its quality during the permit procedure. This evaluation focuses on the extent to which different interests were considered and how input from citizens was processed. As a result, clear and verifiable documentation of the participation process is essential. Therefore, the tool must store all user input prompts and record how this input was incorporated, to ensure transparency and support municipal review.

In conclusion, the semi-structured interviews reinforced key challenges identified in the literature and provided practical insights into developer, municipal, and citizen perspectives. Together, they underscore the need for (1) clear communication, (2) intuitive tool design, and (3) structured evaluation mechanisms, including the ability to document and trace user input, to ensure meaningful digital participation.

2.5 List of Requirements for a Text-to-3D Participatory Design Tool

The following requirements are derived from the previously identified challenges in participatory urban design, based on insights from literature and semi-structured interviews with key stakeholders. This section translates those insights into concrete functional and non-functional requirements, which form the foundation for the development of the text-to-3D participatory design tool developed for this study. The requirements are categorized into functional and non-functional types. Functional requirements define what a tool should do, while non-functional requirements describe how its system should perform. Within each category, the requirements are prioritized using the MoSCoW method (Suchetha Vijayakumar et al., 2024). This is a prioritization technique that categorizes requirements into four groups: Must Have, Should Have, Could Have, and Won't Have (for now). All requirements listed in Table 3 and Table 4 specifically relate to the development and functionality of the text-to-3D tool.

2.5.1 Functional Requirements

In Table 3 the functional requirements for a text-to-3D participatory design tool are presented. The must-have requirements define the essential functionality of the tool, such as generating feasible 3D public space designs from natural language prompts using a GPT-based LLM, while ensuring thematic categorization (urban elements and greenery), design continuity across iterations, and spatial rule enforcement. The should-have requirements include functionalities like undo/redo capabilities, export in industry-standard formats (e.g., IFC), semantic component classification, and contextual site input. The could-have requirements propose additional features that would further enrich the participatory process, such as fallback responses to unsupported prompts, prompt documentation, and an explanation of design outputs by the LLM.

Table 3: Functional requirements for a text-to-3D participatory design tool, derived from literature and semi-structured interviews with key stakeholders, and categorized according to the MoSCoW prioritization method.

	ID	Requirement	Based on
Must Have	1.1	Translate user-inputted natural language prompts into corresponding 3D public space designs.	Section 2.3.3
	1.2	Enable users to design public space according to two thematic categories: urban elements and greenery.	Section 1.2
	1.3	Retain previously placed elements during design iterations, unless the user explicitly requests a reset or replacement.	Section 2.2.1
	1.4	Restrict placement of components that are feasible to implement in real-world public space contexts, based on predefined planning rules and constraints.	Section 2.3.3.2
	1.5	Use a GPT-based LLM for prompt interpretation.	Section 2.2.2

Table 3 (continued)

	ID	Requirement	Based on
Should Have	1.6	Allow participants to undo and redo design steps with at least 2 undo levels.	Section 2.4
	1.7	Support export of designs in IFC format for integration into existing planning and design software.	Section 2.3.3.2
	1.8	Include context-specific information about the site as input for the LLM.	Section 2.2.3
	1.9	Explain beforehand: design space, purpose, how the designs contribute to the decision-making process.	Section 2.4
	1.10	Use a semantic classification structure to categorize components, enabling easy addition of new elements and the assignment of spatial rules.	Section 2.2.2
Could Have	1.11	Detect and respond to out-of-distribution prompts by providing at least 1 fallback suggestion or clarification request.	Section 2.2.4
	1.12	Store all user input prompts for documentation purposes.	Section 2.4
	1.13	Explain the LLM's design choices in natural language using a maximum of 3 sentences.	Section 2.3.3.6
Won't Have	1.14	Ability to generate or edit routing.	Section 1.2
	1.15	Implementation of Retrieval-Augmented Generation (RAG).	Section 2.2.2
	1.16	Engage in conversational dialogue or back-and-forth questioning with users.	Section 2.2.4 & 2.4
	1.17	An integrated KPI-based evaluation model to assess the generated design outcomes.	Section 2.4

The "Won't Haves" describe requirements that, according to the literature, are desirable features for a text-to-3D participatory design tool. However, due to limited development time, these features were not included in the current version of the tool developed in this study, which is explained below.

1.14: Participants generally view the placement of pathways as secondary, focusing more on the quantity than the exact layout (Özden et al., 2025). Therefore, the tool development prioritized urban elements and greenery over routing.

1.15: The literature review on RAG in Section 2.2.2 concludes that RAG enhances LLMs by providing real-time access to external knowledge sources. However, it also highlights that RAG relies on well-structured, semantically tagged datasets. Given the scope of this study, it was therefore decided to use an LLM without RAG integration. As a result, the tool operates solely on the static knowledge embedded in the LLM, which may limit its ability to handle highly specialized or context-specific input during the participatory process. Nonetheless, the semantic classification structured, defined at Requirement 1.10 and Section 2.2.2, can serve as the foundation for constructing a searchable knowledge base.

1.16: Based on the literature in Section 2.2.4, a structured prompting approach is necessary due to four key challenges associated with LLM use: prompts outside the model's data scope,

multi-indicator prompts, vague prompts, and managing scale and level of detail. An interactive dialogue between the tool and the user can guide prompt formulation and help address these four issues (Y. Yang et al., 2023a). However, implementing such a dialogue requires additional design steps that fall outside the scope of this study due to limited development time. To mitigate these challenges as effectively as possible, participants were provided with example prompts on paper during the experiment (Requirement 2.6).

1.17: As concluded in Section 2.4, data processing of the participatory process outcomes is often ineffective. This challenge becomes particularly relevant in the context of a GenAI tool, where a large number of individual design proposals may be produced. In such cases, an integrated evaluation framework is essential to systematically asses participant input. However, the focus during tool development was placed on creating a Minimal Viable Product (MVP). As a result, no integrated KPI-based evaluation framework was implemented. This constitutes a limitation in evaluating the tool's impact on urban planners' decision-making processes.

2.5.2 Non-Functional Requirements

In Table 4 the non-functional requirements for a text-to-3D participatory design tool are presented. The must-have non-functional requirements define baseline performance and usability standards for the tool, including a maximum response time of 10 seconds for generating 3D outputs, a user-friendly interface enabling independent use, and compliance with the EU General Data Protection Regulation (GDPR). The should-have requirements further improve accessibility and inclusivity by supporting multiple device types and ensuring usability for non-experts without prior technical skills. The could-have requirements focus on enhancing usability and inclusivity, such as guided prompting examples, simplified visual language, and multiple viewing perspectives.

Table 4: Non-functional requirements for the text-to-3D participatory design tool, derived from literature and semi-structured interviews with key stakeholders, and categorized according to the MoSCoW prioritization method.

	ID	Requirement	Based on
Must Have	2.1	Ensure a maximum response time of 10 seconds for generating a 3D design output after user input.	Section 2.2.2
	2.2	The User Interface (UI) must be designed so that users can complete a design session without external assistance in under 10 minutes, using example prompts.	Section 2.3.3.6
	2.3	Comply with the EU General Data Protection Regulation (GDPR) by storing only anonymized design proposals and no personal user data.	Section 2.3.3
Should Have	2.4	Support accessibility and functionality on laptop and desktop computer.	Section 2.1.1
	2.5	Usable by non-expert participants without requiring prior technical knowledge or experience with 3D modeling, coding, or urban design tools.	Section 1.1 & 2.3.3.6
	2.6	Users must be guided by prompting examples (integrated in the UI or on paper).	Section 2.2.4 & 2.4

Table 4 (continued)

	ID	Requirement	Based on
Could Have	2.7	Include visual icons and simplified language to ensure usability for participants with low literacy levels.	Section 2.3.3.5
	2.8	The UI should allow users to view the generated design from both a bird's-eye perspective and a human-scale (street-level) perspective.	Section 2.1.1 & 2.3.3.6
	2.9	Support multilingual input and output, operating effectively in all commonly used languages relevant to the user base.	Section 2.3.3.5
Won't Have	2.10	Support scalability across multiple urban planning and design scales or stages.	Section 1.2 & 2.4

The "Won't Have" requirement 2.10 is, according to the literature, a desirable feature for a text-to-3D participatory design tool. As concluded in Section 1.2, digital participation tools often lack robustness across different urban planning and design scales and stages. However, given that the primary aim of this study is to investigate the effect of the text-to-3D approach within the participatory process, implementing Requirement 2.10 is not essential for answering the main research question. Therefore, Requirement 2.10 has been excluded from the scope of this study.

3. Methodology for the Design and Evaluation of a Text-to-3D Participatory Design Tool

As discussed in Section 1.4, this study adopts the Design Science methodology. The Design Science methodology framework is presented once more in Figure 8. The previous chapter (Chapter 0) outlined the application domain of this research, resulting in a list of requirements that forms the foundation for the next phase of the study. Figure 8 illustrates the research progress by highlighting the completed components in green. Chapter 3 describes the core of the Design Science methodology: the Design Cycle. Section 3.1 outlines the development of the text-to-3D participatory design tool. This tool was subsequently tested in a real-world case study, which is described in Section 3.1.3. The 'Evaluate' phase of the Design Cycle is addressed through the participatory experiment conducted as part of this research, described in Section 3.3. Together, the tool development and the participatory experiment enable an evaluation of the text-to-3D approach within participatory urban design processes.

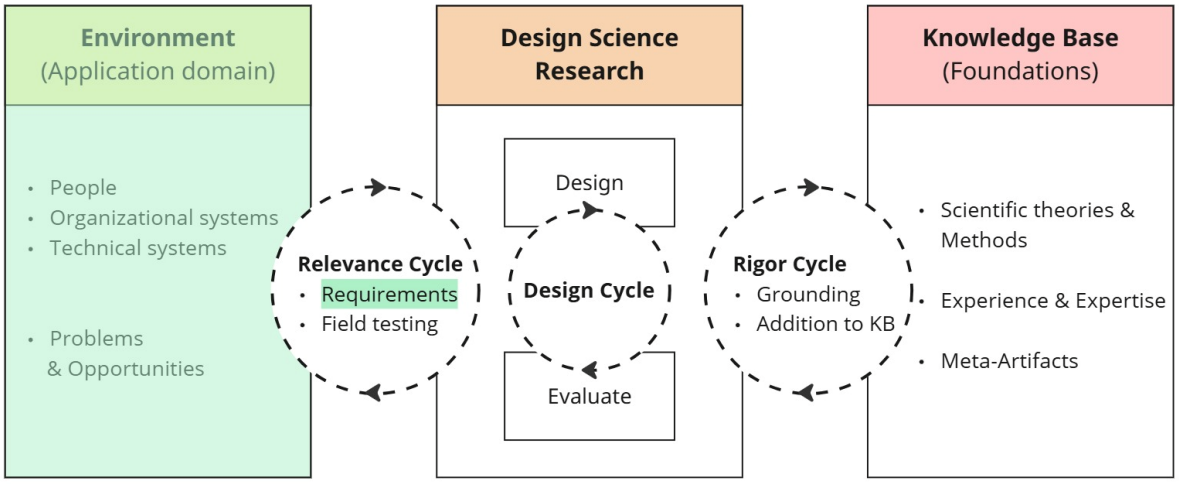


Figure 8: Design Science methodology framework including research progress highlighted in green. The central component 'Design Science Research' is described in Chapter 3.

3.1 Development of the Text-to-3D Participatory Design Tool

This section outlines the development of the text-to-3D participatory design tool through the description of the system architecture (Section 3.1.1) and the system flowchart (Section 3.1.2). The list of requirements described in Section 2.5 serves as the foundation for the development of the text-to-3D participatory design tool developed in this study. As a result, the tool development is grounded in the user needs of the three key stakeholder groups involved in the participatory process: developers, municipalities, and citizens. Section 3.1.3 validates the extent to which the developed text-to-3D participatory design tool meets the predefined requirements.

The list of requirements outlines the decision to integrate a LLM into a 3D modeling environment (Requirement 1.5 and 1.7). For the 3D environment, Rhino in combination with Grasshopper has been selected due to their suitability for 3D modeling, parametric design, and integration with AI components such as LLMs (Jiang et al., 2024). The Human UI plugin is used to make the tool accessible for non-expert users[1]. The GPT-4o mini model from OpenAI

[1] Webpage link: Human UI (*HumanUI*, 2019)

was chosen because this model was readily available by the researcher, and offers low latency and efficient performance suitable for real-time use (OpenAI et al., 2024). A detailed justification for the selection of Rhino+Grasshopper and the GPT-4o mini model is provided in Appendix 4.

In addition to the foundational decisions regarding software environment and LLM deployment, the development of the participatory design tool involves a series of strategic design choices. These decisions will cumulatively shape the system architecture and define the operational workflow of the tool. For each major design consideration, multiple solution pathways have been explored. The final implementation is based on a balanced trade-off between the predefined tool requirements and the integration complexity. This approach keeps the implementation feasible within the project's scope and available technical infrastructure.

One of the three key limitations of LLMs in the context of urban design is their limited spatial awareness. Therefore, an appropriate design decision must be made to address this. Section 2.2.3 presents an overview of three spatial strategies discussed in the literature to address this challenge: the coordinate system, the grid system, and the space syntax approach. While space syntax theoretically offers the most comprehensive potential, its full implementation involves considerable complexity and falls beyond the scope of this study. Moreover, the discretized nature of grids may limit the expressive detail of the generated design. LLMs are capable of effectively handling coordinate-based outputs. By implementing a coordinate system, an appropriate balance is achieved between enhancing the spatial awareness of the LLM and maintaining a manageable level of integration complexity. Therefore, a coordinate system was chosen as the primary spatial structure. However, it is crucial that the LLM receives the correct instructions and contextual information to ensure coherent spatial outcomes (Requirement 1.8 and 1.10). This is established by a prompt structure described in Section 3.1.1.

3.1.1 System Architecture of the Text-to-3D Participatory Design Tool

The system architecture describes the software components of the text-to-3D participatory design tool, which is illustrated in Figure 9. The system architecture is structured into three main components: the User Interface (UI) (yellow), LLM request (blue), and the Grasshopper script that enables component placement and spatial context (orange). To centralize development as much as possible, the LLM request component (blue) was also implemented within the Grasshopper environment, using integrated Python scripts. Having the LLM and parametric script in one environment avoids complexity and simplifies the workflow. The following sections outlines the three main components of the system architecture.

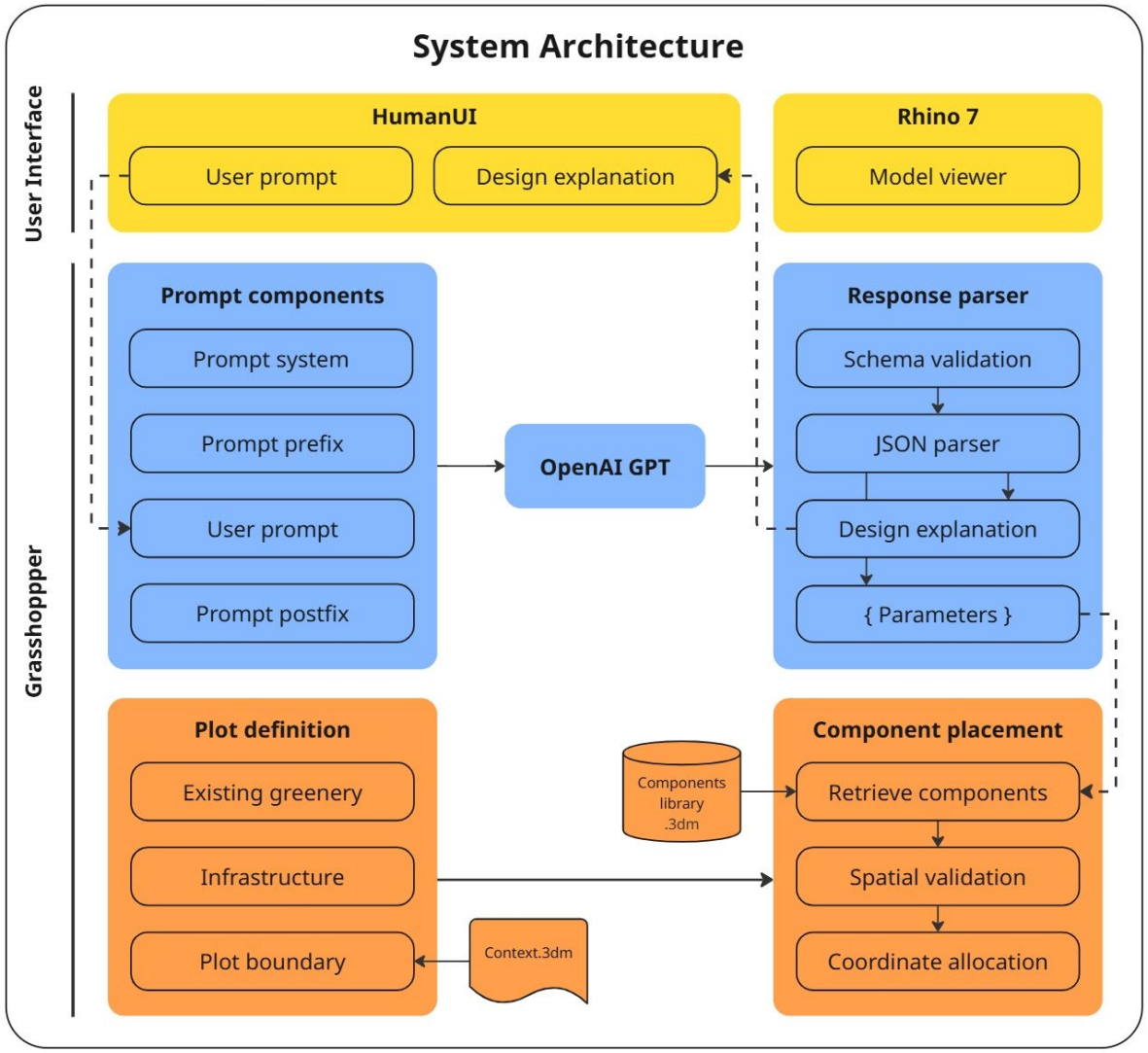


Figure 9: System Architecture of the text-to-3D participatory design tool including the three main components: User Interface, the GPT-based LLM of OpenAI, and the Grasshopper script.

1. User Interface

The UI is visualised in Figure 10. The separate window presents the components of the HumanUI plugin. This interface includes two key components: (1) A text input field, where users can enter and submit their prompts. (2) A response panel, which displays the design explanation given by the LLM. The structure of the explanation is further detailed in Section 3.1.1, describing the prompt postfix. Additionally, the model viewer presents a perspective of the generated 3D model, which is updated in real-time based on to the Grasshopper script. It allows users to rotate the model freely, enabling them to explore the design from various viewpoints.

Figure 10: User Interface of text-to-3D participation tool displayed in Rhino including the HumanUI window

2. Prompt Components

As concluded in Section 2.2.2, implementing a structured prompt framework enhances the performance of LLMs. The prompt framework established for the study consists of four components: (1) System prompt, (2) Prompt prefix, (3) User prompt, and (4) Prompt postfix. Academic literature supports this modular strategy: the system prompt defines global behavior, the prefix establishes shared context, the user prompt captures specific intent, and the postfix constrains the output format (Ouyang et al., 2022). The specific content of the system prompt, prompt prefix, and prompt postfix is attached in Appendix 5.

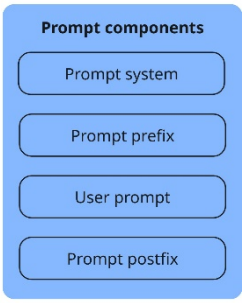


Figure 11: Snippet of System Architecture presenting the four prompt components.

1. The system prompt sets the foundational behavior and identity of the LLM. Here, the LLM's role and objectives are defined. This approach is supported by Morales et al. (2025), who emphasize the importance of a clear system prompt in guiding GenAI systems effectively (Morales et al., 2025). For example, the following role is given to the LLM:
   "You are an experienced urban designer specializing in public park design. Your task is to translate natural language input into a structured set of design parameters for a new public park in Vlaardingen."

2. A prompt prefix offers necessary context and instructions before the user's input. Incorporating a prefix improves instruction-following capabilities of LLMs (Ye et al., 2023). Therefore, three different instructions are given in the prompt prefix: (1) JSON schema, (2) plot boundary, and (3) plot context.
   The JSON schema defines the fixed response format that the LLM must follow. It outlines all possible design components and the parameters that the LLM is allowed to assign to each. The schema represents a semantic class structure that defines all physical elements included in the model, which was generated using a Python script based on the Pydantic module[2]. A snippet of this script is presented in Listing 1. By utilizing a class-based structure, the model becomes easily extensible for anyone able to write object-oriented code.

   Listing 1: Snippet of Pydantic class structure

```
class VegetableGarden(UrbanElement):
    type: Literal["vegetable_garden"] = "vegetable_garden"
    description: str = "A vegetable public garden where people can
grow their own food. Place in calm areas of the park with good
sunlight exposure."
    offset: float = 3
    name: str = "Vegetable garden"
```

   The plot boundary describes the geometric outline of the designated design site, in this case the Maaspark. The coordinates of the boundary polyline are passed to the model to provide spatial awareness of the park's size and shape.
   Lastly, the plot context is represented by coordinate points including specific functions or landmarks such as a residential building, river or access road. This information enables the LLM to incorporate site-specific conditions and orientation into its design logic. See also the example in Listing 2.

   Listing 2: Snippet of the plot context defined in JSON format

```
"name": "Parking lot near hotel & restaurant",
"location": [585, 840]
```

3. The user prompt is just the textual input of the participant, which is retrieved from the HumanUI window. An example is:
   "Place a playground near the Maas river and I want a horeca facility on a prominent location in the park."

4. Also, a prompt postfix is appended to each user query. The prompt postfix provides additional constraints that guide the LLM in its generative process. These rules were iteratively expanded during the development and testing phases to improve the accuracy of the LLM's design output. Primarily, these rules focus on the structure of the design explanation provided by the LLM to the user. Secondly, the postfix encodes spatial placement rules such as ensuring spatial variation and respecting functional proximity. Thirdly, change management logic is included to preserve continuity across iterative design sessions.

[2] Webpage link: Pydantic Module (Pydantic, 2025)

These four components are combined within the Grasshopper script and passed to the OpenAI GPT. Appendix 6 provides a description of the code used for this implementation. During the development of the tool, the content of the system prompt, as well as the prompt pre- and postfix, was progressively refined. Modifications to these prompts had a direct impact on the output generated by the LLM.

3. Grasshopper Script

The orange section of the system architecture represents the components of the parametric model used to generate the park layout. As the full Grasshopper script is too extensive to include in this report, Section 3.1.1 and 3.1.2 highlights its most essential elements. The elements under 'plot definition' are project-dependent but ultimately fixed within the model. As a result, participants can only place physical elements, including selected greenery, through the component placement logic. Infrastructure and existing greenery are predefined and non-editable within the model. This approach aligns with findings from the literature on participant design needs, which indicate that in public space design, infrastructure is generally considered secondary to the selection and positioning of spatial components (Özden et al., 2025). Consequently, it is not essential to provide functionality that allows participants to define the exact location of pathways. Moreover, existing green structures are often protected by law and cannot be altered, justifying their fixed status in the model. The BPMN diagram in Section 3.1.2 further elaborates on how components are placed in the model through the component placement logic in the Grasshopper script, and how communication takes place with the external .3dm file and database.

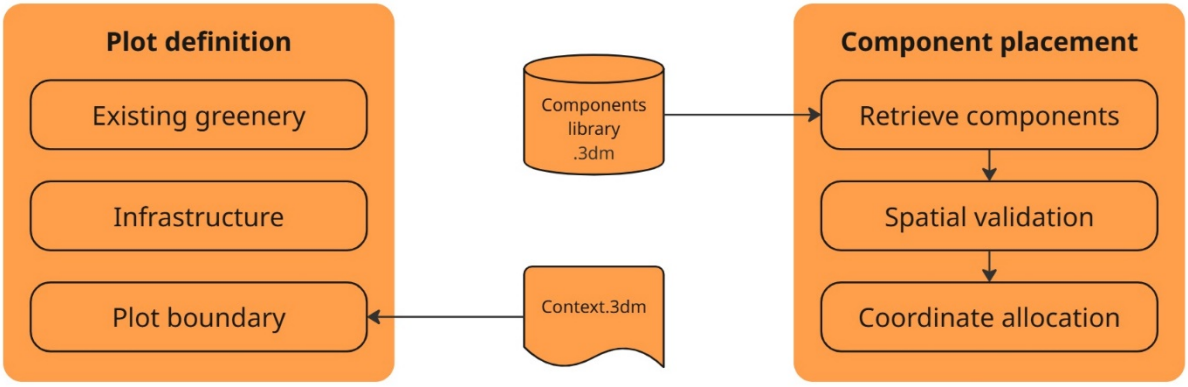


Figure 12: Snippet of the System Architecture illustrating the Grasshopper script used for real-time model visualization and spatial component placement.

3.1.2 BPMN Diagram of the Text-to-3D Participatory Design Tool

To clarify the data flow and logical operations occurring within the system architecture, a Business Process Model and Notation (BPMN) diagram has been developed. A BPMN diagram is a graphical representation that models business processes by depicting the sequence of activities, decision points, and data flow in a standardized manner (van der Aalst, 2009). Since the diagram is too large to be displayed in full within the main text, it is presented in parts across the following sections. The complete version of the BPMN diagram can be found in Appendix 7.

1. API Request

The process begins within the HumanUI interface, where the participant enters a natural language prompt. Subsequently, the user prompt, system prompt, prompt prefix, and postfix are combined and submitted to the OpenAI GPT via a secure HTTP request. To support iterative interaction, the script reads from a locally stored chat history file that stores previous design states. If the user refers to a "previous design," the system retrieves and uses it as the new base state. Conversely, if no such request is made, the current design is maintained and updated accordingly. The constructed prompt is then sent to the OpenAI GPT, which is externally accessed via Azure Cloud.

For more complex data structures, the JSON format was chosen. JSON (JavaScript Object Notation) is highly suitable for this application, as it is both human-readable and easily interpretable by the LLM.

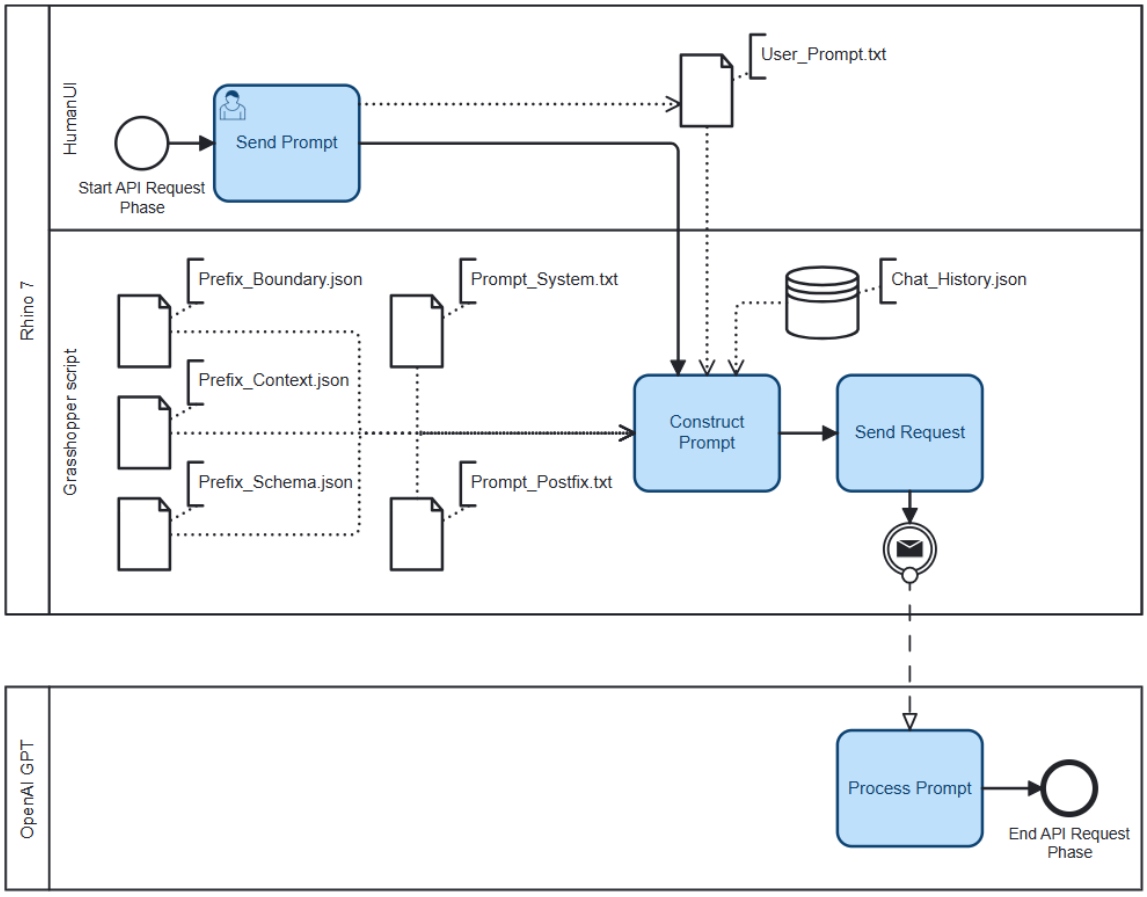


Figure 13: BPMN diagram illustrating the API Request Phase, including associated input files and system components.

2. Data Preparation

The BPMN diagram in Figure 14 illustrates the steps required to process the response from the OpenAI GPT. The model consistently returns its output in a predefined JSON structure, which is specified by the schema.json file (Figure 13). The specific content of the schema.json file is described in Section 3.1.1. However, deviations from this schema may occasionally occur. Therefore, the response must first be validated against the defined JSON schema. If the response does not conform, it cannot be parsed correctly. This is in line with the literature which indicates that fallback behavior needs to be incorporated when using LLMs (Ivgi et al., 2024) (Requirement 1.11). Once validated, the response is stored in the chat_history.json file. The system then parses the response by separating it into two components: the design explanation and the parameter set. The design explanation is displayed directly in the UI, providing immediate feedback to the participant. The parameter set serves as input for the Grasshopper script, which places the physical elements in the design model accordingly (Figure 15).

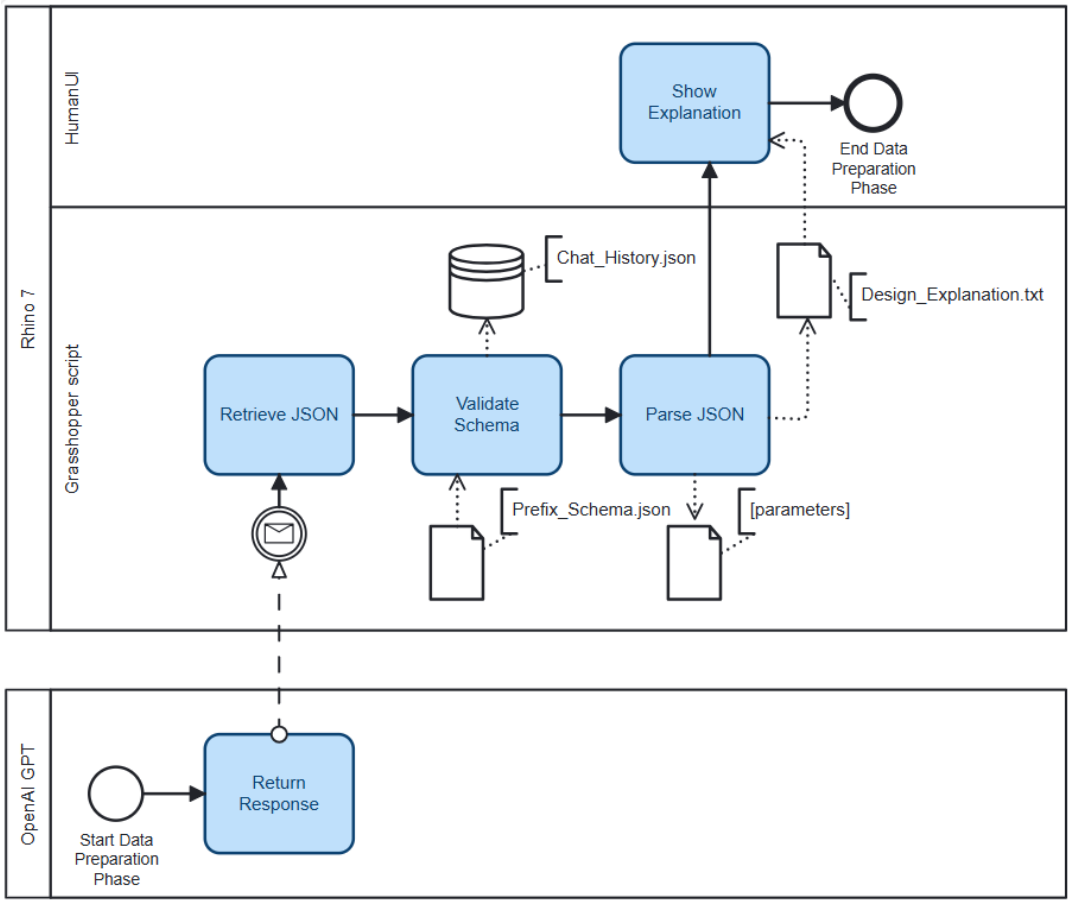


Figure 14: BPMN diagram illustrating the Data Preparation Phase, including associated input files and system components.

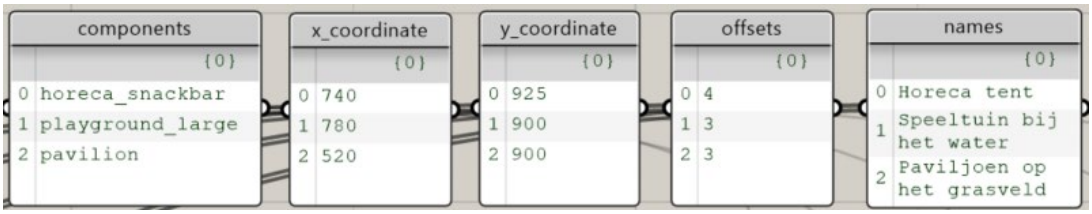


Figure 15: LLM output parameters used as input for component placement in Grasshopper.

3. Component Placement

The final phase in the BPMN diagram involves the placement of components within the parametric model. The component placement phase relies on the parameter dataset extracted from the previous processing stage (Figure 15). Based on the component names provided in the dataset, the corresponding objects are retrieved from the component library (components.3dm). Using the specified x and y coordinates, these components are then assigned a location within the model.

For this study, a predefined set of physical elements was used. These components were selected based on the outcomes of a previous participatory process conducted for the case study project. The model is restricted to using only components from the established library, and their dimensions cannot be modified by participants. However, the semantic class structure ensures that new elements can be added easily if needed (Section 3.1.1). If a participant proposes an element that is not part of the current library, the system places a placeholder object at the designated location, labelled with the name suggested by the participant. An example of this functionality is presented in Figure 16.

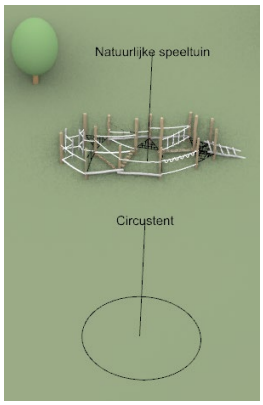


Figure 16: Component representation

However, empirical testing has demonstrated the necessity of a post-processing step to validate and correct component placement. Although the LLM receives the boundary line of the plot as contextual input and the dimensions of all components, there were still frequent misplacements. This was particularly the case along plot edges. This behavior is attributable to the limited spatial awareness of LLMs. To address this, an additional algorithm ensures that all components remain fully within the designated plot and do not intersect with existing greenery. Moreover, the scripts detect overlapping components and iteratively adjust their positions to prevent spatial conflicts. The Grasshopper logic identifies the nearest available location for each component that avoids overlap with both the plot contour and other elements. The script then places the component at this nearest location. Using the 'loop start' and 'loop end' components, this process is repeated until all components are successfully positioned within the available area.

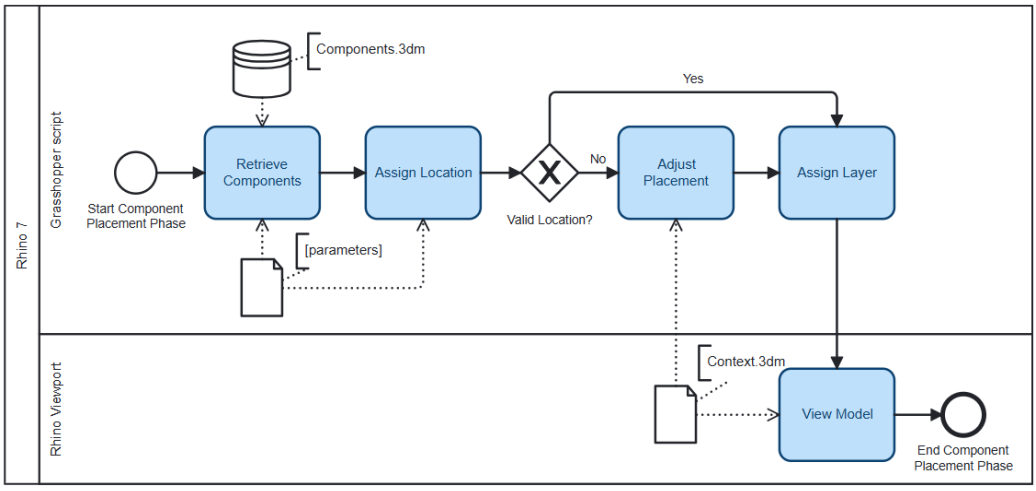


Figure 17: BPMN diagram illustrating the Data Preparation Phase, including associated input files and system components.

3.1.3 Requirement-Based Validation of the Text-to-3D Participatory Design Tool

The tool was developed based on the list of requirements outlined in Section 2.5. This section validates the extent to which the tool meets these requirements. In doing so, the tool is evaluated against literature-defined criteria prior to conducting the participatory experiment. The developed text-to-3D participatory design tool fulfils the majority of the defined requirements. However, requirement 1.9, 1.11, 2.1, 2.7, 2.8, and 2.9 were only partially implemented or not addressed. These exceptions are discussed in further detail. The "Won't Have" requirements were not validated, as they were not implemented in the tool, which is explained in Section 2.5.

1. Validation of Functional Requirements

Table 5: Overview of all functional requirements categorized using the MoSCoW method, including an assessment of whether each requirement was implemented in the text-to-3D participatory design tool.

	ID	Requirement	Included
Must Have	1.1	Translate user-inputted natural language prompts into corresponding 3D public space designs.	☑
	1.2	Enable users to design public space according to two thematic categories: urban elements and greenery.	☑
	1.3	Retain previously placed elements during design iterations, unless the user explicitly requests a reset or replacement.	☑
	1.4	Restrict placement of components that are feasible to implement in real-world public space contexts, based on predefined planning rules and constraints.	☑
	1.5	Use a GPT-based LLM for prompt interpretation.	☑
Should Have	1.6	Allow participants to undo and redo design steps with at least 2 undo levels.	☑
	1.7	Support export of designs in IFC format for integration into existing planning and design software.	☑
	1.8	Include context-specific information about the site as input for the LLM.	☑
	1.9	Explain beforehand: design space, purpose, how the designs contribute to the decision-making process.	☒
	1.10	Use a semantic classification structure to categorize components, enabling easy addition of new elements and the assignment of spatial rules.	☑
Could Have	1.11	Detect and respond to out-of-distribution prompts by providing at least 1 fallback suggestion or clarification request.	☒
	1.12	Store all user input prompts for documentation purposes.	☑
	1.13	Explain the LLM's design choices in natural language using a maximum of 3 sentences.	☑

Table 5 (continued)

	ID	Requirement	Included
Won't Have	1.14	Ability to generate or edit routing.	☒
	1.15	Implementation of Retrieval-Augmented Generation (RAG).	☒
	1.16	Engage in conversational dialogue or back-and-forth questioning with users.	☒
	1.17	An integrated KPI-based evaluation model to assess the generated design outcomes.	☒

Additional clarification is provided below for a selection of the requirements.

1.9: Since the current version of the tool only includes the functionality for users to prompt design proposals, it does not provide information about the design space, the tool's purpose, or how the generated designs contribute to the decision-making process. Therefore, these three aspects were explained verbally to participants during the participatory experiment.

1.11: As explained in Section 2.5.1, this version of the tool does not support a textual dialogue between the system and the participant. As a result, it is not possible for the LLM to request clarification from the participant. The LLM will therefore always generate a design response, even when the participant submits an out-of-distribution prompt. This may result in designs that do not align with the participant's expectations, which will be discussed in more detail in Section 5.3.2.

2. Validation of Non-Functional Requirements

Table 6: Overview of all non-functional requirements categorized using the MoSCoW method, including an assessment of whether each requirement was implemented in the text-to-3D participatory design tool.

	ID	Requirement	Included
Must Have	2.1	Ensure a maximum response time of 10 seconds for generating a 3D design output after user input.	☒
	2.2	The User Interface (UI) must be designed so that users can complete a design session without external assistance in under 10 minutes, using example prompts.	☑
	2.3	Comply with the EU General Data Protection Regulation (GDPR) by storing only anonymized design proposals and no personal user data.	☑
Should Have	2.4	Support accessibility and functionality on laptop and desktop computer.	☑
	2.5	Usable by non-expert participants without requiring prior technical knowledge or experience with 3D modeling, coding, or urban design tools.	☑
	2.6	Users must be guided by prompting examples (integrated in the UI or on paper).	☑
Could Have	2.7	Include visual icons and simplified language to ensure usability for participants with low literacy levels.	☒
	2.8	The UI should allow users to view the generated design from both a bird's-eye perspective and a human-scale (street-level) perspective.	☑/☒

Table 6 (continued)

	ID	Requirement	Included
	2.9	Support multilingual input and output, operating effectively in all commonly used languages relevant to the user base.	☑/☒
Won't Have	2.10	Support scalability across multiple urban planning and design scales or stages.	☒

Additional clarification is provided below for a selection of the requirements.

2.1: The system's maximum response time is 20 seconds, with an average generation time ranging between 10 and 20 seconds. Approximately 60% of this duration is attributed to the processing time of the LLM, while the remaining 40% is caused by the Grasshopper script. The delay caused by the Grasshopper script is primarily due to the repositioning of elements that were incorrectly placed by the LLM. Literature indicates that generation times longer than 10 seconds can lead to reduced user engagement (Nielson, 1994). This limitation should therefore be taken into account when analyzing the results of the participatory experiment.

2.7: In the prompt postfix, the LLM was instructed to provide the design explanation in simplified language. Participants were free to formulate their input at their own language level, as the tool allows open text entry. However, no additional functionalities were implemented specifically to support users with low literacy levels. As a result, lower user engagement may be observed among participants with limited literacy skills.

2.8: Within the Rhino Viewport, participants can navigate through the 3D model using the mouse, allowing them to view the design from a human-scale perspective. However, the default view is a bird's-eye perspective, and switching to a ground-level view requires a certain degree of spatial and navigational skill. This can reduce user engagement, particularly among non-expert users, as difficulties in orientation and interaction within 3D environments may lead to frustration and cognitive overload (Chassin et al., 2019a).

2.9: This study makes use of the GPT-based LLM provided by OpenAI, which is capable of understanding and responding accurately in approximately 50 languages (OpenAI et al., 2024). For the purposes of this research, it is sufficient that the LLM can reliably process English and Dutch. However, its performance in other languages was not evaluated as part of this study.

3.2 Case Description: Maaspark Redevelopment Area

According to the Design Science Cycle, it is essential that the developed artifact is tested in a real-world context. Therefore, a text-to-3D participatory design tool was designed and evaluated using a real-life case study. To ensure the suitability of the selected case, three key selection criteria were established:

1. The case must involve a public space design task in which urban elements and greenery can be positioned.
2. Participants must be accessible and willing to engage in tool testing.

3. The project must provide adequate space for participant input to be meaningfully integrated into the design process.

The Maaspark project in Vlaardingen meets all the established case selection criteria. The park is part of the Rivierzone area development, where significant urban densification is planned over the coming years. As a result, the park is currently undergoing a redevelopment process. Although the initial plans for the Maaspark redevelopment began in 2018, delays in the broader area development postponed design activities. Only now, in 2025, are detailed design variants being prepared by a landscape architect, commissioned by the Municipality of Vlaardingen to collaboratively initiate a participatory design process.

Maaspark covers an area of approximately 46,000 m² and is located near the Maas river. It is surrounded predominantly by apartment buildings, comprising 86% of the housing stock in the area, ranging from 4 to 15 storeys in height. The park is located in the 'Maasboulevard' neighbourhood of Vlaardingen, which has a population of 1,505 residents, including 560 individuals aged 65 and older (Alle Cijfers, 2024). This indicates a relatively high proportion of older people living in the vicinity of Maaspark.

Figure 18: Maaspark Project as part of the Rivierzone area development in Vlaardingen. (Inspire Real Estate, n.d.)

Given the park's central role in this densely populated and demographically diverse neighbourhood, the participation of local residents was considered essential for aligning the design with community needs. A participation session was held in February 2025, where local residents were invited to provide feedback on preliminary design proposals for Maaspark. The event was organized by the Municipality of Vlaardingen in collaboration with the appointed landscape architect. To ensure broad outreach, invitations were distributed door-to-door throughout the Rivierzone, while additional efforts included targeted WhatsApp messages to resident groups, promotional videos on social media and announcements in local media. As a result, nearly one hundred (future) residents and local entrepreneurs attended the session (Municipality of Vlaardingen, 2025).

The objective of this participation event was to understand the desired program for the public space within the Rivierzone and to validate and refine preliminary design concepts based on

community input. Attendees were encouraged to propose design modifications by placing post-it notes directly onto the displayed plans. This method generated valuable input from residents, business owners, and other stakeholders, which was subsequently used to inform the sketch design. A photograph of the feedback board is presented in Figure 19, illustrating the traditional participation approach currently employed in the project.

Figure 19: Final feedback board from the Maaspark participation session, displaying community input collected during the event. (source: author's photograph)

In collaboration with the landscape architect, a document was prepared to outline the scope of participation, defining which aspects of the design can be influenced by citizens. This document is included in Appendix 8, and its key points are:

1. Urban elements (location of):
    - Benches
    - Playground equipment
    - Sport facilities
    - Food & beverage amenities
    - Other small-scale public elements
2. Greenery (type and location of):
    - Perennials, shrubs, solitary trees, tree clusters, and forest areas
3. Routing (type and location of pathways):
    - Main boulevard and secondary routes

The aforementioned urban elements and greenery are included in the component library, which defines the set of components the LLM is able to place within the model. As discussed in Section 2.5, it is essential that the tool operates within the urban design frameworks established by both the Municipality of Vlaardingen and the landscape architect. The document in Appendix 8 serves as the reference for these constraints. Accordingly, the relevant spatial elements and functions described there integrated into the model to reflect the appropriate participation space for this case study.

To tailor the text-to-3D participatory design tool for this specific case study, the following adaptations were required:

1. Extending the component library with .3dm urban elements.
2. Importing the 3D context of Maaspark into Rhino.
3. Defining existing green structured and infrastructure in Grasshopper.
4. Embedding the urban design frameworks (Appendix 8) into the prompt prefix provided to the LLM.

Step 1 is essential to ensure that participants are able to place the desired components within the 3D model. The composition of the component library is based on the outcomes of the participatory meeting held in February 2025 and consultations with the landscape architect. *Step 2* involves the inclusion of the surrounding buildings of Maaspark, enabling the visualization of interactions between the park and its context. *Step 3* incorporates the existing green structure into the model, in accordance with the constraints outlined in Appendix 8, which stipulate that the existing greenery should be preserved as much as possible. Additionally, several roads are included in the model which cannot be altered and therefore fall outside the participatory scope. *Step 4* involves the integration of the urban design frameworks from Appendix 8 into the system by translating textual planning regulations into the prompts submitted to the LLM.

These steps demonstrate the actions required to adapt and deploy the tool for this specific project context. Once these steps have been completed, the model was ready for use in the participation experiment.

3.3 Testing the Text-to-3D Approach Through a Participation Experiment

This section describes the setup, protocol, and evaluation of the participation experiment conducted to test the text-to-3D participatory design tool in a real-world context. The main goal of the experiment was to measure participant satisfaction and engagement with the application. Satisfaction and engagement were assessed qualitatively, focusing on how pleased users were with their experience using the tool. To evaluate this, the User Experience Questionnaire (UEQ) and seven customized statements were employed. Engagement was also measured quantitatively, by analyzing how actively and deeply participants interacted with the tool during the session. In addition to evaluating the participant experience, the impact of the tool's outcomes on urban decision-making was also explored. This was done by discussing the results of the experiment with representatives from the Municipality of Vlaardingen.

The study was conducted anonymously and in accordance with the guidelines of the Ethical Board of Eindhoven University of Technology (TU/e). The consent form signed by all participants is included in Appendix 9.

3.3.1 Participation Experiment Setup

The experiment was conducted on-site at the Maaspark, hosted in a local community center. Throughout the day, residents from the surrounding neighborhood were invited to walk in and participate in the test. The experiment was announced through email invitations sent to selected residents and flyers distributed in the local area.

Participants used the tool on a laptop, while the UI was simultaneously projected onto a screen using a beamer. Figure 20 displays the setup of the experiment.

Figure 20: Setup of the participation experiment in a community center near Maaspark, showing the moment during which the tool was being explained to participants. (source: author's photograph)

3.3.2 Participation Experiment Protocol

A structured test protocol was developed to guide participants through the experiment. The protocol is divided into three main stages: a pre-questionnaire, the design task, and a post-questionnaire. The full questionnaire is included in Appendix 10 and is further discussed in this section.

1. Pre-Questionnaire

Consent form

Each participant began by completing an informed consent form, following the standard template approved by the Ethical Board of Eindhoven University of Technology (TU/e).

Demographic questionnaire

To understand the participant profile, a demographic questionnaire was administered prior to the task. It collected the following information:

- Age
- Gender
- Education level
- Residency near Maaspark
- Frequency of visits to Maaspark
- Attitude towards the redesign of Maaspark
- Experience with previous participation processes of the Maaspark
- Experience with 3D tool

The inclusion of variables such as age, gender, education level, residency, and experience with 3D tools provide valuable insight into the demographic characteristics of participants. This is in line with the testing methodology used by Tomarchio et al. (2019), which tested a similar application in a practical setting.

Additional questions were included to capture variables potentially influencing tool engagement. For example, the frequency of park visits is likely to affect a participant's familiarity with the site and, by extension, their input (Zhan et al., 2021). Furthermore, participants were asked whether they support or oppose the redesign of the Maaspark. Participants attitude strongly influence their behavior in participatory processes (Abbot, 2020). Finally, be measuring prior participation experience, this study aims to assess whether the text-to-3D participatory design tool could enhance perceived engagement compared to traditional participation methods, especially when compared with post-questionnaire results.

2. Task

After completing the pre-questionnaire, participants were invited to begin designing their own version of the park using the tool. The preliminary study had presented that a certain level of structure is necessary to guide participants in formulating effective prompts for the model. To support this, participants were provided with example prompts, such as:

"Create a park where I can walk and sit in peace."
"Add playground facilities near the Maas river."
"Remove the trees in the nearby area of the residential buildings."

Beyond the examples, participants were free to formulate and submit their own prompts. They continued the design process until they felt satisfied with the result.

3. Post-Questionnaire

User Experience Questionnaire

The first part of the post-questionnaire consists of the UEQ, a standardized and validated instrument for assessing the User Experience (UX) of interactive products. This method enables the structured evaluation of both the functional and emotional aspects of user interaction. A detailed explanation of the UEQ is provided in Section 3.3.3.

Customized-statements

In addition to the UEQ, seven customized-statements were included in the post-questionnaire. These statements were specifically designed to capture the participants' experiences with the text-to-3D application in the context of this study. The rationale and content of these statements are also discussed further in Section 3.3.3.

3.3.3 Evaluation Method for Measuring Participant Engagement

There are numerous methods available for measuring user engagement with interactive tools (O'Brien & Toms, 2008). For this study, a combined approach was adopted, consisting of the UEQ and a set of customized-statements tailored to the specific context of the text-to-3D application, which are based on the Technology Acceptance Model (TAM). These findings were complemented by observational insights.

1. User Experience Questionnaire

The UEQ is a widely accepted and validated method for measuring UX in both academic research and professional practice. The UEQ was developed by Laugwitz et al. (2008) and has been validated through empirical studies. It is one of the few UX methodologies that captures both pragmatic aspects (perspicuity, efficiency, and dependability) and hedonic aspects (stimulation and novelty) (Laugwitz et al., 2008).

The UEQ consists of 26 items grouped into six scales, each representing a dimension of UX. The UEQ questionnaire is presented in Appendix 11. Participants respond using a 7-point semantic differential scale between two opposite adjectives (e.g., "annoying" vs. "enjoyable").

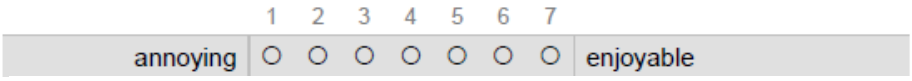


Figure 21: An example of a UEQ item about to what extent the product is annoying or enjoyable.

Table 7: The six categories and their descriptions for the 26 UEQ item clusters.

Attractiveness	Overall impression: Is the product liked or disliked?
Perspicuity	Easy of understanding and learning: Is it easy to get familiar with?
Efficiency	Performance and speed: Can tasks be completed efficiently?
Dependability	Control and predictability: Does the user feel in control?
Stimulation	Excitement and motivation: Is the product engaging and stimulating?
Novelty	Innovation and creativity: Does it feel aesthetically new?

Because the UEQ is a well-established and validated method, a standardized data processing model has been developed for it. This model allows for efficient analysis of both individual item scores and aggregated scale scores.

Determining an appropriate sample size for this study is essential to ensure the reliability of the results. The key factor in determining the nr of participants is the desired precision of the scale means, which is reflected by the width of the 95% confidence interval. According to Laugwitz et al. (2008), a sample of 10-30 participants is typically sufficient for medium precision, which is suitable for the field study in this case.

2. Customized-Statements based on Technology Acceptance Model

In addition to the standard UEQ items, seven customized-statements were included in the post-questionnaire to explore user perceptions specific to the application of text-to-3D within the participation process. These statements are listed below and were evaluated using a 7-point Likert scale.

1. I am satisfied with the overall experience of using the text-to-3D tool.
2. It was easy to understand how to create a 3D design using text input.
3. The final 3D design met my expectations.
4. The translation of text input into a 3D model was helpful in expressing my ideas.
5. Using the tool would make me feel involved in the participation process.
6. I would like to use this tool again in a future participation process.

If participants had previously taken part in the Maaspark participation process, they were also asked to respond to the following statement:

7. Using the tool would make me feel more involved in the participation process for the Rivierzone and/or Maaspark.

These statements are based on the Technology Acceptance Model (TAM) developed by Davis (1989). TAM is one of the most widely used and validated frameworks in the field of Human-Computer Interaction (HCI) to explain and predict user acceptance of new technologies. The model is presented in (Figure 22), with each statement number linked to one of the core components of TAM.

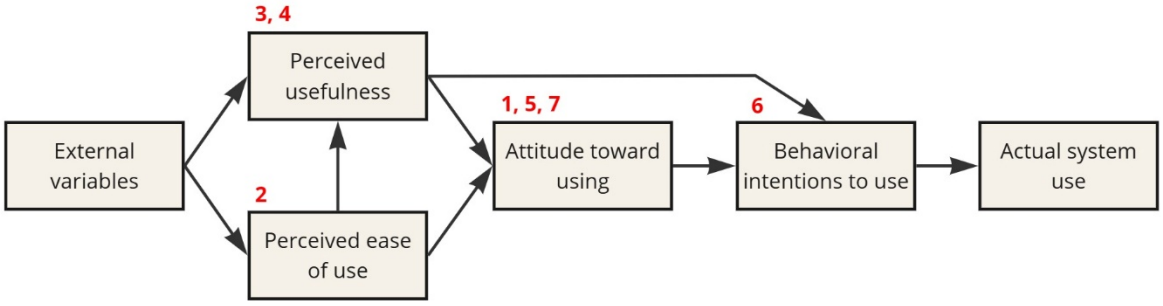


Figure 22: Customized-Statements related to the Technology Acceptance Model (Davis, 1989)

To validate the customized-statements the Cronbach's Alpha score can be calculated. This is a statistical measure used to assess the internal consistency of a set of items. A Cronbach's Alpha value higher then 0.70 suggests that the items consistently measure the same underlying concept (Cortina, 1993). Statements 1 to 4 measure user satisfaction with the use of the text-to-3D tool itself, while statements 5-7 assess participants' preferences regarding the tool's integration into the participatory process. Therefore, in the results section, the Cronbach's Alpha value is calculated separately for these two categories to evaluate the internal consistency within each group of statements.

3. Observations

In addition to quantitatively measuring user engagement, it is also valuable to incorporate observational methods during the experiment. Documenting observations can capture behavioral patterns, user reactions, and moments of confusion that may not be evident from questionnaire responses alone (Marshall et al., 2024a). Including both observational and survey-based data strengthens the validity of the study's findings.

4. Participation Experiment Results

This chapter presents the outcomes of the participatory experiment. It includes the findings from both the User Experience Questionnaire (UEQ) and the customized-statements developed for this study. The results are analysed and interpreted to evaluate user satisfaction and engagement resulting from the integration of text-to-3D technology into the participation process. The chapter begins by outlining the participant demographics in Section 4.1, data cleaning procedures in Section 4.2, and data validity in Section 4.3, which is followed by a description of the experimental outcomes in Section 4.4.

4.1 Participant Demographics and Contextual Background

An overview of the demographic characteristics of the experiment is provided in Appendix 12 and a summary is presented in Table 8. The experiment was conducted with a total of 18 participants, consisting of an equal gender distribution (9 men and 9 women). The average age of the participants was 64 years, indicating that the group was primarily composed of older adults. As the experiment was promoted locally, the participant profile represents the age structure of the neighborhood presented in Section 3.2. It is important to consider the relatively high average age when interpreting the findings.

Nearly all participants reported regular use of the Maaspark, suggesting a strong familiarity with and personal connection to the area. On a scale from 0 to 7, participants rated the average level of support for redesigning Maaspark at 6.2. As concluded in Section 2.3.3.5, individuals who strongly support a redesign tend to engage more actively in participatory processes. Participants who are opposed to the redesign could have exerted a negative influence on the outcomes, this was not observed in this study.

In terms of digital literacy, participants rated their familiarity with 3D design tools at an average of 4 out of 7, indicating a moderate level of experience with 3D technologies among the group. These data provide a basis for drawing connections in Section 4.4.1 between participants' familiarity with 3D design tools and their ease of interacting with the text-to-3D participatory design tool.

Table 8: Overview of participant demographics, including average age, gender distribution, frequency of park use, average support for the Maaspark redesign, and average familiarity with 3D design tools. The last two items are measured on a 7-point Likert scale, where higher scores indicate greater support or familiarity.

Age	Gender	Frequency of Park Use	Support Level	3D Tool Familiarity
64	9 men	9 each day	6.2	4.0
	9 women	2 few times a week		
		3 few times a month		
		4 few times a year		

4.2 Data Cleaning

To ensure the reliability of the dataset, two data cleaning strategies were applied, both recommended by the UEQ methodology: consistency between scales and the detection of identical answer categories (Schrepp, 2016).

The first method identifies suspicious responses by evaluating consistency within individual scales. Since each scale consists of items that collectively measure the same quality aspect, participant responses should not vary substantially within a single scale. A response is considered suspicious if, in at least three scales, the difference between the highest and lowest item score exceeds 3 points (Schrepp, 2016). This rule flagged one participant, whose data was subsequently removed.

The second method involves checking for excessive repetition of answer categories. Empirical analysis of multiple datasets suggests that responses containing more than 15 identical answer categories across the 26 items should be excluded from further analysis, as they likely reflect disengaged or non-differentiated responding (Schrepp, 2016). This criterion led to the exclusion of two additional participants.

In total, three participants were excluded from the dataset, strengthening the integrity and reliability of the results. Therefore, the final number of valid participants is 15, which falls within the desired sample size range of 10 to 30 participants as established in Section 3.3.3.

4.3 Scale Reliability and Validity

This section checks that the scales of the UEQ as well as the customized-statements are reliable before results are interpreted. The data cleaning steps have contributed to a more valid dataset. To assess internal consistency and overall validity, Cronbach's Alpha was calculated. A Cronbach's Alpha value higher then 0.70 suggests that the items consistently measure the same underlying concept (Cortina, 1993).

4.3.1 UEQ Reliability

Table 9 presents the Cronbach's Alpha scores for each UEQ category. The Attractiveness and Efficiency scales display alpha values above 0.70, which indicates good internal consistency and suggests that participants responded consistently to the items within these dimensions. The remaining scales yield Cronbach's Alpha values of roughly 0.60. While this is below the conventional threshold of 0.70, it is still considered acceptable for exploratory research or early-stage usability testing (ten Berge, 1995). Moderate alpha values can occur when a scale includes few items, as Cronbach's Alpha is sensitive to the number of items in a scale. This is the case for all the categories with fewer than five items, except 'Attractiveness'. Despite this, the internal consistency is sufficient to proceed with further analysis.

Table 9: Cronbach's Alpha scores for the UEQ scales. Values range from 0 to 1, with scores above 0.70 indicating strong internal consistency within each category.

	Attractiveness	Perspicuity	Efficiency	Dependability	Stimulation	Novelty
Alpha	0.71	0.59	0.82	0.58	0.58	0.62

4.3.2 Customized-Statement Reliability

To validate the consistency of the customized-statements, seven items were divided into two categories. The first category consists of four statements related to the user experience of the text-to-3D participatory design tool:

1. I am satisfied with the overall experience of using the text-to-3D tool.
2. It was easy to understand how to create a 3D design using text input.

3. The final 3D design met my expectations.
4. The translation of text input into a 3D model was helpful in expressing my ideas.

The second category includes remaining three statements, which are closely related to the application of the text-to-3D tool within the broader participation process.

5. Using the tool would make me feel involved in the participation process.
6. I would like to use this tool again in a future participation process.

If participant had previously taken part in the Maaspark participation process:

7. Using the tool would make me feel more involved in the participation process for the Rivierzone and/or Maaspark.[3]

As presented in Table 10 and Table 11, both categories demonstrate a Cronbach's Alpha score above 0.70. This indicates sufficient internal consistency within both sets of items. It can therefore be concluded that the customized-statements are reliable for drawing further conclusions.

Table 10: Cronbach's Alpha scores of statements 1-4 including their interrelated correlations.

Text-to-3D experience	
Items	Correlation
1, 2	0.40
1, 3	0.54
1, 4	0.47
2, 3	0.54
2, 4	0.61
3, 4	0.77
Average	0.56
Alpha	**0.83**

Table 11: Cronbach's Alpha score of statements 5-7 including their interrelated correlations.

Process satisfaction	
Items	Correlation
5, 6	0.45
5, 7	0.54
6, 7	0.27
Average	0.42
Alpha	**0.74**

[3] Statement 7 is a conditional item and was only answered by respondents who had previously participated in the Maaspark participation process.

4.4 Participation Experiment Outcomes

This section presents the results, beginning with the UEQ findings, followed by the customized-statements and observations. While this section focuses on the empirical findings, their connection to the existing literature is addressed in Chapter 5.

4.4.1 User Experience Questionnaire Item-level Results

Overall, participants responded positively to the tool across all evaluated items, as presented in Table 12. A high score of the UEQ and customized-statements indicates more positive evaluation. However, notable differences emerged between the six categories and the 26 individual items. This section provides a detailed interpretation of these differences and their implications. Each mean score is based on a scale from –3 to 3. Appendix 13 also includes the raw data from the UEQ.

Table 12: Mean scores for individual User Experience Questionnaire items. Each color represents one of the six UEQ categories: Attractiveness, Perspicuity, Efficiency, Dependability, Stimulation, and Novelty.

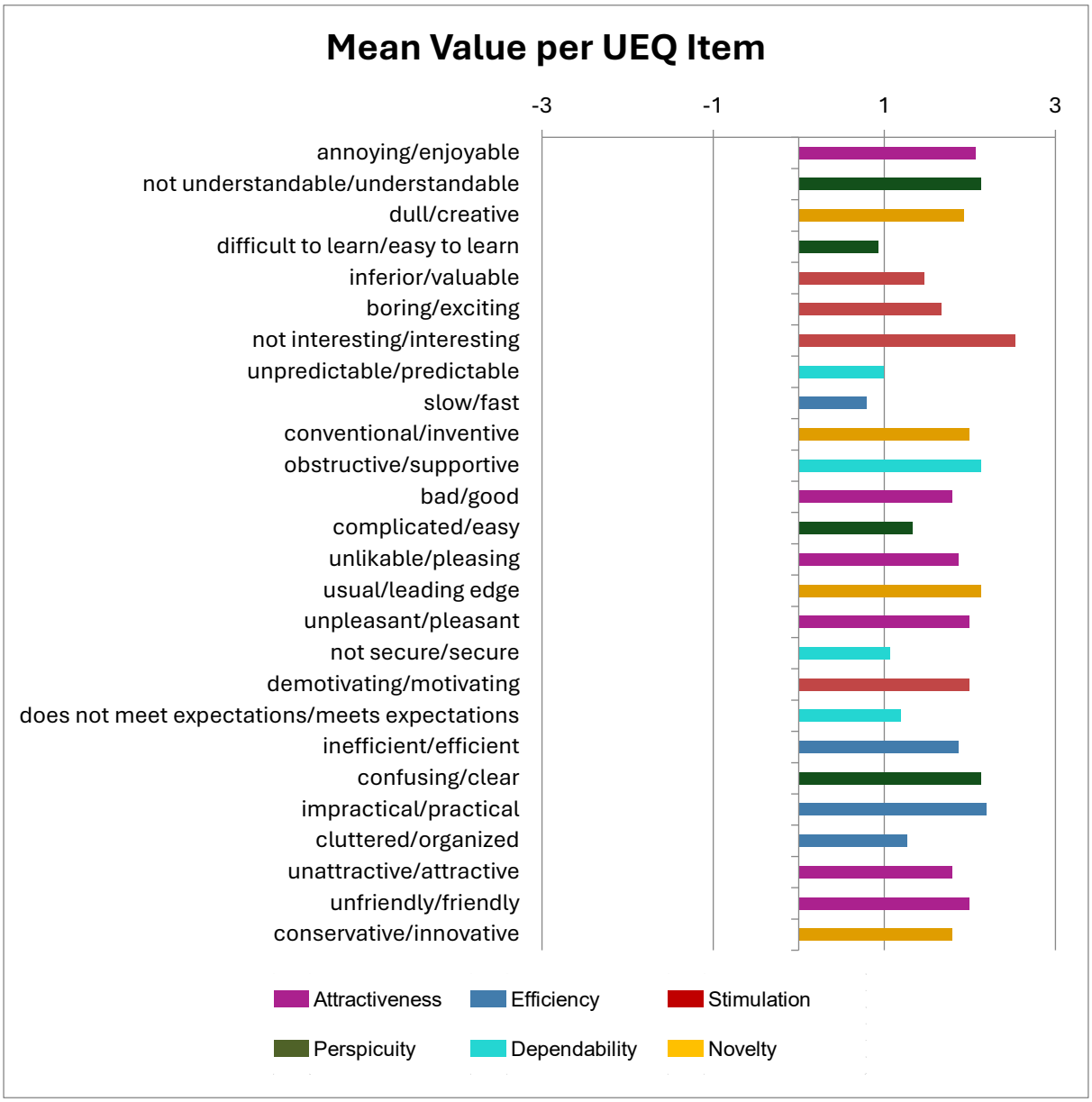
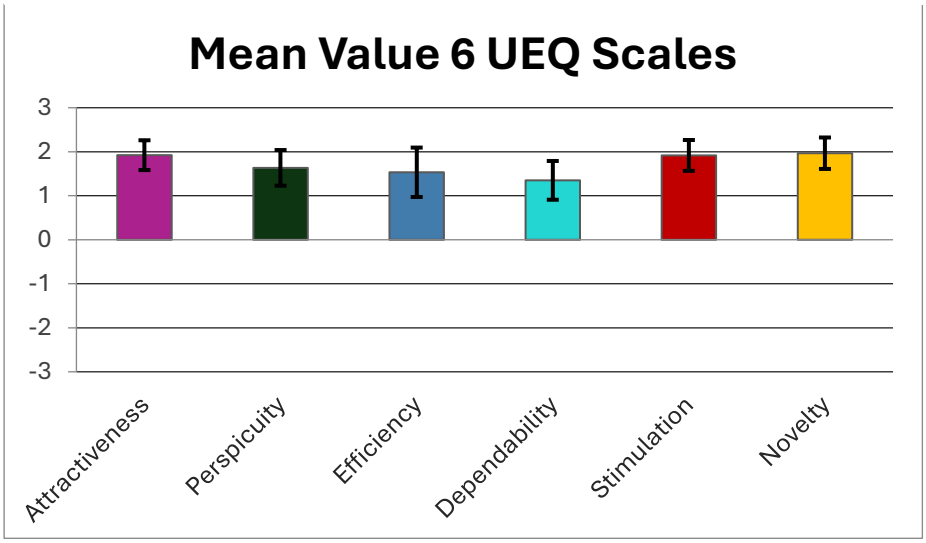


Table 13: Mean scores and 95% confidence intervals for the six User Experience Questionnaire scales.



Attractiveness, m = 1.92, σ^2 = 0.45

The 'Attractiveness' category received consistently high ratings, with a mean (m) score of 1.92. The relatively low variance (σ^2) of 0.45 indicates that participants uniformly appreciated the text-to-3D tool in terms of attractiveness. Participants described the tool as enjoyable (m=2.1), good (m=1.8), pleasing (m=1.9), pleasant (m=2.0), attractive (m=1.8), and friendly (m=2.0). These findings demonstrate a generally positive response from the participants with regard to attractiveness.

Perspicuity, m = 1.63, σ^2 = 0.64

The 'Perspicuity' category, which assesses the extent to which the tool is easy to understand and learn, received a moderate average score of 1.63. While the text-to-3D tool was rated as clear and understandable (m=2.1), the item 'easy to learn' scored lower at 0.9. This discrepancy is explained in Section 5.1.

Efficiency, m = 1.53, σ^2 = 1.23

In the 'Efficiency' category, responses varied significantly, as evidenced by a relatively high variance of 1.23. Participants rated the tool as practical (m=2.2) and efficient (m=1.9). These ratings reflect an appreciation of the goal-directed nature of prompting and the immediate feedback loop. However, lower scores were reported for the tool's speed (m=0.8) and for participants' perception of interface clutter (m=1.3). These lower ratings are likely due to the current generation time of 10-20 seconds per design iteration. Approximately half of this delay is attributed to LLM processing; the remainder arises from the parametric script, particularly during component relocation.

Dependability, m = 1.35, σ^2 = 0.76

The 'Dependability' category received the lowest average score (m=1.35) across all six categories. This category reflects users' sense of control over the design. Participants rated the tool as relatively unpredictable (m=1.0), not secure (m=1.1), and not meeting expectations (m=1.2), although they still found the text-based design method supportive (m=2.1). The relatively high score for 'supportive' suggests that, despite a lack of perceived control, users found the tool helpful in shaping their ideas. Participants with greater 3D modeling experience rated 'Dependability' higher (Pearson R = 0.42, $p < 0.05$).

Stimulation, m = 1.92, σ^2 = 0.48

The 'Stimulation' category is particularly relevant to this study, as it reflects the degree to which text-to-3D encourages users to actively engage in the design process. With a high average score of 1.92 and a low variance of 0.48, the results indicate a broad consensus among participants that the tool was perceived as stimulating. This category scored especially well on perceived interest (m=2.5) and motivation (m=2.0), which suggests that the text-to-3D approach motivates users to constructively contribute.

Novelty, m = 1.97, σ^2 = 0.50

The final category, 'Novelty', received the highest average score of 1.97 and a variance of 0.50, indicating that participants consistently perceived the tool as innovative. Items such as creative (m=1.9), inventive (m=2.0), leading-edge (m=2.1), and innovative (1.8) were rated highly. One consideration is the relatively older age of the participants, which may have influenced the results. This aspect is further elaborated upon in Section 5.3.1.

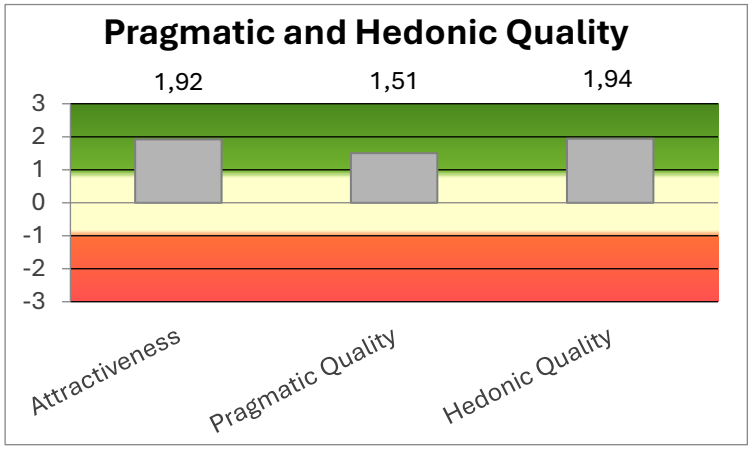
Table 14: Mean scores and variances for the six User Experience Questionnaire scales.

UEQ Scales	Mean	Variance
Attractiveness	1.92	0.45
Perspicuity	1.63	0.64
Efficiency	1.53	1.23
Dependability	1.35	0.76
Stimulation	1.92	0.48
Novelty	1.97	0.50

4.4.2 Pragmatic and Hedonic Quality

The scales of the UEQ can be grouped into pragmatic quality (Perspicuity, Efficiency, Dependability) and hedonic quality (Stimulation, Novelty). Pragmatic quality describes task related quality aspects, whereas hedonic quality non-task-related aspects (Laugwitz et al., 2008).

Table 15: UEQ results grouped by attractiveness, pragmatic quality (perspicuity, efficiency, dependability), and hedonic quality (stimulation, novelty).



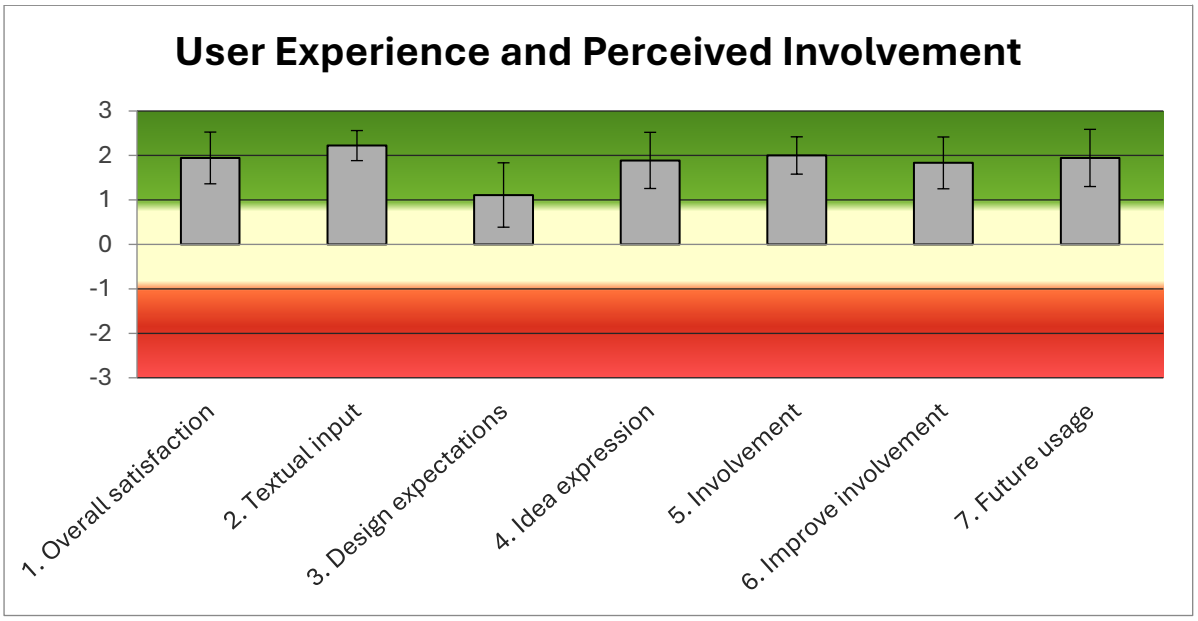
The hedonic quality of the tool received a higher average score (m=1.94) than the pragmatic quality (m=1.51). This finding indicates that users were more positively influenced by the experiential and emotional aspects of the text-to-3D tool than by its task-related efficiency or ease of use. The high hedonic quality suggests that participants perceived the tool as stimulating and innovative.

4.4.3 Customized-Statement Results

The customized-statements are designed to validate and expand upon the findings of the UEQ, and their results are largely consistent with those of the standardized questionnaire. As in the UEQ, the mean scores here are also based on a scale ranging from –3 to 3. Overall satisfaction with the text-to-3D application was rated highly (m=1.94), which indicates that participants were very pleased with their experience. Notably, the method of textual input was highly valued (m=2.22, σ^2=0.54).

One area of concern, is the degree to which the generated designs met participants' expectations. This item scored relatively low (m=1.11) with a high variance of 2.46, indicating a wide range of user experiences. Follow-up conversations with participants revealed several reasons for this discrepancy. First, the design element library was limited, which constrained users' ability to express specific ideas. Second, design freedom was restricted by embedded urban planning and design rules. This observation is consistent with the relatively low score in the Dependability category of the UEQ, which reflects users' limited sense of control and predictability when interacting with the tool.

Table 16: Results of the seven customized-statements evaluating user experience and perceived involvement.



Statements 5, 6, and 7 of the post-questionnaire address the influence of the text-to-3D application on participants' sense of involvement within the participatory process. On average, participants rated their agreement with the statement *"Using the tool would make me feel involved in the participation process"* at 2.0 out of 3.0. The Maaspark project has thus far relied on traditional, physical participation methods such as on-site meetings and feedback boards. Participants who previously engaged in these conventional processes reported that it would have made them feel more involved, giving it an average score of 1.83. These findings indicate that a text-to-3D participatory design approach is perceived as an effective way to enhance participant involvement. Additionally, with a mean score of 1.94, participants expressed a willingness to use the tool again in future participation processes.

Table 17: Means and variances of the seven customized-statements.

Statements	Mean	Variance
1. Overall satisfaction	1.94	1.58
2. Textual input	2.22	0.54
3. Design expectations	1.11	2.46
4. Idea expression	1.89	1.87
5. Involvement	2.00	0.82
6. Improve involvement	1.83	1.06
7. Future usage	1.94	1.94

4.4.4 Observations during the Participation Experiment

In addition to the post-experiment questionnaires, several observations made during the experiment proved relevant to the research findings.

Firstly, it became apparent that participants, despite being provided with prompt examples, tended to formulate very brief inputs, such as *"playgarden near water"* instead of the more complete *"Add a playgarden near the water"*. The LLM had difficulty interpreting these shorter and more ambiguous prompts. This may also help explain the lower Perspicuity score, as some participants indicated experiencing difficulty in learning how to use the tool. This was particularly evident among older participants. For this group, it proved more effective to engage in conversation, allowing the researcher to formulate and input the prompts into the system. This indicates that different age groups interact with prompting in distinct ways.

Furthermore, several participants expressed a desire to manually adjust elements after placement, to fine-tune the model. If the LLM placed an element slightly off the intended location, participants preferred the option to make manual corrections. Some participants exhibited this tendency spontaneously. This further reinforces the findings of Statement 3 from the customized-statements, which indicate that the designs did not always fully meet participants' expectations.

The LLM embedded in the prototype consistently returned a design explanation consisting of two to three sentences. However, this feature was largely disregarded by participants. For them, the generated design itself served as the answer. They felt no need for additional explanations regarding the chosen composition. The 3D model alone sufficiently visualized the response to their prompt.

Lastly, the 3D model was presented in a schematic, architectural maquette style, which participants particularly appreciated the simplified representation of the design. As concluded in Section 1.2, participants considered path structures less important than the elements placed within the space. This was also confirmed during the experiment, as participants presented no interest in adding or modifying walking paths. The need to add routing is not reflected in the quantitative analysis either, as participants perceived that their ideas could be adequately expressed.

4.4.5 Generated Designs by Participants

Each participant created an individual design. One of the resulting designs is presented in Figure 23. The design demonstrates that the participant proposed various components available within the component library. The LLM always adopted the name suggested by the participant for each element (in this case, in Dutch). As presented, the participant included a "hondenuitlaatzone" (dog park, upper right), which was not present in the library.

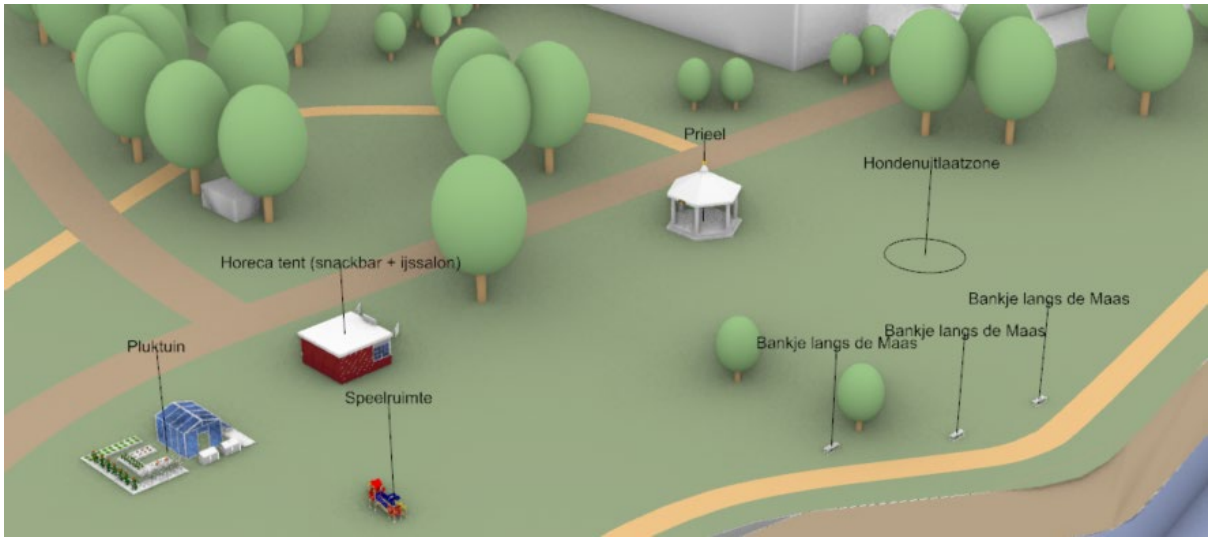


Figure 23: Example of a participant-generated design during the participation experiment, illustrating how components were placed within the 3D model using the text-to-3D tool.

An analysis of the prompts used by all participants revealed several key patterns. Elements were primarily placed or repositioned based on contextual cues, for example *"Move the football field to the primary road".* On average, each participant spent 13 minutes on their design. During this time, conversations took place with the researcher and fellow participants to discuss design ideas. Each participant required an average of seven design iterations to arrive at a final proposal, and used approximately eight components in their final design.

The findings indicate that the text-to-3D participatory design tool facilitated an iterative design process. Participants typically began with no more than three components and then gradually expanded and refined their designs by adding, moving, or removing elements. This step-by-step approach created a direct feedback loop between user input and system response.

4.4.6 Effect on Urban Planners' Decision-Making

As discussed in the methodology (Section 3.1.3), all participant designs were presented to five urban planners from the Municipality of Vlaardingen during a meeting. This session yielded several important insights.

First, the tool enabled urban planners to quickly identify the functions participants attributed to the public space and the elements associated with these functions. The urban planners regarded this as a significant improvement over the current process, in which participants typically provide only textual comments on pre-generated designs created by the planners themselves. In addition, it provided a particularly clear view of where participants preferred to place certain elements and where they explicitly did not, particularly when this spatial data

was interpreted alongside the textual prompts given by the participants. In current methods, it is challenging for urban planners to directly link participant input to specific locations within the design. The session also demonstrated that the tool offers an efficient way to document participatory input, which is particularly relevant in the context of the Dutch Environmental Act.

The urban planners expressed concerns about the potentially large number of designs that would need to be analysed in a real participatory process. To address this challenge, they proposed two strategies for efficiently integrating the text-to-3D participatory design tool into the decision-making process. First, they emphasized the need to integrate optimization techniques to support rapid and advanced analyses. Second, they highlighted the importance of incorporating an integrated heatmap function, which would facilitate quick interpretation of the spatial distribution of proposed functions and elements.

5. Conclusion

This chapter presents the answers to the research questions of the thesis, followed by scientific and societal contributions, limitations, and recommendations for future research and practice.

5.1 Answers to the Research Questions

This section aims to answer the research questions presented in section 1.3 of the thesis, based on the findings of the literature review, interviews, and the participation experiment. It first addresses the initial sub-question concerning the tool design, followed by the second sub-question, which focuses on the outcomes of the participant experiment and the implications for urban planners' decision-making. Finally, the main research question is answered, which is: *How can real time natural language translation into 3D design outputs enhance non-expert participant engagement and urban planners' decision-making in digital participatory urban design?*

The first part of the study focused on the sub-question: *How can a tool be developed to facilitate the real time translation of natural language into 3D design outputs for participatory urban design?* The development of a text-to-3D participatory design tool serves as a means to answer the central research question. The literature review revealed that digital participatory design tools are most suitable for participatory processes in public space design of smaller-scale areas, such as the case study used. From both the literature and semi-structured interviews, the key requirements for a text-to-3D participatory design tool became clear: it should be intuitive and accessible to citizens, and establish a direct feedback loop. For the initiating parties of the participation process (municipalities or developers), these tools should provide insights into participants' design preferences within urban design frameworks.

These requirements were translated into a parametric generative design model, including the integration of an LLM. This integration enabled real-time feedback between the user and the 3D model. However, the use of an LLM introduced several challenges: computational limitations, limited creativity, and poor spatial awareness. The discussion further elaborates on how these factors have influenced user engagement. Nevertheless, by clearly instructing the LLM these issues were sufficiently mitigated to develop a Minimal Viable Product.

Following the participant experiment, the second sub-question can be addressed: *How does the implementation of this tool influence participant engagement and urban planners' decision-making in participatory urban design processes?* The high hedonic quality scores (m=1.94[4]) indicate that participants perceived text-to-3D as stimulating and innovative. This confirms that the text-to-3D participatory design tool encourages participants to actively generate and reflect on design proposals, which directly contributes to sustained engagement in participatory design (Chassin et al., 2019a). In contrast, although pragmatic quality was also rated positively (m=1.51), its lower score reflects some usability issues. These issues are closely related to design decisions during tool development, which are further elaborated upon in Section 5.3.2. However, the high overall participant satisfaction with the tool (m=1.92) indicates that pragmatic quality has a limited impact on overall user engagement.

[4] All mean scores (m) range from -3 to 3, with higher values indicating a more positive participant experience.

The discrepancy observed between 'easy to learn' (m=0.9) and 'understandable' (m=2.1) can be attributed to the initial need for instruction before participants could effectively engage with the tool. Clear instructions were initially required to explain how participants could formulate prompts, which reflects a well-documented challenge in the development of participatory tools. As presented by Kusters et al. (2018), the success of such methods largely depends on participants having a clear understanding of how to use the tool, as well as the presence of a skilled facilitator (Kusters et al., 2018). This latter point was also evident in the current participant experiment, where a skilled facilitator was essential to provide assistance with formulating prompts.

Despite an initial learning curve and the necessity of explaining how to formulate prompts, participants strongly appreciated the textual interaction (m=2.22). Furthermore, participants felt that their intentions were understood and visualized in a meaningful way, even if the final designs were not exactly as they imagined. This discrepancy is mainly due to the LLM's limited spatial awareness, highlighting the difficulty of effectively integrating LLMs in design processes. Nonetheless, participants perceived the text-to-3D participatory design tool as very attractive. Prior studies have noted that tools perceived as attractive are more likely to maintain engagement and reduce drop-out rates.

Additionally, the text-to-3D approach was experienced as supportive during participatory design. Literature also presents that digital participation tools are most effective when used in physical settings, as a complement to other methods. Because the tool stimulates participants to think about the design of public space, it encourage constructive dialogue. In this way, participants experienced greater involvement in the design process than with traditional methods. The tool thus demonstrates an effective means of capturing participant design preferences.

Therefore, the text-to-3D approach provides urban planners with quick insights into participant preferences. This was particularly valued by urban planners, who found it especially useful for understanding both the types of urban elements proposed and their preferred spatial placement. The tool's digital parametric environment provides a foundation for efficient analysis of the design outputs. However, the participation tool meaningfully impacts decision-making only when the generated outputs can also be efficiently assessed. This necessitates future research, which is addressed in Section 5.4.2.

In conclusion, this study established that text-to-3D participation tools can addresses the issue that participants often struggle to articulate their ideas as concrete design proposals. It proved that real-time natural language translation positively influences participant engagement and reveals promising potential to enhance decision-making by urban planners.

5.2 Contributions to Science and Society

This study contributes to both academic literature and societal practice in several ways. The most relevant contributions are elaborated in this section.

5.2.1 Scientific Contributions

This study introduces a novel participatory approach that enables non-expert participants to generate urban design proposals using natural language input. It extends the application of

GenAI by integrating it into the domain of participatory urban design, addressing a gap in the literature where previous research has focused primarily on text-to-2D or drag-and-drop approaches.

Methodologically, the study bridges parametric design environments with LLMs, demonstrating the technical feasibility of real-time, low-threshold urban design generation. This integration contributes to the growing field of human-AI co-creation by offering a scalable and accessible design interaction model.

Theoretically, the research advances knowledge on digital participation by highlighting how AI-supported tools influence engagement, agency, and creativity in participatory processes. It also extends frameworks of human-AI interaction into the domain of spatial design, where such applications remain underexplored.

5.2.2 Societal Contributions

This study responds to the common limitations of existing participatory tools, which are often static and offer minimal interactivity. The findings indicate that a text-to-3D approach not only encourages equitable participation but also enhances user engagement, indicating its added value in participatory urban design processes.

Moreover, the tool was presented to increase participant involvement compared to traditional methods, such as placing post-its on posters. This suggests that the a text-to-3D approach fosters a stronger sense of engagement than conventional approaches. Its strength lies in delivering real-time visual feedback, which effectively bridges the gap between abstract design ideas and concrete design proposals.

Ultimately, the study demonstrates that text-to-3D technology can significantly strengthen participant engagement in design processes. When effectively integrated into the decision-making workflows of urban planners, it contributes to more inclusive and meaningful participation processes.

5.3 Contextual and Methodological Limitations

This section offers a critical reflection on how the research scope and technological choices have shaped and limited the study's outcomes. It is structured into two subsections: the first discusses the influence of the research scope and experimental setting, while the second addresses system-related limitations of the LLM-based text-to-3D tool.

5.3.1 Limitations on Experiment Setting and Research Scope

This section discusses how the participation experiment setting and research scope influenced the research findings.

The tool was tested in a physical setting through direct personal interaction with participants. Personal interaction is known to lead to higher satisfaction levels, which may have influenced the participant experience in such a way that overall evaluations were more positive (Marshall et al., 2024a). Furthermore, literature indicates that participants who hold a positive attitude toward the development plan tend to exhibit higher levels of engagement in the participatory process (Abbot, 2020). In this study, participants expressed strong support for the

redevelopment of the Maaspark, with an average score of 6.2 out of 7.0. This prevailing enthusiasm may partly explain the overall positive evaluation of the text-to-3D approach and should therefore be acknowledged as a limitation of the study.

The relatively high average age of the participants (64 years) may have influenced the results. In particular, the high perceived novelty of the tool can, be partly attributed to the demographic composition of the participant group. Older individuals tend to be less familiar with AI applications and may therefore perceive new technologies as more innovative. Furthermore, the use of conventional participation methods in the current Maaspark planning process likely amplified the sense of novelty associated with the tool. Additionally, as the study predominantly involved older adults, it remains unclear how younger individuals, who are generally more familiar with AI applications, would engage with the tool. Younger participants may be more critical of the text-to-3D participatory design tool due to their extensive familiarity with various GenAI technologies. Recent research indicates that, while young people engage frequently with AI (e.g., 79 % of Gen Z use AI regularly), over half express anxiety or skepticism about its impact on critical thinking and creativity (Walton, 2025). This suggests that their expectations and experience with other GenAI techniques may drive a more critical and evaluative perspective toward new applications like text-to-3D.

A notable limitation of the tool is that the design options available to participants were intentionally kept abstract rather than detailed. For example, users could not select specific pavilion shapes or plant species. This design decision aimed to focus participant input on the broader spatial layout of the public park, leaving the responsibility for detailed specifications and compliance with technical or legal standards to professional designers. While this approach preserved the role of experts in translating participatory input into implementable designs, it may have constrained participants' ability to express more nuanced preferences. This may also help explain why the generated designs did not always meet participants' expectations (m = 1.11; on a scale from -3 to 3). This limitation reflects a broader tension in participatory design: whether citizen contributions should remain open to expert interpretation or be treated as fixed directives throughout participatory planning and design processes (Marshall et al., 2024a; Özden et al., 2025). Moreover, the design freedom of participants was limited in terms of placing urban elements and greenery. Literature indicates that routing is generally of lesser importance to participants in participatory design processes (Özden et al., 2025). This observation was confirmed during the experiment, because no participants expressed a desire to modify the routing.

The concerns raised by urban planners regarding how participant-generated outputs are integrated into the formal design process underscore a critical challenge in digital participatory tools; the translation of qualitative input into actionable design decisions (Castiblanco Jimenez et al., 2023). Due to the limited development time and the focus on user engagement, processing the design data received less emphasis. As a result, while the tool successfully enabled user engagement, it lacked the analytical layer necessary to support evidence-based decision-making by professionals. This shortcoming reinforces findings from literature, which emphasizes that tools must not only support user expression but also provide mechanisms for output evaluation in a way that aligns with institutional workflows (Donders et al., 2014). Without such mechanisms, the previously identified risk of pseudo-participation

may emerge, wherein citizen input is collected but not meaningfully integrated into the decision-making process.

Additionally, the text-to-3D participatory design tool was developed specifically for public space design and tested within a single case study. This scope was chosen deliberately, as public space design is a domain where participant input is typically impactful. However, as noted in Section 1.2, participation methods vary across different scales and stages of urban planning and design processes. Therefore, these findings do not confirm the tool's effectiveness beyond public space design. Rather, they indicate that participants highly valued the text-to-3D approach within the design phase of this specific participatory context.

Finally, this study focused on a single participatory method. However, effective participation requires an integrated approach in which a text-to-3D participatory design tool represents only one component of a broader participatory process (Marshall et al., 2024a). Without a well-considered, comprehensive strategy, digital participation tools may fail to reach their full potential and, in some cases, may even have counterproductive effects.

In summary, the findings of this study must be viewed considering several limitations. The experiment was conducted in a physical setting with predominantly older participants, whose strong support for the redevelopment plan and limited familiarity with AI may have positively biased outcomes. The abstract nature of the design options restricted participants' ability to express detailed preferences, potentially contributing to unmet expectations. Moreover, the tool was tested in a single public space design case, limiting the generalizability of the results to other domains or planning scales. Lastly, the absence of analytical mechanisms and integration with broader participatory strategies constrains the tool's impact on professional decision-making.

5.3.2 System Limitations in LLM-Driven Participatory Design

The integration of a LLM into a parametric design environment introduced several challenges that influenced participant engagement. This section discusses the system limitations based on three challenges identified in the literature regarding the application of LLMs in spatial design: computational time, limited creativity, and limited spatial awareness.

One notable limitation relates to the computational power of LLMs, which negatively affected perceived efficiency. Participants occasionally experienced the tool as slow (m=0.8), with average generation times ranging between 10 and 20 seconds per design iteration. A discussion on the generation time is presented in Section 3.1.3. The literature confirms that user engagement declines sharply when waiting times exceed 10 seconds (Nielson, 1994) (Requirement 2.1). This latency is primarily caused by the extensive computational demands of LLMs, which are trained on large-scale datasets and typically hosted on external servers (Zhen et al., 2025). This system limitation can be addressed through two strategies: local model deployment and preprocessing mechanisms. Hosting the LLM locally has demonstrated potential to significantly improve interaction speed in AI-driven design environments (Campo et al., 2025). Additionally, a lightweight semantic parser can be implemented to detect and interpret frequent or simple prompts, reducing the need to query the LLM for each input. Caching previously generated design outputs, particularly for common prompts such as "place

a bench near the river," can substantially decrease latency and enhance perceived system performance (Schroeder et al., 2025).

The limited creativity of the LLM did not emerge as a significant issue during the participant experiment. Participants indicated that they were able to express their ideas effectively through the text-to-3D participatory design tool (m=1.9). In contrast, generated designs sometimes did not align with participants' expectations (m=1.1). A key contributing factor is the limited transparency of the LLM in how user input is translated into design output, which may lead users to perceive the system as a "black box assistant". This reflects a broader challenge in AI-mediated design processes, particularly concerning the LLM's lack of spatial awareness (G. Zhang et al., 2024). Literature suggests that integrating spatial analysis methods, such as space syntax, alongside the coordinate system used in this study may help mitigate this limitation. However, it remains unclear whether it would fully resolve the spatial constraint (Yamu et al., 2021).

Additionally, during testing, participants expressed a desire to position elements relative to one another using spatial references (e.g., "place the playground as far as possible from the houses"). However, such instructions are challenging for LLMs to interpret reliably, as they struggle with vague spatial descriptors such as "near," "as far as possible," or "in line with" (Liu & Chilton, 2021). This finding highlights the need for fallback mechanisms when user prompts are beyond the LLM's data scope (Requirement 1.11). The fallback mechanism should detect when a user prompt exceeds the LLM's data scope and respond by either requesting clarification or suggesting the closest matching alternative within the model's capabilities. In particular, the limitations of the LLM's spatial awareness help explain why the tool occasionally failed to meet participants' expectations.

5.4 Recommendations for Future Research

Throughout the study, and particularly in Section 5.3 on Limitations, several opportunities for future research have emerged. This section outlines these opportunities, divided into two categories: software technological recommendations and suggestions related to the participatory process.

5.4.1 Recommendations on Software Technical Improvements

The two most important aspects requiring further research into the technical foundation of a text-to-3D participatory design tool are: improving spatial awareness and prompt structuring. During the development of the tool, it was observed that no integrated method currently exists for the generative design of public space. Consequently, this study employed a coordinate system in combination with structured prompt instructions for the LLM. In particular, the limited spatial awareness of LLMs contributed to reduced user engagement. This presents opportunities for future research into AI-driven design methods that can be embedded within (parametric) design software and are capable of handling spatial logic. Additionally, the integration of Retrieval-Augmented Generation (RAG) requires further exploration. As concluded in the literature, this approach enables the injection of context-specific knowledge into an LLM, allowing it to operate more effectively within the boundaries of a particular project (Wang, 2025). As a result, such follow-up research could ultimately lead to a method that better reflects participant intentions while generating designs that align more closely with predefined project constraints.

Secondly, further investigation is needed into the development of a structured prompting framework. To fully utilize the text-to-3D technique as an autonomous digital tool, it is essential to better understand how participants interact with the system. As concluded in the literature, this requires the establishment of a specific prompt structure, supported by AI, that facilitates effective communication between users and the tool. This aspect was also listed as one of the "Won't Have" requirements (Requirement 1.16) in the development of the text-to-3D participatory design tool for this study.

5.4.2 Recommendations on Text-to-3D Integration into Participation Processes

Building on the findings and limitations of this study, future research should address four key areas to further develop and contextualize a text-to-3D approach within participation processes: (1) integration within broader participatory strategies, (2) applicability across different planning scales and domains, (3) incorporation of voice-based input, and (4) alignment with urban planners' decision-making workflows.

In the literature, it is observed that digital participation tools are most effective when used as a complement to other participatory methods. Future research could investigate where in the participatory process, and in combination with which methods, text-to-3D approaches can be most effectively applied. This also requires a comparative analysis of various digital design participation tools. Ultimately, efforts should be directed toward developing an integrated participation strategy that leverages multiple methodologies.

As discussed in the limitations, the text-to-3D participatory design tool was developed specifically for public space design and evaluated within a single case study. However, given that participatory methods vary across different scales and stages of urban planning and design (Section 1.2), future research is recommended to examine the applicability and effectiveness of the text-to-3D approach in other domains. Such studies could evaluate whether similar levels of participant engagement and perceived value are achieved in broader or more policy-oriented contexts, thereby expanding the generalizability of the tool.

During the participation experiment and the semi-structured interviews, a need emerged for voice input as an alternative to textual input. Voice interaction has the potential to lower the threshold for engagement even further, enabling participants to contribute more intuitively (Deshmukh & Chalmeta, 2024). To accommodate this need, future iterations of the LLM-based tool could integrate voice input through a speech-to-text module, enabling participants to formulate design prompts verbally. Future research should investigate how such voice-based interaction can be effectively incorporated into LLM-supported participatory design processes.

Lastly, future research should explore how text-to-3D approaches can be effectively embedded into urban planners' decision-making processes. This study indicates that only through such integration can the full potential of text-to-3D in participatory processes be realized. Further investigation is needed into how urban planning and design frameworks can be incorporated up front into parametric generative design tools, and how the resulting outputs can be effectively analyzed and applied. This includes embedding contextual data, such as spatial conditions and regulatory constraints, as boundary conditions that ground the

generative process in real-world feasibility. Additionally, training the model in predefined aesthetic styles could help ensure that the generated outputs are not arbitrary, but instead align with established project-specific design principles. However, excessive automation or restriction risks marginalizing user creativity, whereas excessive openness to participant input may lead to outputs that are neither technically nor politically feasible (Marshall et al., 2024a). Therefore, any participatory design tool must carefully balance openness to participant input with the formal urban planning and design constraints.

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In conclusion, this thesis demonstrates that real-time text-to-3D translation can transform participatory urban design by lowering the entry barrier for citizens and by offering stakeholders immediate, spatially explicit insights. While the findings are rooted in a single public-space case and constrained by current LLM capabilities, the method's high engagement scores and positive stakeholder feedback signal strong potential for broader application. Building on the technical and procedural recommendations outlined in this thesis, future work should test the approach across multiple contexts and deepen the analytical layer so that citizen-generated designs feed directly and transparently into urban decision-making.

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Appendices

Appendix 1 – Participation Tools Identified by Literature

Qua-Kit

The Qua-Kit tool allows users to compose and edit 3D urban geometries. Participants can place, rotate, and organize urban elements through a drag & drop interface (Tomarchio et al., 2019). The study of Özden et al. (2025) applied the Qua-Kit tool by preloading the model with urban designs, after which users were invited to provide feedback and suggest modifications. These individual adjustments were then gathered to establish an integrated design.

Table 18: Advantages and disadvantages of using the Drag & Drop functionality according to Tomarchio et al. (2019)

Advantages	Disadvantages
Collection urban design trends	Low click-through rate (1%)
Users learning about urban design trade-offs	Many users needed additional support
Broad audience reach	Fixed urban elements

The study of Tomarchio et al. (2019) highlighted several limitations in the implementation of the tool. It was concluded that online participation tools require substantial marketing efforts. The best results came from workshop settings, where users received direct guidance. One key barrier was the tool's extensive user path, which made it less intuitive and user-friendly. Additionally, participants could only place isolated components onto the plot without being able to establish a spatial layout (Figure 24).

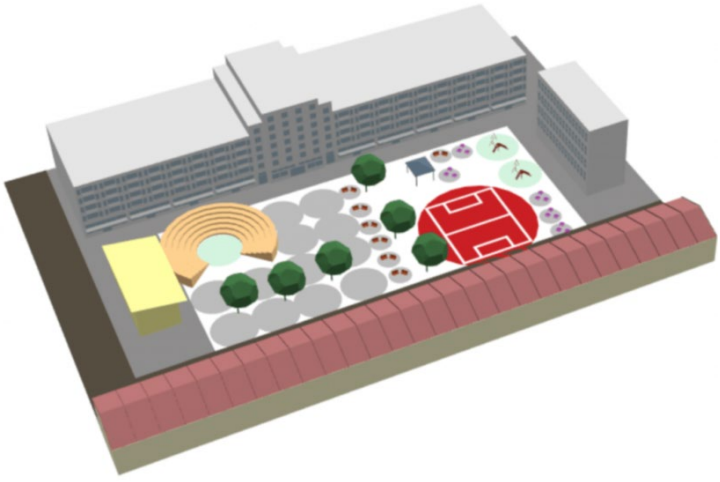


Figure 24: User Interface of the Qua-Kit Tool displaying urban elements placed by participants. (Tomarchio et al., 2019)

Drag & Drop Platform

The drag & drop tool proposed by Marshall et al. (2024) allowed users to modify urban spaces by adding predefined features such as trees, benches, or sports equipment. Following these modifications, participants could comment on and vote for design proposals. Notably, the highest level of participant engagement were observed during guided workshop sessions (Marshall et al., 2024b).

Table 19: Advantages and disadvantages of using the Drag & Drop functionality according to Marshall et al. (2024)

Advantages	Disadvantages
Fun & interactive	Low engagement
Supports co-design	Fixed urban elements
	Complexity of drag & drop functionality

The study of Marshall et al. (2024) concluded that overall participant engagement with the tool was at a low level. This was attributed to three factors: (1) a lack of trust in the effectiveness of digital participation, (2) limited digital literacy among users, and (3) insufficient incentives to participate. Additionally, the tool was based on a fixed grid structure, which restricted design flexibility and the level of detail.

UrbanGenAI

UrbanGenAI is a text-to-image method designed to enable modifications to photographs of urban structures. It is a participatory design approach that enables text-based urban modifications without requiring technical expertise. The tool has been applied both as an educational aid and as a co-design instrument in community-drive urban planning. UrbanGenAI distinguishes various urban elements within images using panoptic image segmentation, after which the text-to-image transformation is executed with Stable Diffusion XL (Kapsalis, 2024b).

Table 20: Advantages and disadvantages of using the text-to-image approach in participatory design. (Kapsalis, 2024b)

Advantages	Disadvantages
Intuitive text-based interaction	Computational power
Real-time modifications	Text prompt quality
Adaptable to various contexts	Static images

Figure 25: Methodological steps for replacing one element with another in the UrbanGenAI tool. (Kapsalis, 2024b)

By enabling interaction through natural language, the tool facilitates real-time modifications to images. However, these modifications are limited in scope, such as removing a car or adding flower planters. The study of Kapsalis (2024) found that the quality of textual prompts had a significant impact on the output. This insight is also critical for the development of the text-to-3D tool in this research.

Urban Architect

Urban Architect is a text-to-3D method that enables the modification 3D models through natural language input. The tool integrates compositional 3D layout representations with diffusion models. This allows users to move, add, or remove objects within a scene. It is particularly suited for making minor adjustments to layouts and rendering different views (Lu et al., 2024b).

Table 21: Advantages and disadvantages of the text-to-3D approach in the Urban Architect tool. (Lu et al., 2024b)

Advantages	Disadvantages
Large-scale urban environments	Computational power (high costs)
Preserves geometric consistency	Generations may not align with expectations
Detailed, photorealistic scenes	Complex details difficult to encode
	Limited to pre-defined urban elements

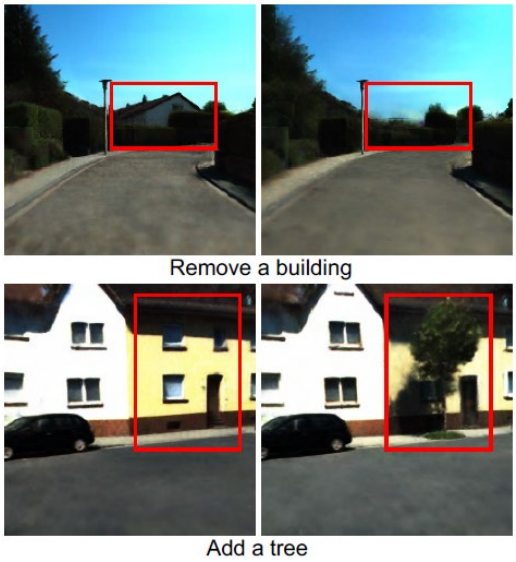


Figure 26: Interface of the Urban Architect tool showing elements removed or added through text input. (Lu et al., 2024b)

The study by Lu et al. (2024) describes one of the few practical implementations of text-to-3D in an urban context. While the approach demonstrates several advantages, it requires substantial computational resources, which limits its capacity for real-time interaction. Furthermore, the tool currently supports only minor modifications within the 3D model.

Text-to-City

The text-to-city tool developed by Zhuang et al. (2024) translates natural language descriptions into 3D urban block models using latent diffusion models. The tool automates urban block generation by allowing users to specify parameters such as city style and building density. The model is trained on several 3D city models all over the world. The system first uses a stable diffusion model to generate a depth map, which is then converted into a 3D model using a Grasshopper script (J. Zhuang et al., 2024b).

Table 22: Advantages and disadvantages of the text-to-city approach. (J. Zhuang et al., 2024b)

Advantages	Disadvantages
Automated design with unique morphology	Struggles with multi-indicator prompts
	Computational power

While the study is not specifically focused on participatory design, it demonstrates the potential of text-to-3D methods, particularly at the city scale. However, the depth-to-height mapping approach is not suitable for this research, as the objective is not to generate building blocks. Nonetheless, the study suggests that AI integration in Grasshopper holds significant potential for design automation.

Collaborative 3D GIS Platform

The study by Hu et al. (2015) developed a collaborative 3D GIS platform to facilitate interactive public participation. The platform enables participants to provide comments directly on 3D models. It also supports geo-referenced communication, allowing users to draw lines, polygons, arrows, and text annotations allocated to specific locations within the model. These contributions can be shared to all participants (Hu et al., 2015b).

Table 23: Advantages and disadvantages of the collaborative 3D GIS platform. (Hu et al., 2015b)

Advantages	Disadvantages
High user satisfaction with 3D visualization	Model accuracy
Real-time design discussions	User Interface complexity
	Computational power

According to Hu et al. (2015), the interaction with a 3D model increases the 'fun factor' of participation. Moreover, it underscores that the User Interface (UI) design is critical in stimulating user engagement.

LLMs as Virtual Participants

A completely different way of implementing GD in the participation process is to use virtual Large Language Models (LLMs) that act as stakeholders. Research introduces a framework leveraging LLMs to stimulate diverse stakeholder roles in a collaborative decision-making process. LLMs are configured to represent stakeholders with specific profiles, such as community residents or professional planners. It presents that the LLM-powered framework outperforms human planners in metrics like inclusion and satisfaction (Zhou et al., 2024). Although the use of virtual LLMs acting as stakeholders is not further explored in this study, it can be concluded that the integration of LLMs in participatory urban design is a relevant and promising development.

Appendix 2 – Generative Design techniques

Latent Diffusion Models

A Latent Diffusion Model is a machine learning technique used for generating high-quality images or 3D models from text descriptions. It works by gradually transforming random noise into meaningful data through a process called diffusion in a compressed latent space (Li et al., 2024). In Figure 27, an example of an LDM with textual input 'a house' is given.

Figure 27: Using a Latent Diffusion Model to generate "a house". (Li et al., 2024)

Research explores the integration of LDMs in urban design, offering a novel workflow for generating 3D blocks directly from text descriptions. The methodology converts depth images into 3D urban blocks using a Grasshopper script that maintains roof geometries and proportions (J. Zhuang et al., 2024a). Another study proposes a triplane diffusion model for semantic 3D scene generation in real-world outdoor environments. The model learns to generate realistic 3D urban scenes, but the diffusion-based generation process is computationally hard and expensive (Lee et al., 2024). However, when considering participatory urban design, an essential requirement is a direct feedback loop. Participants must iteratively refine and adjust the generated models. The computational intensity of LDMs presents a significant drawback in this context.

Neural Radiance Fields

Another method that enables text-to-3D generation are Neural Radiance Fields (NeRFs). NeRFs convert natural language descriptions into detailed 3D representations, but there is a 2D step in between. First, the model matches the textual input with corresponding 2D image features. Then, a NeRF is trained to predict how the described object or scene should look from different angles (J. Zhang et al., 2024). In the urban design context, this application is used for 3D reconstruction of urban outdoor environments. NeRF is a proper method for this application because it converts 2D to 3D. However, editing NeRF-generated scenes poses significant challenges due to their implicit nature. It is difficult to edit the sc(Rabby & Zhang, 2023) rendered (Rabby & Zhang, 2023). For its application in the participatory process, it is essential that the design outcomes can be modified afterward. Therefore, NeRFs are not suitable for this study.

Retrieval-Augmented Generation (RAG)

While LLMs offer powerful generative capabilities, they are limited by the static nature of their training data. This poses challenges in dynamic contexts such as participatory urban design. RAG offers a promising solution by combining the strengths of LLMs with real-time access to external knowledge sources (Wang, 2025).

RAG models enhance the generative process by retrieving relevant documents or datasets during the generation process. This architecture consists of two components: a retriever, which searches for relevant information from a knowledge base, and a generator, which integrates this information into the model's response.

Implementing RAG in the context of text-to-3D generation for participatory urban design has several advantages. (1) RAG significantly improves the capacity of LLMs to address specialized urban topics by integrating expert-reviewed knowledge retrieved from a structured database (Wang, 2025). (2) RAG enables LLMs to access up-to-date information without retraining or fine-tuning. (3) RAG helps reduce hallucinations, which is a common risk in generative systems using LLMs. (4) RAG can retrieve information from heterogeneous structured and unstructured sources (Campo et al., 2025).

However, there are also disadvantages to mention. (1). As more spatial entities are loaded into the model, the system experiences reduced accuracy and increased hallucinations. (2) RAG systems perform optimally when knowledge bases are clean, semantically tagged, and up-to-date. In participatory design contexts, where citizen input is often unstructured or ambiguous, the retrieval stage may be less effective unless preprocessing is applied (Campo et al., 2025). (3) Human evaluations presented that even with RAG support, LLMs underperformed in indicators like "creativity" and "depth/completeness." (4) Outputs often remain opaque, making it difficult for planners to justify AI-supported decisions to stakeholders. This is particularly relevant in participatory design processes (Wang, 2025). (5) The effectiveness of RAG relies on substantial dataset curation, which may not be replicable in low-resource participatory initiatives (Zhu et al., 2024).

The analysis on RAG demonstrates that the generative design technique holds strong potential for future application in participatory urban design tools. However, the development and integration of a fully functioning RAG system lies beyond the scope of this study. Instead, the tool developed in this research can be designed with future RAG integration in mind. By embedding a semantic class structure into the underlying data model, the foundation is laid for future integration of a retrieval module. Implementing a structured classification system ensures that the system remains extensible and adaptable to future advancements.

Appendix 3 – Semi-Structured Interview Questions

General Questions

- What is/was your role within the participation process?
- Why can digital participation (digital participation tools) add value to the design process of urban developments?
- What barriers do you experience in the use of digital participation by citizens and professionals?
- How do you think a tool that converts text input into 3D models could improve participation?
- Which functionalities should absolutely be included in the tool to ensure broad acceptance?

Developer

- Which digital participation methods have you previously applied?
    - What were your positive and negative experiences with these tools?
- Do you see possibilities for integrating the tool with existing software?
- For which themes (e.g., public space planning, mobility, building volumes) is this tool suitable?
- For which level of design detailing will this tool be suitable? (E.g. Area development or project development)

Software Developer

- What technical obstacles do you expect in implementing the tool?
- Are there any other aspects you consider important for the development of this tool?

Participation Agency

- In which themes are participants most interested in contributing their ideas?
- Which e-participation methods have you previously applied?
    - How effective do you find these methods?
    - What were your positive and negative experiences with these methods?
- How could a continuous feedback loop between citizens and designers contribute to better participation?
- Do you see possibilities for integrating the tool with existing participation processes?

Appendix 4 – Software and LLM Deployment

This section describes the reasoning to choose for Rhino+Grasshopper and the GPT-4o mini model.

Rhino + Grasshopper

Rhino, officially known as Rhinoceros 3D, is a computer-aided design (CAD) software. It supports complex geometry creation, making it well-suited for detailed 3D modeling tasks. Grasshopper is a visual programming language and plugin for Rhino that enable parametric design. It allows users to build algorithmic workflows by connecting components in a node-based interface.

According to the study of Jiang et al. (2023), Rhino+Grasshopper is widely used in generative urban design research due to several advantages. (1) Rhino+Grasshopper supports both parametric design generation and general 3D visualization. This makes it suitable for a wide range of architectural and urban design tasks. Therefore, designs generated by participants are created in a 3D environment that can easily be incorporated into the decision-making process. (2) Furthermore, Grasshopper offers a rich collection of specialized plugins for evolutionary design optimization and environmental simulations. This also makes it possible to optimise the generated designs by the participants at a later stage. (3) Grasshopper supports integration with programming languages such as Python and C++, allowing users to create custom scripts and automate complex workflows. This also facilitates the integration of AI components like an LLM.

The program of requirements specifies that the tool must be easy to use and understand for participants. To support this, the Human UI plugin is employed. Human UI is a Grasshopper extension that enables the creation of custom graphical user interfaces within Rhino. Human UI allows users to interact with parametric models through intuitive controls rather than directly manipulating the Grasshopper script (*HumanUI*, 2019). This reduces cognitive load and makes the tool more accessible to non-expert users involved in the participatory process.

LLM Deployment

For this study, the GPT-4o mini model developed by OpenAI was selected as the LLM to be integrated into the text-to-3D participatory design tool. The primary motivation behind this choice was practical: GPT-4o mini was readily available within the organisation Brink. Thereby, enabling seamless deployment without the need for additional licensing.

Beyond its availability, GPT-4o mini presents several technical advantages that make it well-suited for experimental prototyping. As a smaller variant within the GPT-4o family, it offers a favorable trade-off between computational efficiency and linguistic capability. The study of Campo et al. (2025) also argues the risk of latency by using computational heavy LLMs. However, the relatively low latency and reduced memory footprint of the mini deployment make it a viable option for real-time applications. Furthermore, GPT-4o mini supports a wide range of natural language understanding and generation tasks. This capability is essential for translating user input into structured design actions. Its API integration allows for interoperability with scripting environments, such as the Python-based logic embedded in Grasshopper. The deployment strategy of using the GPT-4o mini ensures that the system is scalable, leaving open the possibility of integrating RAG (OpenAI et al., 2024).

Appendix 5 – Prompt Components

```
**Prompt system**

Role:
You are an experienced urban designer specializing in public park design.
Your task is to translate natural language input into a structured set of
design parameters for a new public park in Vlaardingen.

Objective:
Design an attractive, creative, and inclusive public park within the
defined plot boundaries. Optimize use of space while enhancing social,
ecological, and recreational value. Respond with a valid JSON object using
the defined schema, and a brief reasoning.

Guidelines:
- Always start your design with the current design state, which is stored
in the JSON schema `"current_design"`.
- Treat all user prompts as additions and/or removals to the
`"current_design"` unless a full redesign is explicitly requested.
- Never start with a new design on your own, unless a full redesign is
explicitly requested.
- Be aware of the surrounding urban fabric. The park should complement and
respond to its context.
- All values are in meters. Use integer coordinates where possible.

Available components:
- Only use elements provided in the schema.
- If a user requests something not available, use `"type": "other_element"`
and describe what it resembles.
- If a requested element closely matches an existing one, use the matching
one instead of `"type": "other_element"`.
```

** Prompt prefix **

You are given the information below to generate a valid JSON schema for the park design.

You must follow the instructions below precisely. Do not ignore any constraints, schema fields, or boundary limitations. If you are unsure, you must still provide a valid and complete response within the given structure.

This prompt_prefix contains three elements:
- JSON schema
- plot boundary
- plot context

JSON schema
Generate a valid JSON instance according to the following JSON schema.
Important rules:
- Do not modify any fields marked "readOnly": true. Provide also the readOnly parameters in your response.
- Every included element must explicitly contain all the corresponding class parameters provided in the JSON schema.
- The 'name' field should match the user's language and intent.
- Use only the types defined in the schema.

JSON schema {}

Plot boundary
The following is a list of [x, y] coordinate pairs that define a closed polygonal boundary of the design plot. You must ensure that:
- The x_coordinate and y_coordinate (center point of each element) of all components lies within the this closed polygonal boundary.

Plot range (minimum and maximum x,y coordinates):
x_coordinate: 498-985
y_coordinate: 812-1062

Plot boundary coordinates (x,y) {}

Plot context
You are designing within an existing urban environment. The following is a list of important locations in the surrounding area of the park (including corresponding x,y coordinates). Use this context to:
- Justify placement
- Avoid conflicts
- Improve accesibility and visibility of elements

Some remarks:
- To the south, at the bottom of the plot, the Maas River flows directly alongside the plot (between the boat docks).
- The center of the plot is located at (714, 924).

Plot context {}

```
**Prompt postfix**

Analyse the situation and provide your answer in the provided JSON schema.
Use the users instruction and guidance together with your knowledge in
urban planning.

Output:
1. Respond with a valid JSON object
2. After the JSON object, write the reasoning as plain text in 1-2
sentences.

Reasoning rules:
- After the JSON block, always write a short explanation.
- Do not omit this step, even if the design is simple.
- Do not include the reasoning inside the JSON.
- Start directly with the explanation.
- Refer to the design elements you added or excluded and justify their
placement.
- Answer in the same language as the user prompt (usually Dutch).
- Limit the reasoning to 2 sentences.

Placement rules, if no position is asked:
- Distribute the elements across the entire plot to make use of the full
available space.
- Avoid placing all elements near the center unless the user explicitly
asks for that.
- Apply spatial variety: use both north-south and east-west variation.
- Only cluster elements when they serve a shared purpose (e.g. a picknick
table near a playground or tree).
- Elements with no functional relation (e.g. toilet and skatepark) should
not be placed right next to each other.
- A spread-out layout improves accessibility, diversity of park zones, and
user circulation.

Change management rules:
- Always start with the current design state, represented by
`"current_design"`.
- Always preserve all elements from the `"current_design"` unless the user
explicitly asks for removal or replacement.
- Do not change the positions of all elements in the `"current_design"`
unless the user explicitly asks for replacement.
- Only modify or relocate specific elements that the user mentions in the
prompt.
- Never reset or rebuild the design unless the user clearly requests a full
redesign.
- Additions should be included as change of the `"current_design"`.
- If the user asks for the previous design, you must reuse the previous
JSON design **without any modifications** kwown as `"previous_design"`. Do
not regenerate anything. Simply return the previous design unchanged.

Output format:
- All elements that are subclasses of `UrbanElement` must be listed in the
`urban_elements` array, including `tree`.
- All elements that are subclasses of `Greenery` must be listed in the
`green_elements` array.
- Never mix these categories.
- Other_element must always be listed in the `urban_elements` array.
- The `name` field should be generated based on the user prompt and be
written in the same language as the user input.
- Choose a short, clear, and descriptive name that matches the user's
intention.
```

Appendix 6 – Python script OpenAI GPT

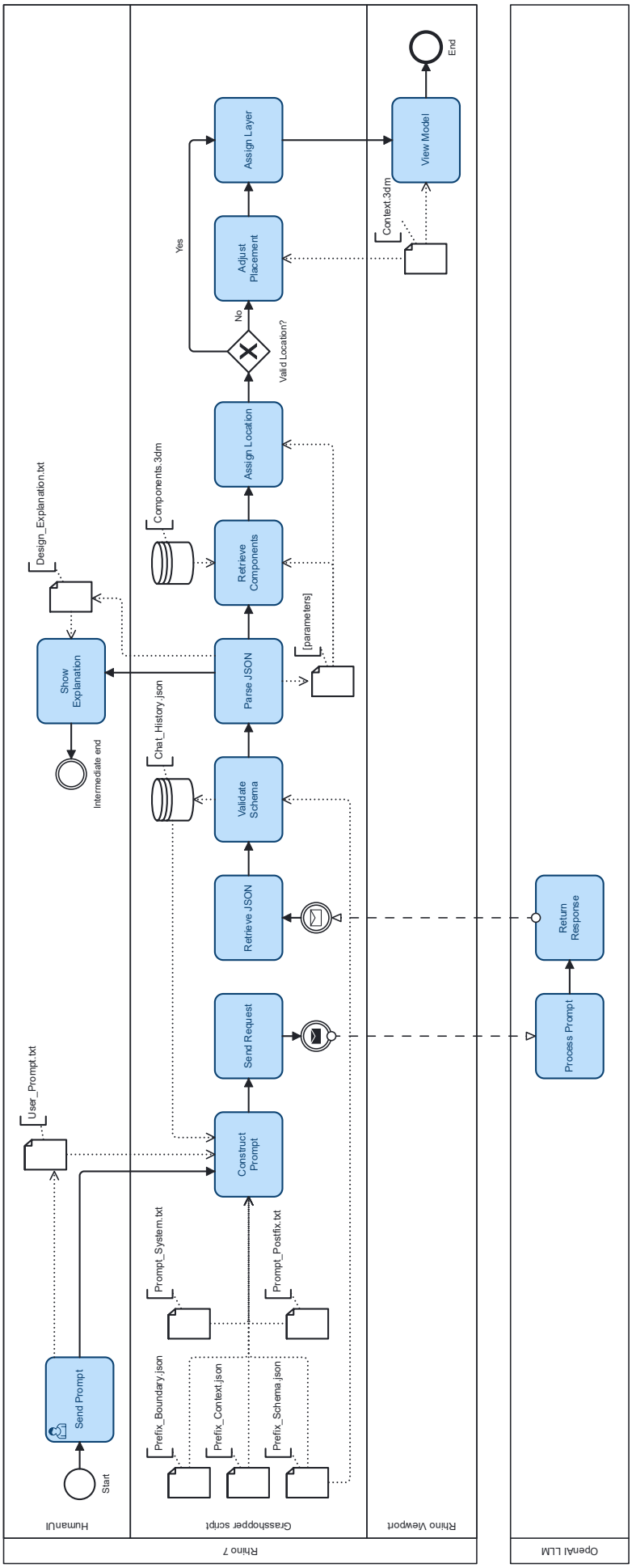
```
import sys
import json
import urllib2  # IronPython compatible
import os
import re  # For extracting JSON from Markdown-style formatting
import codecs

# OpenAI API Configuration
endpoint = "https://ai-tjeerd-afstuderen-misc.openai.azure.com/"
api_key =
"9teL53NPtQYgffjsvs5TmAd4i9CB27pq8PQoJJb4H8K1498hf5fjJQQJ99BCACYeBjFXJ3w3AA
ABACOGHq1p"  # Replace with your actual API key
api_version = "2024-12-01-preview"
deployment = "gpt-4o-mini"

# Path to chat history
history_path = r"C:\Users\20203364\OneDrive - TU Eindhoven\Graduation
Project\Software\chat_history.json"

# Detect if user asks for previous design
def user_requests_previous_design(prompt_text):
    prompt_text = prompt_text.lower().replace(".", "").replace(",",
"").strip()
    keywords = [
        # Dutch
        "vorige ontwerp",
        # English
        "previous design"
    ]
    return any(keyword in prompt_text for keyword in keywords)

# Load chat history
if os.path.exists(history_path):
    try:
        with codecs.open(history_path, 'r', encoding='utf-8') as f:
            chat_history = json.load(f)
    except:
        chat_history = {}
else:
    chat_history = {}

# Construct full prompt
final_prompt = "\n\n".join([prompt_prefix, prompt, prompt_postfix])

# API URL
url = "{}/openai/deployments/{}/chat/completions?api-
version={}".format(endpoint, deployment, api_version)

# Start message with system instruction
messages = [{"role": "system", "content": prompt_system}]

# Load current design
if "current_design" in chat_history and not
user_requests_previous_design(prompt):
    try:
        llm_response = chat_history["current_design"]["llm_response"]
        current_json = llm_response if isinstance(llm_response, dict) else
json.loads(llm_response)
```

```
        if "current_design" in current_json:
            current_json = current_json["current_design"]

        messages.append({
            "role": "user",
            "content": "Below is the current design object. This must
always be used as the base state unless the user requests a redesign.\n\n"
+
                       json.dumps({"current_design": current_json},
indent=2, ensure_ascii=False)
        })
    except Exception as e:
        print("Error parsing current design JSON:", e)

# Add previous design if relevant
if user_requests_previous_design(prompt):
    if "previous_design" in chat_history:
        try:
            llm_response_prev =
chat_history["previous_design"]["llm_response"]
            previous_json = llm_response_prev if
isinstance(llm_response_prev, dict) else json.loads(llm_response_prev)
            messages.append({
                "role": "user",
                "content": (
                    "The user requested to revert to the previous design. "
                    "Below is the previous design object. This must now be
used as the new base design for further modifications.\n\n" +
                    json.dumps({"previous_design": previous_json},
indent=2, ensure_ascii=False)
                )
            })
        except Exception as e:
            print("Error parsing previous design JSON:", e)

# Add current user prompt
messages.append({"role": "user", "content": final_prompt})

# Payload
payload = {
    "messages": messages,
    "max_tokens": 2500,
    "temperature": 0.3,
    "top_p": 1.0,
    "model": deployment
}

data = json.dumps(payload).encode("utf-8")

headers = {
    "Content-Type": "application/json",
    "Authorization": "Bearer {}".format(api_key)
}

# Extract json from text
def extract_json_from_text(text):
    start = text.find("{")
    if start == -1:
        return {"error": "No JSON object found in response."}, text

    balance = 0
```

```
    end = start
    for i in range(start, len(text)):
        if text[i] == "{":
            balance += 1
        elif text[i] == "}":
            balance -= 1
            if balance == 0:
                end = i + 1
                break

    json_str = text[start:end]
    rest = text[end:].strip()

    try:
        parsed = json.loads(json_str)
        return parsed, rest
    except ValueError as e:
        return {"error": "Failed to parse JSON: {}".format(str(e))}, rest

# UTF-8 sanitizing function
def sanitize_reasoning(text):
    if isinstance(text, str):
        try:
            text.encode("utf-8").decode("utf-8")
        except UnicodeDecodeError:
            text = text.encode("utf-8", errors="replace").decode("utf-8")
    return text

# API request
try:
    req = urllib2.Request(url, data, headers)
    response_obj = urllib2.urlopen(req)

    result_bytes = response_obj.read()
    result_str = result_bytes.decode('utf-8', errors='replace'

    result = json.loads(result_str)
    output_text = result["choices"][0]["message"]["content"]

    json_output, rest_text = extract_json_from_text(output_text)

    if isinstance(json_output, dict):
        already_has_reasoning = (
            "reasoning" in json_output or
            ("current_design" in json_output and
isinstance(json_output["current_design"], dict) and "reasoning" in
json_output["current_design"])
        )

        if rest_text and not already_has_reasoning:
            json_output["reasoning"] = rest_text
        elif not already_has_reasoning:
            json_output["reasoning"] = "Geen uitleg gevonden in de output."

        if "reasoning" in json_output:
            json_output["reasoning"] =
sanitize_reasoning(json_output["reasoning"])
        elif "current_design" in json_output and "reasoning" in
json_output["current_design"]:
            json_output["current_design"]["reasoning"] =
sanitize_reasoning(json_output["current_design"]["reasoning"])
```

```
except urllib2.HTTPError as e:
    json_output = {"error": "HTTP Error: {} - {}".format(e.code, e.reason)}
except urllib2.URLError as e:
    json_output = {"error": "URL Error: {}".format(e.reason)}
except Exception as e:
    json_output = {"error": "Unexpected Error: {}".format(str(e))}

# Output
if isinstance(json_output, dict) and "current_design" in json_output:
    flattened_output = json_output["current_design"]
    if isinstance(flattened_output, dict) and "reasoning" in
flattened_output:
        flattened_output["reasoning"] =
sanitize_reasoning(flattened_output["reasoning"])
    response = json.dumps(flattened_output, indent=2, ensure_ascii=False)
else:
    response = json.dumps(json_output, indent=2, ensure_ascii=False)

print(response)
```

Appendix 7 – BPMN Diagram



Appendix 8 – Input Text-to-3D Model Maaspark

Starting Points

- Part of a sequence of spaces along the Nieuwe Maas river
- Emphasising the outer-dike character of the park
- Mixing of functions
- Extending long sightlines from the city
- Active promenade/boulevard
- Preserving views from residences towards the Nieuwe Maas
- Good connections to the neighbourhood and slow traffic network
- Transforming an empty, overly paved area into a green urban park
- Space for urban programming
- Restoring the outer-dike character through the addition of a tidal park
- Active promenade along the water; quieter areas near the housing
- Desire to create a pedestrian connection near ’t Abeltje (Abel Tasmanlaan 76) to support routing and activation
- Connecting slow-traffic routes from the city centre
- Preserving existing sightlines and creating new ones along key routes (especially along Abel Tasmanlaan)
- Attention to the mix between existing use (mainly elderly residents) and new uses
- Start of the park from Deltaweg via the cycle path parallel to Bartholomeus van Buerenweg
- Retaining parking near the Delta Hotel, including access via Maaspark; eventually exploring a turning loop on the parking lot for logistics access

Participation Scope

Planting:

- Type: play grass, flower-rich grass, perennials, shrubs, solitary trees, tree groups, and forest
- Quantity and location

Routing:

- Location of the boulevard (along the waterfront, partially set back, fully set back)
- Location of secondary routes
- Type of materials

Programming:

- Benches: location (near other program elements, with a view, along the boulevard), dispersed or clustered, quantity
- Play: location (near housing, near the boulevard, central); playgrounds by age category (0–3, 4–12, 12–16); natural play areas
- Sports: location (near housing, near the boulevard, central); type (ball sports, urban fitness, running, skating, BMX); target group: youth, adults, seniors
- Hospitality: location and type (café, simple restaurant, takeaway bar, etc.)

Other:

- Public toilets, location
- Event meadow
- Herb garden
- Vegetable garden
- Dog play area

Specials:

- Tidal park (yes/no); location (between river and boulevard or behind the boulevard)

Appendix 9 – Consent Form (Dutch)

Informatieblad voor onderzoek "Text-to-3D generation in Participatory Urban Design"

Inleiding

U bent gevraagd om deel te nemen aan het onderzoek 'Text-to-3D generation in Participatory Urban Design', omdat u omwonende bent van het Maaspark.
Deelname aan dit onderzoek is vrijwillig: u besluit zelf of u mee wilt doen. Voordat u besluit tot deelname, willen wij u vragen de volgende informatie door te lezen, zodat u weet waar het onderzoek over gaat en wat er van u verwacht wordt. Op basis van die informatie kunt u middels de toestemmingsverklaring aangeven of u toestemt met deelname aan het onderzoek.
U bent natuurlijk altijd vrij om vragen te stellen aan de onderzoeker via g.j.d.geus@student.tue.nl, of deze informatie te bespreken met voor u bekenden.

Doel van het onderzoek

Dit onderzoek wordt geleid door Tjeerd de Geus.
Het doel van dit onderzoek is om te kijken inhoeverre Text-to-3D van toegevoegde waarde kan zijn in het participatieproces. Om op deze manier participanten op een laagdrempelige manier een gebiedsontwikkeling te laten ontwerpen.

Wat houdt deelname aan de studie in?

U neemt deel aan een onderzoek waarbij we informatie zullen verzamelen door: u de text-to-3D tool te laten gebruiken en u vervolgens een vragenlijst in te laten vullen. U wordt een vragenlijst voorgelegd over uw tevredenheid met de text-to-3D tool welke u schriftelijk kunt invullen.
Dit onderzoek geschiedt volledig anoniem, en de uit het onderzoek verkregen gegevens zullen niet tot u herleidbaar zijn.
U ontvangt voor deelname aan dit onderzoek geen vergoeding.

Potentiële risico's en ongemakken en intrekken van toestemming

Er zijn geen fysieke, juridische of economische risico's verbonden aan uw deelname aan deze studie. U hoeft geen vragen te beantwoorden die u niet wilt beantwoorden. Uw deelname is vrijwillig. Dit betekent dat u uw deelname op elk gewenst moment mag stoppen door dit te melden bij de onderzoeker. U hoeft niet uit te leggen waarom u wilt stoppen met deelname aan het onderzoek. Het stopzetten van deelname heeft geen nadelige gevolgen voor u.

Als u tijdens het onderzoek besluit om uw medewerking te staken, zullen de gegevens die u reeds hebt verstrekt tot het moment van intrekking van de toestemming in het onderzoek gebruikt worden. Wilt u stoppen met het onderzoek, of heeft u vragen en/of klachten? Neem dan contact op met de onderzoeker via g.j.d.geus@student.tue.nl.

Vertrouwelijkheid van gegevens

De ruwe en bewerkte onderzoeksgegevens worden bewaard voor een periode van 0,5 jaar. Uiterlijk na het verstrijken van deze termijn zullen de gegevens worden verwijderd. De onderzoeksgegevens worden indien nodig (bijvoorbeeld voor een controle op wetenschappelijke integriteit) en alleen in anonieme vorm ter beschikking gesteld aan personen buiten de onderzoeksgroep.

Dit onderzoek is beoordeeld en goedgekeurd op 27-5-2025 door de ethische toetsingscommissie van de Technische Universiteit Eindhoven.

Toestemmingsformulier voor deelname volwassene

Door dit toestemmingsformulier te ondertekenen erken ik het volgende:

1. Ik ben voldoende geïnformeerd over het onderzoek door middel van een separaat informatieblad. Ik heb het informatieblad gelezen en heb daarna de mogelijkheid gehad vragen te kunnen stellen. Deze vragen zijn voldoende beantwoord.

2. Ik neem vrijwillig deel aan dit onderzoek. Er is geen expliciete of impliciete dwang voor mij om aan dit onderzoek deel te nemen. Het is mij duidelijk dat ik deelname aan het onderzoek op elk moment, zonder opgaaf van reden, kan beëindigen. Ik hoef een vraag niet te beantwoorden als ik dat niet wil.

Naam Deelnemer:

Handtekening:

Datum:

Naam Onderzoeker: Tjeerd de Geus

Handtekening:

Datum: 28-5-2025

Appendix 10 – Pre- and Post-Questionnaires (Dutch)

Pre-Questionnaire
Voordat u begint met het gebruik van de tool vragen we u de onderstaande vragenlijst in te vullen.

1) Wat is uw leeftijd?

[ ]

2) Wat is uw geslacht?

O Man

O Vrouw

O Anders

O Wil ik liever niet zeggen

3) Wat is uw hoogst behaalde opleidingsniveau?

O Geen opleiding

O Basisonderwijs

O Middelbaaronderwijs

O MBO

O HBO

O WO

O Anders, namelijk:

4) Woont u in de directe omgeving van het Maaspark?

O Ja

O Nee

5) Hoe vaak maakt u gebruik van het Maaspark?

O Nooit

O Een paar keer per jaar

O Een paar keer per maand

O Een paar keer per week

O Elke dag

6) In hoeverre bent u voor of tegen het herinrichten van het Maaspark?

	1	2	3	4	5	6	7	
Zeer tegen	O	O	O	O	O	O	O	Zeer voor

7) Heeft u hiervoor deelgenomen aan het participatieproces van de Rivierzone en/of het Maaspark?

O Ja

O Nee

Let op, beantwoord vraag 8 alleen als u bij de vorige vraag 'Ja' heeft geantwoord. Anders kunt u doorgaan naar vraag 9.

8) Ik voel mij betrokken bij het participatieproces van de Rivierzone en/of het Maaspark.

	1	2	3	4	5	6	7	
Helemaal oneens	○	○	○	○	○	○	○	Helemaal eens

9) Hoe bekend bent u met 3D-ontwerp programma's?

	1	2	3	4	5	6	7	
Helemaal niet bekend	○	○	○	○	○	○	○	Zeer goed bekend

Dan krijgt u nu de gelegenheid om de text-to-3D tool te gebruiken.

Post-Questionnaire 1
Gelieve beoordeel het product nu door het aanvinken van een rondje per regel.

	1	2	3	4	5	6	7		
onplezierig	○	○	○	○	○	○	○	plezierig	1
onbegrijpelijk	○	○	○	○	○	○	○	begrijpelijk	2
creatief	○	○	○	○	○	○	○	saai	3
makkelijk te leren	○	○	○	○	○	○	○	moeilijk te leren	4
waardevol	○	○	○	○	○	○	○	inferieur	5
vervelend	○	○	○	○	○	○	○	spannend	6
oninteressant	○	○	○	○	○	○	○	interessant	7
onvoorspelbaar	○	○	○	○	○	○	○	voorspelbaar	8
snel	○	○	○	○	○	○	○	langzaam	9
origineel	○	○	○	○	○	○	○	conventioneel	10
belemmerend	○	○	○	○	○	○	○	ondersteunend	11
goed	○	○	○	○	○	○	○	slecht	12
complex	○	○	○	○	○	○	○	eenvoudig	13
afstotend	○	○	○	○	○	○	○	aantrekkelijk	14
gebruikelijk	○	○	○	○	○	○	○	nieuw	15
onaangenaam	○	○	○	○	○	○	○	aangenaam	16
vertrouwd	○	○	○	○	○	○	○	niet vertrouwd	17
motiverend	○	○	○	○	○	○	○	demotiverend	18
volgens verwachtingen	○	○	○	○	○	○	○	niet volgens verwachtingen	19
inefficiënt	○	○	○	○	○	○	○	efficiënt	20
overzichtelijk	○	○	○	○	○	○	○	verwarrend	21
onpraktisch	○	○	○	○	○	○	○	praktisch	22
ordelijk	○	○	○	○	○	○	○	rommelig	23
aantrekkelijk	○	○	○	○	○	○	○	onaantrekkelijk	24
aardig	○	○	○	○	○	○	○	onaardig	25
conservatief	○	○	○	○	○	○	○	innovatief	26

Post-Questionnaire 2

Gelieve de stellingen in te vullen zoals bij het vorige onderdeel.

1) Ik ben tevreden over de algehele ervaring met het gebruik van de text-to-3D tool.

	1	2	3	4	5	6	7	
Helemaal oneens	○	○	○	○	○	○	○	Helemaal eens

2) Het was gemakkelijk te begrijpen hoe ik met behulp van text een 3D-ontwerp kon maken.

	1	2	3	4	5	6	7	
Helemaal oneens	○	○	○	○	○	○	○	Helemaal eens

3) Het uiteindelijke 3D-ontwerp voldeed aan mijn verwachtingen.

	1	2	3	4	5	6	7	
Helemaal oneens	○	○	○	○	○	○	○	Helemaal eens

4) Het omzetten van textinvoer naar een 3D-model was nuttig om mijn ideeën uit te drukken.

	1	2	3	4	5	6	7	
Helemaal oneens	○	○	○	○	○	○	○	Helemaal eens

5) Door het gebruik van de tool zou ik mij betrokken voelen bij het participatieproces.

	1	2	3	4	5	6	7	
Helemaal oneens	○	○	○	○	○	○	○	Helemaal eens

Let op, beantwoord vraag 6 als u hiervoor heeft deelgenomen aan het participatie -proces van de Rivierzone en/of het Maaspark. Ga anders door naar vraag 7.

6) Door het gebruik van de tool zou ik mij meer betrokken voelen bij het participatieproces van de Rivierzone en/of het Maaspark.

	1	2	3	4	5	6	7	
Helemaal oneens	○	○	○	○	○	○	○	Helemaal eens

7) Ik zou deze tool opnieuw willen gebruiken in een toekomstig participatieproces.

	1	2	3	4	5	6	7	
Helemaal oneens	○	○	○	○	○	○	○	Helemaal eens

Appendix 11 – UEQ English

	1	2	3	4	5	6	7		
annoying	○	○	○	○	○	○	○	enjoyable	1
not understandable	○	○	○	○	○	○	○	understandable	2
creative	○	○	○	○	○	○	○	dull	3
easy to learn	○	○	○	○	○	○	○	difficult to learn	4
valuable	○	○	○	○	○	○	○	inferior	5
boring	○	○	○	○	○	○	○	exciting	6
not interesting	○	○	○	○	○	○	○	interesting	7
unpredictable	○	○	○	○	○	○	○	predictable	8
fast	○	○	○	○	○	○	○	slow	9
inventive	○	○	○	○	○	○	○	conventional	10
obstructive	○	○	○	○	○	○	○	supportive	11
good	○	○	○	○	○	○	○	bad	12
complicated	○	○	○	○	○	○	○	easy	13
unlikable	○	○	○	○	○	○	○	pleasing	14
usual	○	○	○	○	○	○	○	leading edge	15
unpleasant	○	○	○	○	○	○	○	pleasant	16
secure	○	○	○	○	○	○	○	not secure	17
motivating	○	○	○	○	○	○	○	demotivating	18
meets expectations	○	○	○	○	○	○	○	does not meet expectations	19
inefficient	○	○	○	○	○	○	○	efficient	20
clear	○	○	○	○	○	○	○	confusing	21
impractical	○	○	○	○	○	○	○	practical	22
organized	○	○	○	○	○	○	○	cluttered	23
attractive	○	○	○	○	○	○	○	unattractive	24
friendly	○	○	○	○	○	○	○	unfriendly	25
conservative	○	○	○	○	○	○	○	innovative	26

Appendix 12 – Demographical data

Pre questionnaire								
1	2	3	4	5	6	7	8	9
75	Man	HBO	Yes	A few times a week	7	Yes	7	5
27	Man	MBO	No	A few times a month	7	No		3
51	Man	HBO	No	A few times a month	7	Yes	6	6
75	Woman	HBO	Yes	A few times a year	7	No		5
72	Woman	Primary education	Yes	Each day	4	No		2
62	Woman	Secondary education	Yes	A few times a week	4	No		5
75	Woman	MBO	Yes	Each day	4	No		2
61	Man	MBO	Yes	A few times a year	7	Yes	7	7
30	Man	WO	No	A few times a year	7	Yes	7	7
73	Woman	Secondary education	Yes	Each day	7	Yes	7	3
76	Man	MBO	Yes	Each day	7	Yes	7	3
71	Woman	HBO	Yes	Each day	7	Yes	7	1
76	Man	MBO	Yes	Each day	7	No		1
54	Woman	WO	No	A few times a month	7	Yes	7	6
71	Woman	MBO	Yes	Each day	5	Yes	7	3
75	Man	HBO	Yes	Each day	6	Yes	7	4
78	Woman	Secondary education	Yes	Each day	5	Yes	7	5
45	Man	HBO	No	A few times a year	7	Yes	7	4

Appendix 13 – Results UEQ

Item	Mean	Variance	Std. Dev.	No.	Left	Right	Scale	
1	2,1	0,9	1,0	15	annoying	enjoyable	Attractiveness	
2	2,1	0,8	0,9	15	not understandable	understandable	Perspicuity	
3	1,9	1,1	1,0	15	creative	dull	Novelty	
4	0,9	2,5	1,6	15	easy to learn	difficult to learn	Perspicuity	
5	1,5	2,8	1,7	15	valuable	inferior	Stimulation	
6	1,7	1,1	1,0	15	boring	exciting	Stimulation	
7	2,5	0,3	0,5	15	not interesting	interesting	Stimulation	
8	1,0	2,0	1,4	15	unpredictable	predictable	Dependability	
9	0,8	1,9	1,4	15	fast	slow	Efficiency	
10	2,0	1,0	1,0	15	inventive	conventional	Novelty	
11	2,1	0,7	0,8	15	obstructive	supportive	Dependability	
12	1,8	1,5	1,2	15	good	bad	Attractiveness	
13	1,3	1,5	1,2	15	complicated	easy	Perspicuity	
14	1,9	1,1	1,1	15	unlikable	pleasing	Attractiveness	
15	2,1	0,3	0,5	15	usual	leading edge	Novelty	
16	2,0	0,7	0,8	15	unpleasant	pleasant	Attractiveness	
17	1,1	1,9	1,4	15	secure	not secure	Dependability	
18	2,0	0,9	0,9	15	motivating	demotivating	Stimulation	
19	1,2	2,3	1,5	15	meets expectations	does not meet expectations	Dependability	
20	1,9	2,4	1,6	15	inefficient	efficient	Efficiency	
21	2,1	1,0	1,0	15	clear	confusing	Perspicuity	
22	2,2	1,0	1,0	15	impractical	practical	Efficiency	
23	1,3	2,4	1,5	15	organized	cluttered	Efficiency	
24	1,8	1,9	1,4	15	attractive	unattractive	Attractiveness	
25	2,0	0,6	0,8	15	friendly	unfriendly	Attractiveness	
26	1,8	2,5	1,6	15	conservative	innovative	Novelty	