

Human-AI Collaboration in Spatial Planning: Designing an Interface for Visualizing Multi-Objective Trade-offs for Non-Expert Users

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Abstract: In public-space planning, non-expert users can often spot that something is off. However, understanding the multi-objective trade-off logic behind a planning decision is a different story. This gap limits how deep public participation can actually go. Prior work on explainable AI (XAI) has mostly centered on explanation and user trust. Multi-objective decision support tools, meanwhile, tend to be built with expert users in mind. How non-experts might actually make sense of a complicated trade-off structure has gotten much less attention. To help close that gap, this study designs an explainable interface for non-expert users in public-space planning. It's tested through a preliminary questionnaire and a between-subject user study comparing a conventional interface against the explainable one. The comparison looks at users' understanding of trade-offs, their decision confidence, and how transparent the reasoning behind a recommendation feels to them. The explainable interface came out ahead on all three fronts. Users understood the pros and cons of different plans more clearly, along with the trade-offs among competing objectives and the reasoning behind recommendations. Their confidence increased too, without any drop in their sense of autonomy. Taken together, these results support explainable interfaces as a way to improve non-expert understanding of public-space plans. They also offer some empirical grounding for discussions of algorithmic transparency and public communication in planning.

Keywords: Explainable Artificial Intelligence (XAI); Spatial Planning; Non-expert Users; Multi-objective Trade-offs; Decision-support interface; Public Participation.

1. Introduction

In public-space planning and design, decisions often require balancing and negotiating between multiple objectives. For example, adding more greenery may improve comfort, but it may also reduce activity space; adding more commercial facilities may increase spatial vitality, but it may also bring noise and congestion. Therefore, multi-objective trade-offs are a core feature of spatial planning decisions.

For non-expert users, although they do not have professional planning knowledge, they are still able to notice problems in public spaces, such as confusing circulation, a lack of shade, or insufficient activity space. Despite this, non-expert users often find it difficult to further understand the decision logic and goal trade-offs behind planning proposals in actual urban renewal processes. As a result, public participation often stays stuck at the level of gut-level preference. It rarely develops into something more structured.

Explainable artificial intelligence (XAI) has drawn growing interest in recent years, particularly in fields like healthcare and finance. Multi-objective decision support and interactive visualization techniques have matured alongside it. However, existing XAI studies mainly focus on the relationship between explanation and trust, and research on multi-objective decision support is also largely designed for expert users, paying less attention to how non-expert users can understand and engage with complex trade-off structures. Based on this gap, this study explores an explainable interface design approach for non-expert users in spatial planning, so that the public can not only see planning outcomes, but also better understand planning goals and the trade-off logic behind them.

Accordingly, this study investigates how an explainable interface can help non-expert users better understand trade-offs in multi-objective spatial planning. In this study, XAI is not regarded as the only solution to multi-objective planning problems, but rather as a design strategy worth testing for supporting non-expert users' understanding of trade-off logic in spatial decision-making. To address this question, this study introduces XAI and multi-objective decision-support methods into the context of public-space planning, designs an explainable interface, and evaluates its effect through user research. In doing so, it aims to provide a reference for algorithmic transparency and public participation in urban planning.

2. Literature Review

2.1. Explainable AI and Non-expert Users

Barredo Arrieta et al. (2020) provided a systematic review of the field of explainable artificial intelligence (XAI), arguing that the core purpose of XAI is to make the decision logic of AI systems understandable to specific audiences, and emphasizing that the effectiveness of explanations is closely related to users' cognitive abilities[1]. Therefore, XAI is concerned not only with model transparency, but also with whether explanatory content can be effectively understood by its target users.

At present, XAI has been widely applied in high-risk decision-making domains such as healthcare and finance, where existing studies mainly focus on how explanation mechanisms influence user trust, willingness to adopt, and perceived transparency. For example, Abbas et al. (2025), in their review of clinical decision support systems, pointed out

that current XAI research is mainly oriented toward professional users and pays limited attention to the usability and understanding needs of non-expert users[2].

Research on XAI interfaces for non-expert users further suggests that the form of explanation directly affects user understanding. Bove and Lesot (2023) found that multiple counterfactual examples and comparative analysis functions can improve non-expert users' understanding of algorithmic decision logic. Zhang et al. (2025) also showed that, compared with static explanations, conversational explanations that support follow-up questions are better able to respond to the diverse information needs of non-AI users[3,4]. These studies suggest that the presentation and interaction design of explanations play an important role in helping non-expert users understand AI-supported decisions.

A key gap remains in that existing XAI research still mainly focuses on domains such as healthcare and finance, and pays less attention to non-expert users in public-space planning. In particular, in multi-objective spatial decision-making, the public needs not only to know what AI recommends, but also to understand the trade-offs between different planning goals. Therefore, there is still room for further research on how XAI can be applied to public-space planning and how it can help non-expert users understand complex trade-off structures.

2.2. Multi-objective Decision Support and Trade-off Visualization

A good number of mature methods now exist for multi-objective decision support and trade-off visualization, mostly aimed at helping decision-makers see where objectives conflict and compare alternatives that would otherwise be hard to parse. Indicator visualization, rule extraction, interactive interfaces — these are the usual tools for turning high-dimensional decision information into something visual and easier to work through.

Smedberg and Bandaru (2023) built an interactive decision-support system that pairs multi-objective optimization visualization with knowledge discovery, giving decision-makers a clearer view of how the decision space relates to the objective space[5]. Yadav et al. (2023) took a different route, combining explainable self-organizing maps with the NIMBUS framework to lay out high-dimensional Pareto solution sets and make the trade-offs between objectives more visible[6]. Both point to the same conclusion: visualization and interactive presentation genuinely help reduce the difficulty of parsing complex multi-objective information.

The catch is that most of these systems are built for engineering optimization or professional decision-making, and they tend to assume the user already has some grounding in optimization theory or professional analysis. Hand a non-expert a Pareto solution set, a weight relationship, or a high-dimensional indicator chart, and the cognitive load goes up fast. These methods lay a solid technical foundation for trade-off visualization, but whether that foundation is actually understandable to the public is still an open question.

Hong et al. (2021) offer a useful data point here — their controlled experiment found that a two-dimensional visualization layout improved users' perceived transparency and usefulness in multi-criteria decision-making interfaces, compared with a traditional one-dimensional layout[7]. In other words, how an interface represents information externally shapes how well users grasp the trade-offs behind it. This study builds on that idea, bringing multi-objective

trade-off visualization into public-space planning and asking how interface design for non-expert users can help them better understand the trade-off logic embedded in spatial planning schemes.

2.3. Public Participation in Spatial Planning

Public participation has long been treated as a key mechanism for improving transparency and decision quality in spatial planning and urban governance. As AI and data-driven tools work their way into planning processes, whether the public can actually follow the analytical logic behind these tools has become a real factor shaping how good that participation is.

Lartey and Law (2025) reviewed AI applications in urban planning governance and found that most existing research stays at a theoretical level, without much integration into real governance frameworks. Their study flagged something important: the black-box nature of AI systems can get in the way of stakeholders understanding and overseeing planning decisions, and the tools available tend to chase efficiency while paying less attention to inclusiveness or community values[8]. In other words, just dropping AI into public-space planning doesn't automatically make participation better. The real issue is whether the public can actually understand what the AI-assisted decision is based on.

Work on planning support systems points to similar problems. Pettit et al. (2018) found that Planning Support Systems (PSS) get plenty of discussion in smart-city contexts, but actual adoption stays limited — usability issues, lack of transparency, and a mismatch with what users actually need are the main culprits[9]. Hanan and Carhart (2025) push this further, arguing that urban planning tools tend to get stuck between two extremes: professional GIS tools that are too complex for non-experts, and lightweight tools that don't go deep enough analytically[10]. So making something easier to operate isn't the same as making it understandable. What matters more for participation quality is whether an interface can actually explain its own analytical process and decision logic.

In summary, existing studies on public participation and planning support suggest that the key issue in current public-space planning is not only whether the public is allowed to participate, but also whether they have the ability and the tools to understand complex planning logic. Therefore, this study focuses on non-expert users' understanding of multi-objective trade-off logic in AI-assisted decision-support interfaces, and explores whether explainable interface design can help bridge the cognitive gap between planning analysis and public understanding.

2.4. Research Gap

Existing studies have established a certain foundation in the fields of XAI, multi-objective decision support, and public participation. Nevertheless, effective integration across these three areas is still limited. XAI research has mainly focused on explanation and trust in domains such as healthcare and finance. Research on multi-objective decision support, although capable of presenting complex trade-off relationships, has been mainly designed for expert users. Studies on public participation have highlighted problems of transparency and understanding in planning processes, but have rarely proposed specific explainable interface methods.

Therefore, there is still a lack of AI-assisted spatial decision-support interfaces designed for non-expert users to

help users understand the multi-objective trade-off logic in public-space planning schemes. In response to this gap, the present study explores how explainable interfaces can transform complex planning logic into forms of comparison, visualization, and explanation that are more understandable to the public.

3. Research Methodology and Evaluation

3.1. Preliminary Questionnaire Survey

Before designing the explainable interface, this study ran a preliminary questionnaire to get a sense of how non-expert users actually interpret public-space planning schemes, and what kind of explanatory information they need. The questionnaire covered four areas: everyday perception of public-space design problems, demand for explanations in AI-assisted spatial decision-making, difficulties in understanding multi-objective spatial schemes, and preferences for how information gets presented on an interface.

55 valid responses came in, from a fairly mixed group — architecture, urban planning and design, engineering and technology, humanities and social sciences, business, among other fields. These results fed directly into the interface design that followed, especially in deciding which types of information and which explanation formats actually belonged on the interface.

3.2. Experimental Design and Evaluation Method

This study takes a research-through-design approach as its overall strategy, using interface prototyping to explore explainable support for non-expert users, paired with a user experiment for evaluation. The experiment follows a between-subjects design: participants split into two groups, one working with a conventional interface, the other with an explainable interface. Both groups get the same public-space case and task scenario, which makes it possible to compare how different ways of presenting information affect users' understanding of planning goals, spatial changes, and trade-off logic.

3.2.1. Experimental Variables

The independent variable here is interface type, with two conditions. The conventional interface sticks to scheme

images, brief descriptions, and an overall score — no further explanation offered. The explainable interface shows the same schemes but adds multi-scheme comparison, strengths-and-weaknesses descriptions, and trade-off explanations on top.

As for dependent variables: how well participants understood each scheme's strengths and weaknesses, how well they grasped the trade-off relationships between different objectives, their decision confidence, and how clear the system's recommendation reasons felt to them. These get measured through a five-point Likert-scale questionnaire, backed up by participants' stated reasons for their choices and some brief open feedback.

3.2.2. Experimental Materials and Task

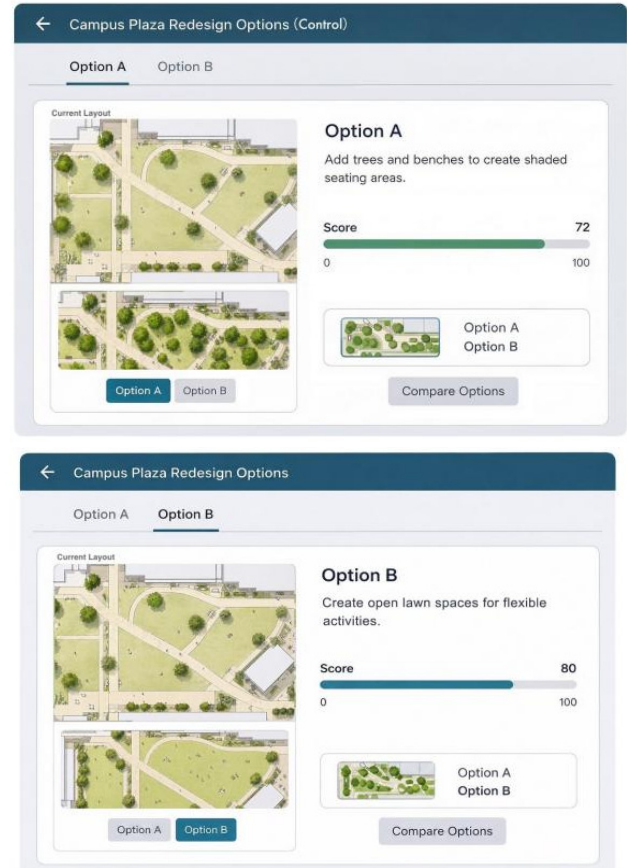


Figure 1. Conventional interface: Option A and Option B

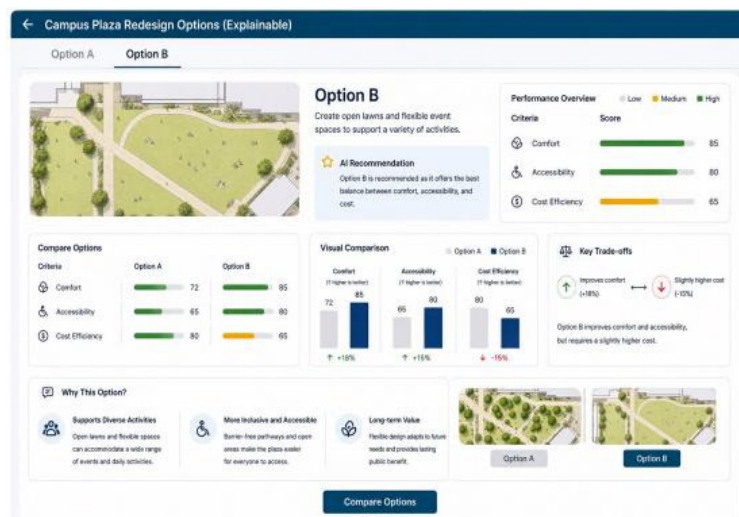


Figure 2. Explainable interface: option comparison and trade-off explanation

The materials include the conventional interface prototype (Figure 1), the explainable interface prototype (Figure 2), the questionnaire, and a handful of short interview questions. Both prototypes were built in Figma to simulate how a public-space scheme might actually get presented and supported in a real decision process.

The scenario centers on redesigning a campus public space. Participants compare two design options: Option A adds trees and benches to create a shaded resting space, Option B goes with an open lawn to provide more flexible activity space.

Participants review both options under whichever interface condition they're assigned to, pick the one they support more, then answer questions about how well they understood the schemes and what the decision-making experience was like for them. The point here isn't to test professional planning ability — it's to see whether the interface condition itself helps non-expert users better grasp the differences between schemes and the trade-off relationships between competing objectives.

3.2.3. Experimental Procedure and Evaluation Method

The researcher starts by briefly introducing the task background, then assigns participants to either the conventional interface group or the explainable interface group. Once they finish the scheme reading and selection task under their assigned condition, participants fill out a five-point Likert-scale questionnaire covering their perceptions of the schemes' strengths and weaknesses, trade-off relationships, decision confidence, and how clear the recommendation reasons felt. The researcher also collects their stated reasons for choosing what they chose, plus open-ended feedback, to get a fuller picture of how each interface condition shapes non-expert users' understanding process.

3.3. Data Analysis and Results

3.3.1. Analysis of Preliminary Questionnaire Results

The preliminary questionnaire results show that respondents generally had a decent level of spatial perception, and a fairly strong demand for explanations in AI-assisted spatial decision-making. But when it came to spatial schemes involving multiple objectives, users still struggled — especially with grasping trade-off relationships between different goals and turning gut feelings into something closer to a structured judgment.

Table 1. Main Information Needs in the Preliminary Questionnaire

Information Type	Number of Responses	Percentage (%)
Brief Text Explanation	5	9.09
Charts/Data Visualization	15	27.27
Multi-Scheme Comparison	13	23.64
Step-by-Step Explanation	6	10.91
Combination of Text and Graphics	16	29.09

On the information-needs side, respondents weren't just looking for a single recommendation. What they actually wanted was information structured in a way that helped them understand and compare different schemes. Most hoped the system would offer comparisons of strengths and weaknesses across options, recommendation reasons, and the trade-off relationships among different objectives. As for preferred

explanation formats (Table 1), respondents leaned toward a combination of text and graphics, charts/data visualization, and multi-scheme comparisons. Text-and-graphics combinations came out on top at 29.09%, followed by charts/data visualization at 27.27% and multi-scheme comparison at 23.64%.

Based on this, the explainable interface design that follows builds around four core information modules — multi-scheme comparison, indicator visualization, recommendation reasons, and trade-off explanation — aimed at turning complex planning logic into something more structured and easier for non-expert users to work with.

3.3.2. Comparative Analysis of Experimental Results

To get a first read on how the explainable interface affects non-expert users' understanding of spatial schemes, this study compared results between the conventional interface group and the explainable interface group — 10 participants each. Everyone rated, on a five-point Likert scale, their understanding of the schemes' strengths and weaknesses, their grasp of trade-off relationships between objectives, their decision confidence, and how clear the recommendation reasons felt. Table 2 has the full breakdown.

Table 2. Comparison of Experimental Results Between the Conventional Interface and the Explainable Interface

Evaluation Indicator	Conventional Interface Group (Mean Score)	Explainable Interface Group (Mean Score)
Understanding of the Strengths and Weaknesses of the Schemes	1.8	4.2
Understanding of Trade-off Relationships Between Objectives	1.8	3.9
Decision Confidence	2.0	4.2
Clarity of Recommendation Reasons	1.6	3.6

The conventional interface group scored low across the board. Understanding of scheme strengths and weaknesses averaged 1.8, and understanding of multi-objective trade-offs came in at the same 1.8. Decision confidence averaged 2.0, while clarity of recommendation reasons was the lowest at 1.6. What this suggests is that when participants only get scheme images, brief descriptions, and an overall score, they can still complete the selection task — but building a structured understanding of what actually differs between schemes, or why, is much harder. Their judgments end up leaning on visual impressions, personal taste, or just guessing at what the scores mean.

The explainable interface group scored noticeably higher on every measure. Understanding of strengths and weaknesses jumped from 1.8 to 4.2, and understanding of trade-off relationships went from 1.8 to 3.9. Decision confidence rose from 2.0 to 4.2, and clarity of recommendation reasons climbed from 1.6 to 3.6. Multi-scheme comparison, indicator visualization, and trade-off explanation, in other words, do seem to help non-expert users understand both the differences between spatial schemes and the logic behind planning decisions — and they boost

decision confidence and perceived transparency along the way.

One more thing worth noting: in the final scheme selection, most participants in the explainable interface group went with the system-recommended Option B, though a handful stuck with Option A based on their own judgment. The explainable interface, in other words, didn't push people toward the AI's pick — it gave them comparative information and explanatory support, and let them make a more informed, still autonomous, decision. A few participants also mentioned that the AI recommendation still felt a bit mechanical, which points to something for future interface design to work on: not just clearer information structure, but explanations that feel more natural and human.

4. Conclusion

This study takes public-space planning as its application context and focuses on how non-expert users understand trade-off logic in multi-objective spatial decision-making. It designs and preliminarily evaluates an AI-assisted explainable decision-support interface. The study first used a preliminary questionnaire survey to examine users' information needs and cognitive difficulties in understanding spatial schemes. Based on these findings, an interface prototype was developed, including multi-scheme comparison, indicator visualization, recommendation reasons, and trade-off explanation. A comparative experiment between a conventional interface and an explainable interface was then conducted to preliminarily examine how different information presentation methods affect users' understanding and decision confidence.

The results show that non-expert users do not simply want to passively accept AI recommendations. Instead, they prefer to form their own judgments based on the strengths and weaknesses of schemes, recommendation reasons, and trade-off relationships between objectives. The experimental results further indicate that, compared with the conventional interface, which only provides scheme images, brief descriptions, and overall scores, the explainable interface can significantly improve users' understanding of scheme differences and multi-objective trade-off logic, while also enhancing their decision confidence and their perceived clarity of recommendation reasons. At the same time, users still retained room for autonomous judgment, which suggests that the role of the explainable interface is not to replace public decision-making, but to provide clearer support for understanding.

The value of this study lies in introducing ideas from XAI and multi-objective decision support into the issue of public understanding in public-space planning, and in preliminarily exploring the potential of explainable interfaces to support non-expert users' understanding of trade-off logic through an interface prototype and a small-scale user experiment.

However, this study still has several limitations. For example, the experimental sample size was relatively small, the interface prototype remained at an early stage, and the experimental scenario was relatively simplified. Future research could expand the participant sample, further improve the high-fidelity interactive prototype, and test the long-term use of the interface in more realistic urban renewal or public-space participation contexts.

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