Research on Human-AI Collaborative Participatory Spatial Design Pathway Based on AIGC

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Abstract: The technology of Artificial Intelligence Generated Content (AIGC) is profoundly influencing the design field. It is particularly important to explore how to utilize AIGC technology to integrate into the workflow of traditional interior design, providing innovative ideas and methods for the traditional interior design process. Taking the interior space of the "One-stop" student community of Shanghai University of Technology as an example, by drawing on the participatory method of AIGC technology in landscape design, a participatory design workflow for interior space is constructed. Compared with the traditional design process, this workflow can effectively enhance users' participation willingness, deepen the depth of scheme discussions, improve work efficiency, and assist in the decision-making of design schemes. The research has verified the feasibility of Human-AI collaboration in participatory design, providing a reference for the future application of AIGC in space design.

Keywords: Artificial Intelligence Generated Content; Human-AI Collaboration; Participatory Design

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1. Introduction

1.1 Current Status of Design Development Driven by Artificial Intelligence

In recent years, AIGC tools such as Midjourney, DALL·E 3, and Stable Diffusion have profoundly transformed the design industry. The integration of artificial intelligence has overcome the previous reliance on designers' individual experience and aesthetic judgment [1], fostering a fusion of artistic and technical elements in design solutions [2][3][4], enhancing design efficiency [5], and encouraging broader public participation [6]. However, design drawings generated by AIGC tend to undermine designers' reflective, creative, and meticulous design processes. Moreover, artificial intelligence still has limitations in understanding scale perception and spatial behavior, making individual generated images insufficient to achieve design objectives [7]. Consequently, how to leverage AI to enhance efficiency while ensuring the fulfillment of design goals has become a critical concern in this field.

1.2 The Human-Machine Collaboration Dilemma

Current collaboration among designers, space users, and AIGC faces two primary challenges: First, the lack of sketch-based solutions suitable for early design discussions in participatory scenarios hinders effective user engagement; Second, although artificial intelligence has evolved from a mechanical tool into a collaborative entity with certain cognitive capabilities [8], traditional AI approaches fail to fully leverage the complementary strengths of humans and AI through dynamic adjustments in design leadership. Therefore, there is an urgent need to develop a design workflow that facilitates moderate discussion while dynamically adjusting design leadership across different participatory design phases, enabling synergistic human-machine collaboration with enhanced stability.

1.3 Research on Human-Machine Collaborative Participatory Design Workflows

Previous studies have explored the application of AIGC technology integrated into participatory design methodologies in landscape design [7]. This study utilized the sustainable agricultural landscapes of the U.S. Corn Belt as a case study, employing intentionally preserved, AIGC-generated "unsaturated" sketch proposals during community participatory discussions, thereby providing a process model suitable for human-machine collaborative participatory design. The approach first intentionally maintained an unfinished state during the AIGC sketch generation phase—while ensuring the designs met basic spatial functional requirements, it preserved openness in local details and stylistic elements to facilitate discussion. Subsequently, spatial user feedback was collected during community workshops, and updated AIGC visuals were developed based on stakeholder input. The results demonstrated that this methodology enhances in-depth design discussions and increases user engagement and awareness. In its future implications, the study suggests potential applications of this approach in time-constrained participatory design practices, such as single-day workshops.

However, the study still has the following limitations: First, its participatory design workflow was applied solely to landscape schemes and was not validated in interior schemes. Second, the experimental conclusions were primarily based on users' verbal feedback and lacked data support. Third, it did not explicitly outline how to integrate the strengths of both humans and artificial intelligence in human-machine collaboration. Fourth, it failed to provide a comparison with traditional process design.

1.4 "One-stop" Student Community

The "one-stop" student community is a

vital component of the modern university governance system. It primarily utilizes student living complexes such as colleges and dormitories to explore reforms in student organizational structures, management models, and service mechanisms. This initiative integrates the leadership, management, service, and ideological-political resources of both the university and college levels into student education and services, aiming to create an educational and living hub that combines student ideological education, faculty-student interaction, cultural activities, and daily life support [9]. Given its multifunctional spatial design, high space utilization efficiency, and diverse user demographics, its planning requires comprehensive input from multiple stakeholders. Using the "one-stop" student community as an experimental case for participatory interior design fully demonstrates user participation and establishes a comprehensive participatory design workflow.

In summary, this paper adopts the participatory design approach that integrates AIGC technology into landscape design, using the ShanghaiTech University's "one-stop" student community as the experimental case to develop an AIGC-powered participatory interior design workflow (Interior Participatory Design Workflow, IPDW). The study compares this workflow with traditional design processes, demonstrating the feasibility and advantages of human-machine collaboration in participatory design.

2. research technique

2.1 Research Site: ShanghaiTech University's "One-Stop" Student Community

The ShanghaiTech University "One-Stop" Student Community (Figure 1) is located on the basement level of Building 3, Dormitory 5 at the University's Jun Gong Lu Campus, covering an area of approximately 150 square meters. This space integrates functions for learning, social interaction, reading, self-service, and Party-building activities, serving users including faculty, students, dormitory staff, cleaners, and security personnel. Designed to accommodate diverse usage needs and adopt a participatory design approach, it serves as the subject of this IPDW experiment to engage users and establish a comprehensive participatory design workflow.

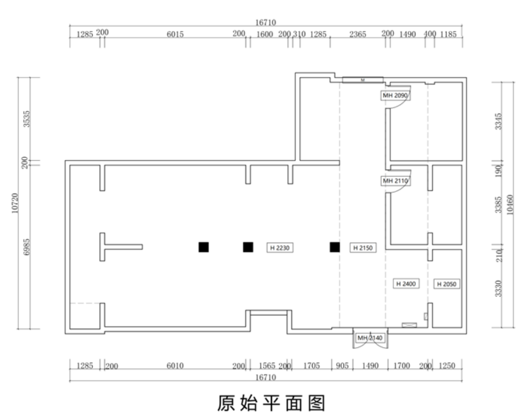

Figure 1: Original interior floor plan of the "one-stop" student community at Shanghai University of Technology (Source: Author's self-drawn)

2.2 Experimental Design: A Human-Machine Collaborative Participatory Design Workflow for Indoor Spaces

In November 2025, researchers conducted a "one-stop" student community co-creation workshop on the campus of ShanghaiTech University, inviting 30 participants (including students, faculty, dormitory administrators, cleaners, and security personnel), yielding 26 valid samples. The participants exhibited variations in gender, age, academic background, and spatial usage frequency (Table 1).

Table 1 Basic demographic characteristics of the participant sample

sex	age	Professional Background	Space usage frequency (times/week)	sex	age	Professional Background	Space usage frequency (times/week)
man	25	environmental design	4/1	man	62	architectural design	3/1
man	23	environmental design	4/1	woman	52	not have	2/1
man	27	architectural design	3/1	woman	47	not have	5/1
woman	25	environmental design	1/2	man	23	environmental design	7/1
man	45	journalism and communication	1/1	man	23	environmental design	7/1
woman	40	economics	1/1	woman	25	journalism and communication	1/2
woman	47	landscape architecture	3/1	woman	50	ideological and political education	3/1
woman	49	landscape architecture	3/1	man	31	Publish	5/1
woman	49	network engineering	1/3	woman	42	psychology	4/1
man	38	physical distribution management	1/1	woman	50	psychology	4/1
woman	25	Digital Media Design	3/1	woman	48	not have	3/1
woman	27	Digital Media Design	3/1	man	44	not have	3/1
man	54	not have	5/1	man	37	landscape architecture	3/1

The experiment primarily employed participatory design, semantic annotation, and Likert scale methodologies. The specific implementation of IPDW proceeds as follows: The workflow consists of four consecutive stages (Figure 2). Stage 1: AI-driven sketch generation; Stage 2: Designer-user-led design discussions and problem identification; Stage 3: Designer-AI collaborative refinement and regeneration of proposals; Stage 4: Designer-user-led finalization and comprehensive evaluation. At each design stage, the strengths of both humans and AI are dynamically allocated to achieve complementary advantages and stable collaboration (Figure 3).

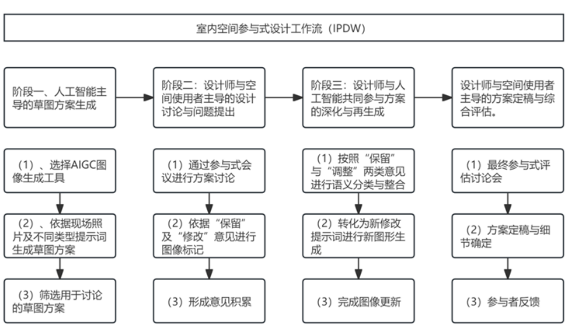

Figure 2: Participatory Interior Space Design Workflow (IPDW) (Source: Author’ s illustration)

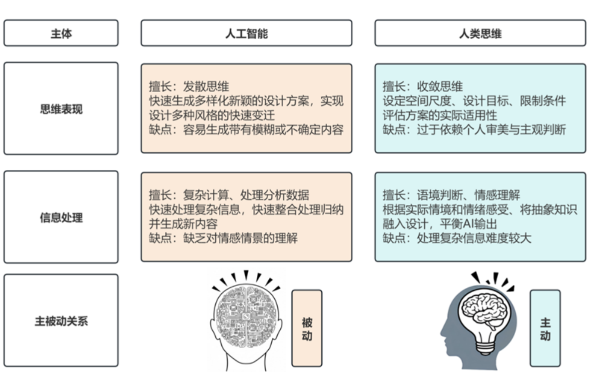

Figure 3: Distinct Advantages of Humans and Artificial Intelligence (Source: Author’ s illustration)

Phase One: AI-Dominated Sketch Generation

In the early design phase, artificial intelligence was employed to rapidly generate “ongoing” sketch proposals for design discussions. The study first compared images produced by mainstream AIGC image generation tools (including Midjourney, Stable Diffusion, DALL-E3, and Nano Banana). Evaluation criteria included operational complexity, generation speed, artistic quality, and controllability (Table 2). After comprehensive comparison, Nano Banana was selected for this experiment due to its lower operational complexity, consistent ability to accurately reproduce spatial structures, and fewer image artifacts.

Secondly, to ensure the generated content aligns with the actual site, the team created an initial set of 25 sketch proposals within the same spatial context using different prompt phrases based on on-site photographs. Subsequently, designers selected six representative AIGC proposals for participatory discussion (Figure 4) based on their alignment with the physical site (structural consistency or approximate similarity) and design quality (diversity of elements and style), while excluding images that contradicted the site conditions, exhibited disproportionate scales, or featured disorganized element arrangements.

Table 2 Comparison of Performance of AIGC Generation Tools

AIGC generating tools	Operation Difficulty	Generation Speed	controllability	artistic expression	image defect
Midjourney	You need to master the logic of specialized keywords and specific descriptive parameters.	Average generation time: 35 seconds Peak hour: You need to wait in line for 3–5 minutes to generate (4 cards can be generated at once)	It is difficult to understand the spatial structure of the uploaded photos. The generated effects are random and hard to control.	The artistic expression is excellent, with delicate rendering effects that lean more towards an illustration style.	The generated images exhibit significant variations, which is detrimental to experimental control.
Stable Diffusion	It requires local deployment and specialized training for the model (with GPU requirements).	The duration varies depending on the graphics card model (approximately 5.19 minutes per RTX 3060 Ti).	It can stably reduce spatial structures and generate images in various styles according to different models.	The artistic expression is moderate, generating different visual representations based on various proprietary models.	Insufficient model training can easily lead to image artifacts.
DALL.E3	You can communicate directly using natural language.	Average generation time: 55 seconds	It can understand some spatial structures but cannot stably reconstruct them.	The artistic expression is moderate, with poor realism.	The realistic effect is poor and unsuitable for raw images used in participatory discussions.
Nano Banana	You can communicate directly using natural language.	Average generation time: 30 seconds	It can basically stabilize the reduction of spatial structures and precisely modify them according to different exchange content.	The artistic expression is well-balanced, meeting the needs of most stylistic requirements.	The attention to detail is not thorough enough.

At this stage, artificial intelligence rapidly generates sketch proposals based on input prompts, while designers define essential constraints such as spatial scale and design intent. The AIGC-generated sketches intentionally maintain an “ongoing” state—where the images effectively convey spatial design concepts and fulfill most functional requirements, yet retain sufficient flexibility for furniture arrangement and wall decoration without imposing rigid element specifications. This approach prevents discussions from being overly constrained by definitive visuals, establishing an open foundation for subsequent participatory design processes.

Phase Two: Design Discussions and Problem Identification Led by Designers and Space Users

Following preliminary preparations and drawing on the framework of the “World Cafe” [10] workshop, the World Cafe is a participatory model first introduced in 1995 by American scholars Juanita Brown and David Isaacs. Inspired by the social atmosphere of coffee shops, it encourages people to engage in in-depth, cross-disciplinary, and multi-level dialogues and knowledge sharing in a relaxed environment, aiming to foster collective wisdom and inspire creativity.

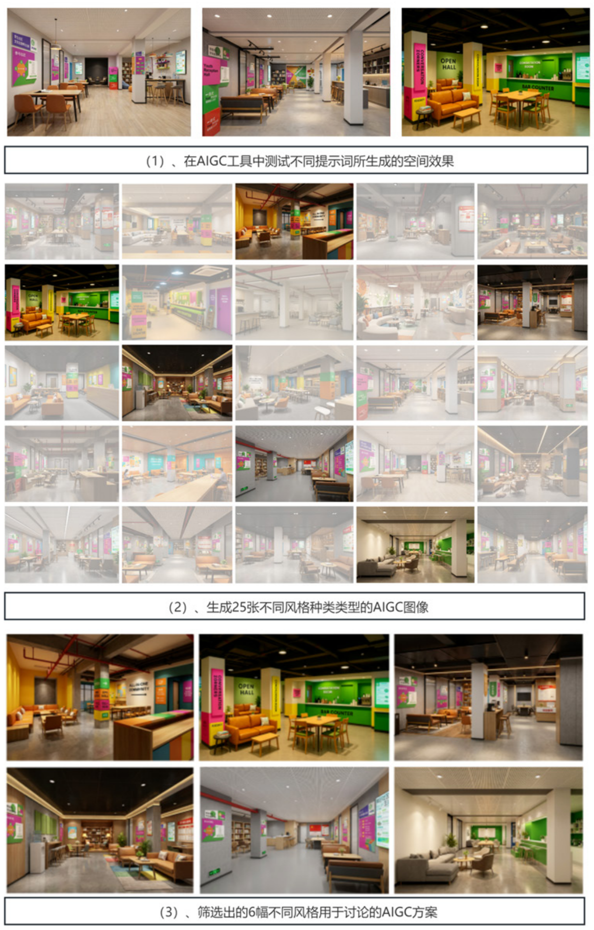

Figure 4 shows a sketch generated using the AIGC tool for a participatory discussion (Source: Author’ s own drawing)

The participants were divided into five groups, each conducting a participatory discussion around an A3-sized sketch generated by AIGC. The facilitator guided the discussion using two questions: “Which elements meet your expectations?” and “Which elements require adjustment?” Participants used colored sticky notes to mark the images and decide whether to “retain” or “adjust” the design details (Figures 5–8).

Through s 不 emantic annotation and group rotation, participants engage in thorough discussions centered on the AIGC-generated sketch proposals. Each discussion session lasts 7–10 minutes, after which groups rotate through different images to ensure diverse and comprehensive feedback. The new rotating groups are required to build upon the previous group’ s insights to avoid repetition, ultimately accumulating input and establishing clear revision directions.

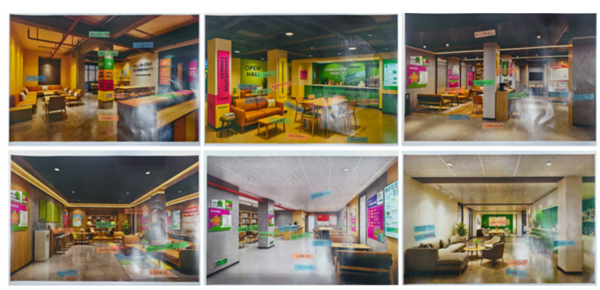

Figure 5: Participants annotate six sketch proposals generated by AIGC (Source: Author’ s own illustrations)

Figure 6: Participants annotate a single AIGC-generated sketch proposal image (Source: Author’ s own drawing)

Figure 7: Participants annotate a single AIGC-generated sketch proposal image (Source: Author’ s own drawing)

Figure 8 Participants annotate a single sketch generated by AIGC (Source: Author' s own drawing)

Phase Three: Designers and Artificial Intelligence Collaboratively Refine and regenerate the solution

In this phase, the discussion outcomes from the second stage are first semantically categorized and consolidated into two types— "retained" and "adjusted" —with similar elements unified. Subsequently, designers identify specific modification directions based on high-frequency feedback and convert these into updated prompt descriptions for input into the same AIGC image generation tool to produce revised AIGC image proposals. The designers then conduct a new round of image screening (Figure 9) to select the design proposal best meeting spatial users 'needs, while retaining both versions of the generated proposals (' incomplete') for final participatory evaluation discussions (Figures 10 and 11).

At this stage, artificial intelligence rapidly generates new visual sketches based on input prompts, while designers conduct logical evaluations of the results, eliminate impractical expressions, and make necessary adjustments to ensure the final image better meets spatial users' needs while maintaining a degree of openness.


Figure 9: A new round of image screening after the update scheme (Source: Autorally drawn)


Figure 10: New design proposal ①


Figure 11: New design proposal ②

Phase 4: Designer and User-Dominated Comprehensive Evaluation and Outcome Generation

Building on the aforementioned participatory discussions and subsequent revisions, a final evaluation session was organized, inviting participants to finalize the optimized design. Participants ultimately selected Option ② , noting that the background wall paired with greenery creates a warmer and more vibrant atmosphere, better reflects the student community spirit, offers more flexible spatial circulation, and achieves greater color harmony throughout the space.

Subsequently, participants' feedback evaluations on IPDW were collected using a 5-point Likert scale (Table 3), with particular focus on the following four aspects:

(1) The degree of alignment between the final image and the spatial users' requirements

(2) Satisfaction with the spatial atmosphere and stylistic experience

(3) Level of Informedness and Participation in the Design Process

(4) Acceptance of the IPDW model under human-machine collaboration

Table 3 Likert Scale for Evaluating the Optimized Human-Machine Collaborative Participatory Design Workflow

order number	question	Agree completely	agree	basically agree	disagree	I strongly disagree.
1	Are you satisfied with the final image?	5	4	3	2	1
2	Do you want to make further edits to the image?	5	4	3	2	1
3	Do you agree that this model is better than the traditional one?	5	4	3	2	1
4	Do you agree that this model produces more efficient and precise designs?	5	4	3	2	1
5	Do you agree with the design pattern where AI generates images and participates in discussions?	5	4	3	2	1
6	Do you agree that this layout allows you to see the design more intuitively?	5	4	3	2	1
7	Do you agree that this format is more likely to spark your discussion?	5	4	3	2	1
8	Do you agree that the designs resulting from this approach are more profound?	5	4	3	2	1
9	Do you agree that this model will make things easier for you?	5	4	3	2	1

3. Experimental Results

3.1 Participants' feedback on the final AIGC-generated image

The Likert scale results (Table 4) indicate that participants expressed high overall satisfaction with the final generated images regarding their alignment with spatial user needs, with scores ranging from 3.00 to 5.00 and a mean of 4.15. Approximately 85% of participants agreed or strongly agreed that the final images met design expectations, demonstrating that this workflow approach effectively addresses the diverse needs of various spatial users.

Regarding acceptance of this workflow model, participants 'scores for Item 3 ("Do you agree this model is better than the traditional one?") ranged from 2.00 to 5.00, with a mean of 3.46, indicating overall acceptance but some resistance. Similarly, scores for Item 5 ("Do you agree with the design approach that involves AI-generated visuals and participation in discussions?") ranged from 2.00 to 5.00, averaging 4.12, suggesting that most participants readily accept and adapt to AI-integrated participatory design methods. However, a minority still favor traditional approaches—a preference likely stemming from participants' limited familiarity with AI and concerns about its development.

Table 4 Statistical Results of the Likert Scale

Item	question	crest value	least value	mean	standard deviation
1	Are you satisfied with the final image?	5	3	4.15	0.68
2	Do you want to make further edits to the image?	5	2	3.50	0.90
3	Do you agree that this model is better than the traditional one?	5	2	3.46	0.76
4	Do you agree that this model produces more efficient and precise designs?	5	2	3.65	0.75
5	Do you agree with the design pattern where AI generates images and participates in discussions?	5	2	4.12	0.95
6	Do you agree that this layout allows you to see the design more intuitively?	5	4	4.65	0.49
7	Do you agree that this format is more likely to spark your discussion?	5	3	4.00	0.75
8	Do you agree that the designs resulting from this approach are more profound?	5	3	3.73	0.78
9	Do you agree that this model will make things easier for you?	5	3	4.04	0.66

In terms of awareness and engagement, Item 6— "Do you find this model more intuitive for understanding the design?" —achieved the highest average score of 4.65, indicating that the integration of AIGC technology into participatory design workflows significantly enhances users 'comprehension and awareness of design content while lowering the barrier to discussion. This finding confirms that AIGC' s visual advantages effectively facilitate participation from non-professional users in design processes.

For Item 7 ("Do you agree that this

format is more effective at sparking your discussion?"), participants 'scores ranged from 3.00 to 5.00, with a mean of 4.00; approximately 73% of participants responded "Agree" or "Agree strongly." Item 2 ("Do you agree that you would like to make further modifications to the image?") received a mean score of 3.50, indicating that participants still had numerous supplementary suggestions after reviewing the image results. This suggests that the workflow effectively stimulates participants' spatial imagination and promotes deeper conceptual thinking about design solutions.

In conclusion, the statistical results confirm the effectiveness of IPDW in facilitating discussions, enhancing comprehension, and improving the participatory experience, providing robust data support for its further application in interior design contexts.

3.2 Comparison between IPDW and Traditional Design Workflows in Human-Machine Collaboration

To compare the efficiency differences between IPDW and traditional design workflows, two graduate design students were invited to complete the same design task using the conventional approach (Figures 12 and 13), with their respective time spent recorded. The results (Figure 14) show that the traditional workflow required approximately 34 hours from conceptual sketch to final output, enabling only one single-style solution while offering advantages in detail consideration. In contrast, IPDW achieved a total runtime of just 13.5 hours during the image generation phase—strictly adhering to the principle that the total AIGC-generated image time should not exceed one hour—with each individual AIGC-generated image taking about 30 seconds. The purple boxes in the figure indicate the optimized components in IPDW. Although significant differences exist between the two methods in terms of participant numbers and engagement patterns, making direct comparisons challenging, the results still demonstrate IPDW's superiority in time efficiency and enhancing communication with participants.

Furthermore, traditional design processes often rely heavily on designers 'personal experience and aesthetic preferences, limiting their creative thinking and the diversity of solutions. In contrast, IPDW effectively combines artificial intelligence's capabilities for divergent thinking and integration with human logical judgment and emotional understanding, developing a human-machine collaborative approach better suited to meeting participants' diverse needs. Through IPDW, participants can engage in spatial decision-making in an intuitive and transparent manner, communicate and discuss design proposals promptly, ensuring that the final designs better align with practical requirements.

Figure 12: Spatial rendering generated through human-machine collaboration

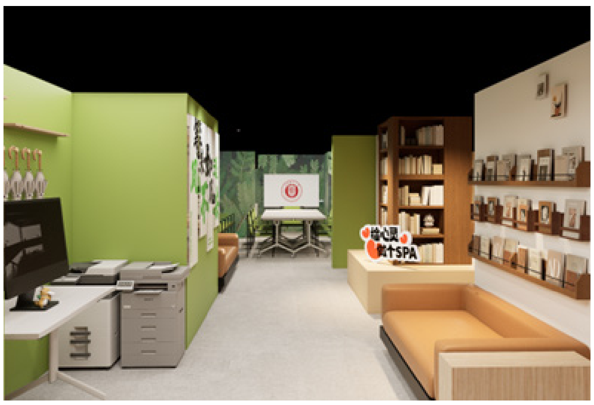

Figure 13: Spatial rendering produced by the traditional workflow

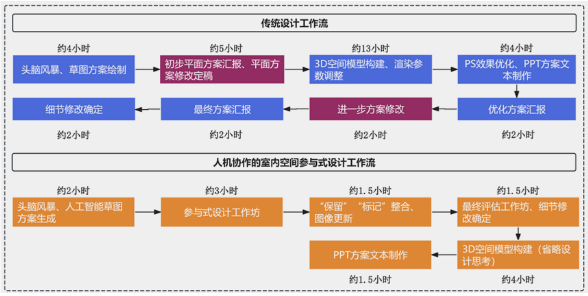

Figure 14 Comparison of time consumption between IPDW and traditional design workflows (Source: Author’ s own illustration)

4. Discussion and Conclusion

4.1 Implications for Human-Machine Collaborative Design

The essence of human-machine collaboration lies not in simply combining human and AI capabilities, but in fully leveraging their respective strengths to establish a dynamic mechanism for distributing leadership. During the sketch generation and brainstorming phases, AI can efficiently generate diverse design proposals; in the stages of opinion integration and logical evaluation, humans excel at using spatial reasoning and emotional intuition to refine and validate these proposals. Through human-machine collaboration, IPDW enhances spatial users’ engagement and awareness, reduces communication barriers, and facilitates effective project advancement. Future participatory design methodologies are poised to further harness the strengths of both humans and AI, empowering the evolution of spatial design.

4.2 Methodological Limitations and Future Prospects

Although the study has demonstrated the advantages of IPDW under human-machine collaboration and validated its feasibility in participatory design through comparative analysis, the following limitations remain: 1. The participant group in this study was primarily concentrated in campus settings, and the applicability of the workflow in more complex social contexts requires further validation; 2. The experiment relied solely on a single AIGC image generation tool, which imposes limitations in evaluating the workflow's performance from a single perspective. Future research could leverage the strengths of various AIGC tools and integrate participatory design methodologies to develop a more effective collaborative workflow; 3. The study did not incorporate elements such as structural dimensions and engineering constraints, warranting further development by incorporating Building Information Modeling (BIM) and simulation models.

Furthermore, future research could incorporate immersive technologies such as eye-tracking and VR, enabling participants to understand and experience design scenarios more directly. Eye-tracking data reveals users' focal points, while VR assists non-professional users in engaging more intuitively with design decisions, thereby enhancing the authenticity and practicality of human-machine collaborative creation.

4.3 Research Conclusion

The integration of AIGC technology into design, leveraging its high production efficiency and robust computational capabilities, holds promising prospects for broader application in the design field. This study takes the "one-stop" student community at ShanghaiTech University as a case study, adopting the participatory approach of AIGC technology in landscape design to develop an AIGC-driven participatory interior space design workflow (IPDW). The results demonstrate that participatory design workflows are equally applicable to the field of interior design. The optimized Participatory Interior Design Workflow (IPDW) effectively leverages the strengths of both humans and artificial intelligence, enhancing users' willingness to participate in expression, deepening design discussions, enriching design diversity, and supporting decision-making processes. Compared to traditional design workflows, this approach offers superior efficiency and versatility, validating the feasibility of human-machine collaboration in participatory design. Future efforts should integrate advanced AIGC tools to develop participatory design workflows with enhanced human-machine synergy and contemporary advantages, thereby empowering new advancements in spatial design.

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