COCOBOT: DEVELOPING A CONSENT COMMUNICATION TOOL BASED ON CO-EVOLUTIONARY MODEL

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Abstract. In architecture and interior design, consent communication is crucial for the collaboration between clients and designers. With clients often needing assistance articulating particular design requirements, this study introduces CocoBot (Collaborative Consensus Bot), which integrates artificial intelligence-generated content (AIGC) technology into the communication of the design collaboration. This tool facilitates collaborative evolution between clients and designers by transforming requirements into tangible images, enhancing communication efficiency and consensus formation. The co-evolutionary model is at the core of CocoBot, which stimulates interaction and consensus formation between clients and interior designers by extracting semantic information from the communication process and generating images. It utilizes visualization to mitigate linguistic ambiguity and subjectivity, facilitating consensus attainment. Through qualitative research and expert interviews, we validate the effectiveness of CocoBot in improving communication between clients and designers, particularly in addressing language uncertainties and ambiguities, ushering in a new collaborative mode for designers and clients.

Keywords. co-evolutionary model, Artificial Intelligence Generated Content (AIGC), design communication, collaboration, visualization, consensus formation

1. Introduction

The collaboration process between interior designers and clients faces linguistic

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ambiguity and subjectivity challenges in architecture and interior design. Clients often express their design needs through subjective verbal descriptions, leading to interactive design exploration between both parties. The ambiguity in language during the communication process can lead to misunderstandings and design errors (Chuang & Chien, 2021). We define the consent communication mechanism as a means to address communication challenges between designers and clients. When designers need to interpret and understand subjective descriptions provided by clients, they may encounter challenges in understanding the requirements. These descriptions often lack specific guidelines, making it difficult to ascertain the actual design needs. Clients typically use uncertain, generalized terms or adjectives. For example, if a client expresses a desire for a modern-style interior space, discrepancies in the interpretation of the style among designers may lead to design errors. Therefore, the goal of the consent communication mechanism is to address these challenges and foster mutual understanding and consensus formation between designers and clients. Through this mechanism, we aim to eliminate linguistic ambiguities, reduce interpretation gaps in subjective descriptions, and thereby ensure mutual understanding of design objectives.

This study employs Poon and Maher proposed co-evolutionary design framework to establish an effective communication mechanism (Poon & Maher, 1997). The distinctive feature of this framework lies in the separate evolution of design requirements and solutions, with mutual influence between the two. Through the co-evolutionary model, we redefine design as a collaborative exploration of problem and solution space. This shift in perspective emphasizes the dynamic interaction between problems and solutions, creating an ongoing process in which designers iteratively understand the problem before initiating the design. Such an approach views design as a continuous iterative process, encompassing the evolutionary exploration of both the design problem space and solution space, ultimately generating design requirements or solutions. The design communication process is characterized by uncertainty and ambiguity, making it challenging for designers to define problems (Cheng & Chang, 2007). Therefore, one cannot assume that designers clearly understand the problem or that the solution is already determined. Clients often provide incomplete descriptions of the problem, lacking sufficient clues for problem resolution. Hence, designers require extensive experience to guide clients in articulating their requirements clearly. In this process, the focus should not be solely on searching for solutions within predetermined scopes. Instead, explicit design requirement definitions should be carefully considered, transforming the process into an exploration and understanding of the problem rather than confined to predefined search boundaries.

Within the framework of co-evolutionary, we further delve into the role of AIGC technology in human-machine interaction, considering it a vital mediator that assists interior designers and clients in more effectively understanding and expressing design concepts. AIGC is not just a tool but an integral component of the evolutionary process that adapts to the evolution of design requirements and solutions. In terms of human-computer interaction, generative artificial intelligence facilitates user interaction through natural language, transforming it into desired text prompts, voice commands, and more, making the entire interaction process smoother and more intuitive. Based on AI-powered text-to-image techniques and image generation methods, AIGC consists of digital visualization tools that designers can leverage in the design process. These resources include Midjourney, Dall-E 2, and Stable Diffusion (Ploennigs & Berger, 2022). These tools make the design process more tangible and encourage designers to be more imaginative in understanding client needs. Take the definition of a client's style as an example; style, as a common visual element in design, is often judged through the presentation of text or images. However, such presentations may be subject to subjective influences, leading to differences in understanding between both parties.

This study addresses the understanding gap between interior designers and clients through an in-depth analysis. By employing expert interviews and qualitative research methods, face-to-face conversations provide a comprehensive understanding of both parties' thought processes, collaboration needs, and communication patterns. To address the understanding of differences, we propose CocoBot, which utilizes AIGC technology within a co-evolutionary framework. CocoBot acts as a mediator, assisting interior designers and clients in more effectively understanding and expressing design concepts. Through further integration of contextual investigations and two experiments, the first experiment observes potential issues in collaborative communication using CocoBot, identifying pain points in the cooperative scenario. The second experiment aims to refine the identified issues to optimize collaborative communication, enhance efficiency, and facilitate consensus formation. By introducing AIGC technology and the co-evolutionary framework, this study improves and optimizes collaboration models in interior design, ensuring effective consensus-building between both parties.

2. Related Work

Connecting the entire research theme through three perspectives, we establish a comprehensive, collaborative model guided by the co-evolutionary framework. Our approach provides creative design solutions, starting with the co-evolutionary of problems and solutions, progressing to the human-machine interaction of text-to-image generation, and culminating in the visual definition of design styles.

2.1. THE CO-EVOLUTIONARY OF PROBLEMS AND SOLUTIONS

Utilizing the co-evolutionary framework, we transform the traditional approach to robot manufacturing. Designers can directly engage in physical design, and simultaneously, robots contribute novel design suggestions, fostering human-machine collaboration and co-evolutionary in the design process. This shifts robot manufacturing from a mere execution of predetermined plans to an active participation in the design process (Jensen & Das, 2020). J. Poon and M. L. Maher proposed the Problem-Design Exploration Model (PDEM) in their literature, applied in the case study of the Sydney Opera House. The PDEM outlines two distinct search spaces: the problem space and the design space. The problem space encompasses uncertainty and changes in goals within the design, while the design space includes specific solutions. These two spaces evolve, forming a dynamic process horizontally and diagonally (Figure 1). In the end, the design of the Sydney Opera House, while not wholly meeting all initial requirements, found a balance point between the problem and solution spaces (Poon & Maher, 1997).

The solution for design exploration comprises three fundamental elements: cues, rules, and objectives. The design exploration is conducted engagingly using the interactive interface collage table to identify suitable clues for problem-solving (Cheng & Chang, 2007).

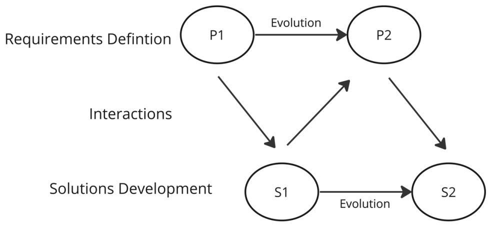

Figure 1. The co-evolutionary model of requirements and solutions (Poon & Maher, 1997)

2.2. TEXT-TO-IMAGE GENERATION THROUGH HUMAN-MACHINE INTERACTION

Natural Language Processing (NLP) techniques are employed for image generation, utilizing Stable Diffusion as the interface for image generation, integrating the ControlNet model (L. Zhang et al., 2023). Through text prompts, user ideas are translated into tangible images. This process utilizes NLP algorithms in deep learning, where text descriptions are converted into a format understandable by the generative model. The prompt is crucial as a mediator, facilitating dialogue between the user and the text-to-image generation system. Typically, practitioners run a prompt, observe the generated image results, and adjust the prompt based on the observed outcomes to achieve more desirable image synthesis. This iterative process involves continuously trying different prompts, delving into the latent space of the generative model, and aiming to guide the model to generate images that align with expected styles and features (Oppenlaender, 2023). AIGC is applied to the interior design workflow based on the text-to-image framework of Stable Diffusion. During the design process, users can achieve variations in style through different text inputs, generating diverse styles and providing users with a rich array of design choices (Zhou & Park, 2021).

2.3. VISUAL DEFINITION OF DESIGN STYLES

Defining keywords within styles helps users understand various designs and facilitates effective interaction and communication during the design process. In this context, operational definitions include defining style vocabulary such as colour, texture, material, etc. For example, modern style often embraces a minimalist monochromatic palette and favours modern materials like glass, marble, and metal to create a fashionable design ambiance. Such clear definitions provide a foundation for deep learning style recognition models. These models can automatically attach style information to reference design images, establish a database of style information, and enhance the efficiency of searching for design references. Additionally, it introduces the concept of users customizing their style recognition models (Kim & Lee, 2020). In practical applications, the operation of such models emphasizes user involvement. Users can guide the generation process by providing specific style examples, enabling the synthesis tool to generate appearances based on the preferences of clients and designers. This lightweight synthesis tool offers users a more diverse range of design choices (J. Zhang et al., 2023).

3. Research methods

In this study, experiments were conducted using the co-evolutionary model to explore how the intervention of CocoBot contributes to consensus-building between clients and interior designers. Through continuous communication and feedback, clients and interior designers engage in collaborative exploration and understanding, shaping the dynamic interaction between requirements and solutions into a continuous process.

3.1. THE CO-EVOLUTIONARY MODEL FRAMEWORK INTEGRATED WITH AIGC TECHNOLOGY

This study introduces a collaborative framework named CocoBot that integrates AIGC technology. In the communication process between clients and interior designers, CocoBot is a mediator. It transforms the vocabulary definitions representing the understanding differences between both parties into concrete textual prompts and generates images accordingly. CocoBot collaborative cooperation aids in handling uncertainties and vague descriptions, even when client requirements are not fully articulated. Within this co-evolutionary framework, designers can interpret and refine client descriptions by analysing the speech content through CocoBot. The communication becomes visualized by generating images based on textual prompts representing client needs. Clients may generate new requirements or adjust vocabulary definitions throughout the communication process. In this iterative process, both parties can understand the definitions of specific terms, leading to consensus formation. The exploration process of requirements defines the prompt generated as rules and the images as goals. Analysing the interactive process and the prompt produced helps identify consensus through the prompts' associations.

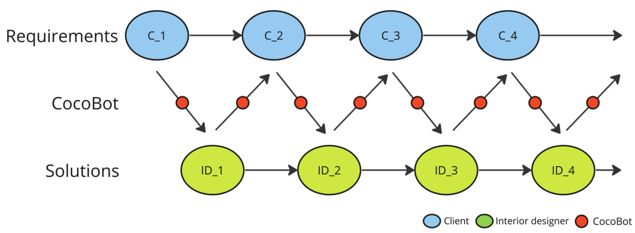

Figure 2. CocoBot in the co-evolutionary model framework

3.2. INTEGRATION MODULE FOR TECHNOLOGY

In the technical integration process, CocoBot serves as the online interface for both parties, integrating the entire technical workflow into the co-evolutionary model framework. The square elements in Figure 3 represent behaviors during the interactive process, while circular elements signify deep learning modules within the integrated technical modules, including the models and packages used. At this stage, sketches or drawings from the designer can be used as input, and after input, both parties engage in conversation, utilizing Google Cloud Speech-to-Text to transcribe the conversation into text. Once converted to text, Natural Language Processing (NLP) techniques are employed to parse and understand the language, organizing the information from the conversation into a keyword pool. Next, applying the prompt maker transfers into specific prompts used for the subsequent generation by AIGC. These generated images are stored in an image pool, presenting a variety of visualizations. Finally, in the visualization stage, the generated images are sent to both parties, returning to the context and forming a cyclical interactive process. The keyword pool and prompts are associated with the visualizations throughout this process, providing a clear and concrete framework for the entire interactive co-evolutionary process.

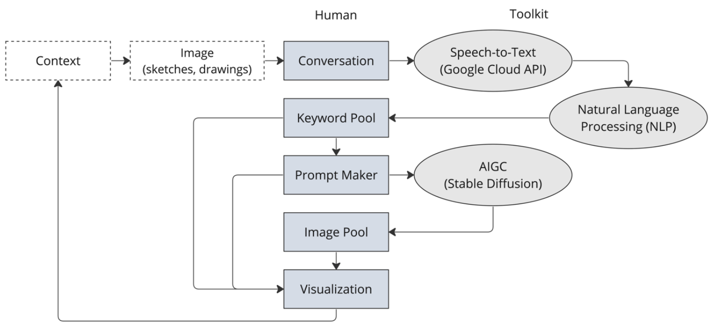

Figure 3. CocoBot System Architecture Diagram

3.3. THE INTERACTIVE PROCESS OF CO-EVOLUTIONARY

Based on the co-evolutionary model, this study establishes a continuous interactive and feedback process in Figure 4, presenting the evolution of requirements statements and design solutions. In this model, clients and interior designers utilize CocoBot as a mediator, achieving consensus through converting text to images in a visual format during communication. The entire design solution undergoes a cyclical process, forming a dynamic and evolving design solution. The main process is as follows:

1. Client requirement presentation: Customers verbally express their design requirements, and CocoBot utilizes Google Cloud Speech-to-Text to record the dictated demands.
2. Interior designer interpretation and inquiry: The interior designer interprets the client's description and engages in further inquiry to refine and clarify the client's specifications.
3. Interior designer integration into generated prompt: Interior designers integrate textual messages into the format of CocoBot prompts, utilizing Natural Language Processing (NLP) techniques to parse and understand the language and generate prompt keywords.
4. Visualization presentation: Utilizing AIGC technology Stable diffusion, the prompt keywords are transformed into images, generating visual design concepts.

5. Designer selects from generated images: The designer chooses suitable images from the generated set-in preparation for review and communication with the client.

6. Customer feedback: The customer provides feedback based on the received images, and the designer adjusts the design accordingly (Step 3).

In the iterative process of the interactive flow within the framework of co-evolutionary, the inclusion of CocoBot facilitates the mutual understanding of design requirements through interaction and communication between the customer and the interior designer.

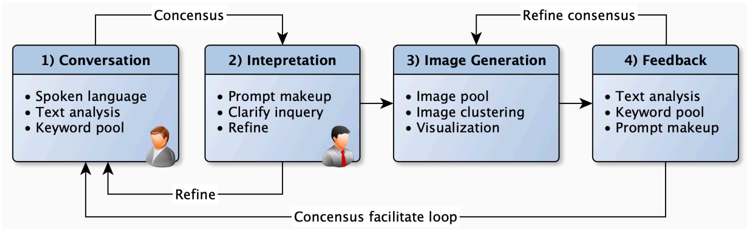

Figure 4. The interactive process of consensus facilitating loop

4. Two experiments and one result

Two experiments were conducted in the interior designer's studio to explore the impact of CocoBot intervention on communication. In terms of experimental design, we first defined the criteria for participant selection, including interior designers and a technology industry entrepreneur planning to redesign an office, to ensure designers have experience and background.

4.1. EXPERIMENT ONE - OFFICE SPACE DESIGN

The focus of this study was on clients' expectations for office space design. Clients desired to create an open office environment with a modern desk layout while maintaining a warm atmosphere. They preferred wood textures and a green ambiance, emphasizing a touch of technology. In the communication process, we introduced CocoBot as a mediator to record information during communication between designers and clients via Google Cloud Speech-to-Text technology. The information recorded was then utilized for Natural Language Processing (NLP) to generate keywords, which were further used by Stable diffusion to generate images for communication, facilitating communication between clients and designers.

We analysed the prompt used in communication and categorized prompt rules (Table 1) to gain a clear understanding of the client's requirements. The iterative variations of the office style in the design process are presented in Figure 5. However, in experiment one, we observed that due to the intervention of CocoBot, the client attempted to present different design styles, leading to a divergence in the entire design process and making it challenging to focus on a specific design direction. This posed a challenge for the designer, increasing the time required to address design changes and making it difficult to reach a consensus.

Regarding data and results, in addition to describing iterative changes in the design process and challenges encountered during the experiment, we also collected feedback and evaluations from participants, including whether CocoBot facilitated a better understanding and expression of their design expectations.

Table 1.Prompt rule classification

Classification Names	**Descriptions**
Themes	Participants' common goals
Space Layout	Expectations for space arrangement
Functionality	Description of specific functional requirements
Style	Expectations for specific style
Material	Expectations for visual perception of space
Color	Color preferences
Modifiers	Prompts after Designer's Interpretation and Guidance
Images	Illustrate Style or Theme through Images

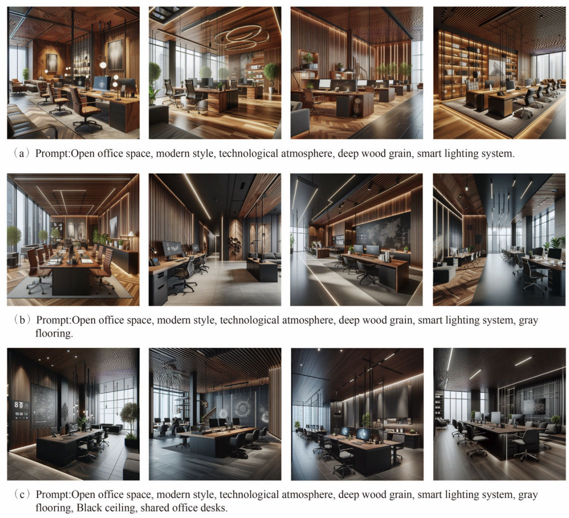

Figure 5.Iterative changes in office style design

4.2. EXPERIMENT TWO - OFFICE STYLE DESIGN FOR EXISTING SPACE LAYOUT

Building upon the foundation of the first experiment, the second experiment further explores the application of CocoBot in office style design. Similar to the first experiment, CocoBot was employed as a communication medium to facilitate more effective communication between clients and designers.

In this experiment, the designer inputted an image of the office layout, while the client aimed to achieve a Nordic-style office design. Specifically, the client desired a clean, bright, and comfortable office environment while maintaining a warm atmosphere. We guided communication between the designer and the client, utilizing CocoBot to generate images of different styles to facilitate their communication and understanding (Figure 5).

Simultaneously, we categorized the prompts used during the communication process to better understand the client's requirements. This helped reduce attempts at different layouts and styles, enhancing design efficiency, and ensuring that client expectations were fully understood.

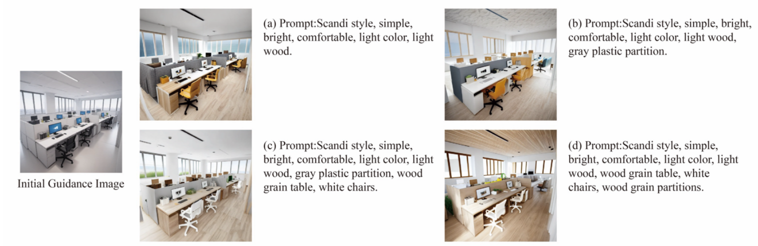

Figure 6. Design the office style with the initial image

4.3. EXPERIMENT RESULTS

At this stage, we conducted in-depth interviews with two industry experts, both of whom are interior designers. Their professional insights provided practical feedback for our experimental results. Firstly, the experts unanimously agreed that CocoBot played a significant advantage in communication between clients and interior designers. They pointed out that this technological intervention helps break down understanding differences, providing both parties with a more intuitive and concrete visual presentation, making it easier for clients to understand and express their design expectations.

The experts also raised some concerns. They pointed out that the diversity and flexibility introduced by CocoBot may sometimes lead clients to exhibit excessive divergence in design requirements, resulting in more communication time and complicating the entire design process. This could increase the difficulty of understanding and reaching consensus.

In summary, the expert evaluations highlight the positive role of CocoBot in communication between clients and interior designers. However, they also remind us of the importance of continuous adjustment and optimization of this technology to meet the diverse needs of users, ensuring a smoother design process that aligns with the expectations of both parties.

A comparison of the results from the two experiments, targeting different design stages, was conducted to assess the effectiveness of CocoBot. In Experiment one, the client attempted numerous space layout and functionality adjustments, leading to a divergent design process and difficulties in focusing on specific design directions. We optimized this process in Experiment Two, reducing the designer's attempts on different configurations and making the design process more focused.

5. Conclusion

This study integrates AIGC technology into a co-evolutionary model framework to enhance communication between clients and interior designers. Through the co-evolutionary model, we highlight the dynamic interaction between problems and solutions, making the design process a continuous and iterative exploration.

The key contribution of this research lies in introducing CocoBot as a communication intermediary, providing a more concrete and intuitive means of communication through text-to-image conversion. This approach helps address the understanding of differences arising from language ambiguity and subjectivity. Results from two experiments demonstrate the positive impact of CocoBot intervention on communication, facilitating understanding and consensus formation between clients and interior designers. Further, observations from expert interviews suggest that CocoBot may lead to client divergence in design requirements, potentially increasing communication time. Analysing the communication generated through images and examining these prompt rules further emphasizes the importance of consensus formation.

References

Cheng, Y.-B., & Chang, T.-W. (2007). Solving design puzzle with physical interaction–a collage table implementation. Proceedings of the 12th Conference on Computer-Aided Architectural Design Research in Asia (CAADRIA 2007), Nanjing, China,

Chuang, C. L., & Chien, S. F. (2021). Facilitating architect-client communication in the pre-design phase. Projections-Proceedings of the 26th International Conference of the Association for Computer-Aided Architectural Design Research in Asia, CAADRIA 2021,

Jensen, M. B., & Das, A. (2020). Technologies and Techniques for Collaborative Robotics in Architecture: establishing a framework for human-robotic design exploration. In 25th International Conference of the Association for Computer-Aided Architectural Design Research in Asia (CAADRIA) 2020: Faculty of Architecture Chulalongkorn University,

Kim, J., & Lee, J.-K. (2020). Stochastic detection of interior design styles using a deep-learning model for reference images. Applied Sciences, 10(20), 7299. https://www.mdpi.com/2076-3417/10/20/7299

Oppenlaender, J. (2023). A taxonomy of prompt modifiers for text-to-image generation. Behaviour & Information Technology, 1-14. https://doi.org/10.1080/0144929X.2023.2286532

Ploennigs, J., & Berger, M. (2022). AI Art in Architecture. arXiv preprint arXiv:2212.09399.

Poon, J., & Maher, M. (1997). Co-evolution in design. Proceedings of the Second Conference on Computer Aided Architectural Design Research in Asia, CAADRIA 1997,

Zhang, J., Fukuda, T., Yabuki, N., & Li, Y. (2023). Synthesizing Style-Similar Residential Facade from Semantic Labeling According to the User-Provided Example. In 28th International Conference of the Association for Computer-Aided Architectural Design Research in Asia (CAADRIA) 2023,

Zhang, L., Rao, A., & Agrawala, M. (2023). Adding conditional control to text-to-image diffusion models. Proceedings of the IEEE/CVF International Conference on Computer Vision,

Zhou, Y., & Park, H.-J. (2021). Sketch with Artificial Intelligence (AI). In 26th International Conference of the Association for Computer-Aided Architectural Design Research in Asia (CAADRIA) 2021.