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Exploring the use of generative AI for material texturing in 3D interior design spaces

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Material selection is important yet difficult in interior design, as designers need to consider technical factors beyond aesthetics, such as maintenance, sustainability, and costs that are often considered in later stages of the design process. As a result, making design changes due to unanticipated technical constraints in the later stages can be costly. We attempt to approach this problem by anticipating these as early as the conceptualization stage, where designers model and assign textures to their 3D scenes. To this end, our study explores the use of generative AI tools, namely ChatGPT and DALLE-2, in both texturing 3D scenes and selecting materials for interior design projects. Through a prototype, we evaluated the generative AI tools by conducting a user study with professional designers and students (n = 11). Based on creativity support (CSI), participants averaged a score of 72.82/100, while in task load (NASA-TLX), they scored 47.36/100. Based on qualitative feedback, designers could easily search and explore textures and materials while also receiving informative and contextually relevant suggestions on materials and colors from ChatGPT. However, these tools can be improved by fine-tuning on domain-specific datasets. Lastly, we analyze how designers interacted with these tools and reflect on how they can benefit from using generative AI in texturing and material selection in the interior design process.

KEYWORDS

generative AI, human-AI co-creation, material selection, textures, interior design

1 Introduction

The interior design process can be challenging and repetitive. One task that affects this process is material selection, which involves choosing surface materials, colors, and finishes for the interior space (Grimley and Love, 2018; Godsey, 2012). Material selection is an essential yet challenging task in interior design as it requires considering multiple factors like aesthetics, durability, and sustainability, among others (Alfuraty, 2020; Sadıklar and Tavşan, 2016; Zhang and Peng, 2015; Zhang, 2019; Yi, 2011). Designers may also need to explore alternative materials if their preferred choice is unavailable due to sourcing and cost constraints, which can take time. Moreover, if not resolved during the early stages of the design process, choosing unsuitable materials can be consequential, leading to actions such as making frequent repairs or even taking down the entire space, which ultimately increases costs (Peretyatko, 2018). To address such challenges, studies have developed systems that assist with material selection and assessing material suitability during the early stages of the design process. These include expert systems that filter candidate materials based on multiple criteria (Castro-Lacouture et al., 2009; Rahman et al., 2012; Zarandi et al., 2011). While these may be well-suited for engineers and contractors, interior designers, who usually do not need to be fully knowledgeable in the materials' technical properties, might find them difficult to use.

Early in the process, before sourcing materials and using them to construct the interior space, designers first create a visualization of the space through sketching and 3D modeling. In 3D modeling interior spaces, physical materials are virtually and partially represented as textures. Textures are images that represent the surfaces of 3D objects, and along with other aspects such as roughness, gloss, color, and scene lighting it is an important element in defining the 3D object's material (Kitchens et al., 2008; Kilic, 2020; Zijia, 2009). Furthermore, textures are important as they enhance the visual richness and photo-realism (Wang et al., 2003; Kagawa et al., 2010; Xiao, 2013) of 3D interiors. In 3D modeling, designers are tasked to assign materials to furnishings and components of the indoor scene (Yan et al., 2020; Chen et al., 2015).

Material selection and 3D texturing are tasks often done separately in the interior design process. For example, material selection is often done later in the design development and construction stages, where the designers are preparing the list of materials and finishes and estimating their costs. On the other hand, 3D texturing is part of the conceptual design stage of interior design, which happens early prior to construction (Grimley and Love, 2018; Ching and Binggeli, 2018). However, considering both tasks in tandem can smoothen the interior design process and potentially address challenges in material selection. While textures can visually represent colors and surface finishes, knowing an approximation of the technical properties of their corresponding physical materials can preemptively reduce design changes that can occur in later stages due to reasons like budget constraints, maintenance issues or sustainability issues. This approach has been explored in previous studies, where they allow designers or homeowners to texture 3D scenes while also being informed about properties like cost (Juan et al., 2021; Balali et al., 2020), environmental impact and maintenance (Zhang et al., 2019; Huang, 1995). However, these tools require meticulous setting up of databases of material properties and characteristics and are only limited to that data.

To this end, we look into large-scale generative artificial intelligence (AI), models trained on significantly large datasets for texturing and material selection. Generative AI has been progressing over the past decade, with models being able to quickly synthesize human-like textual responses (Ouyang et al., 2022; Brown et al., 2020), 3D shapes (Jun and Nichol, 2023; Wei et al., 2023), and images (Rombach et al., 2022; Ramesh et al., 2020, 2022) including textures (Carson-Katri, 2022) by simply typing in text prompts. With textures, other generative models can texturize 3D models using input images (Yeh et al., 2022; Perroni-Scharf et al., 2022; Hu R. et al., 2022) or text (Richardson et al., 2023; Michel et al., 2022; Chen et al., 2023; Jin et al., 2022; Chen et al., 2022). Prior works on generative AI models can quickly create texture maps and texture 3D shapes and scenes, enabling users to easily explore the possibilities of textures. In interior design and other similar domains, however, little is known about how such generative AI tools, especially text-to-image generators, can be utilized by designers in texturing their 3D objects and scenes. With the overall material selection, large language models (LLMs) like ChatGPT have been shown to help in this task by providing information on characteristics like expenses, durability, and environmental impact (Rane et al., 2023) when constructing medical devices (Li et al., 2024), buildings (Rane, 2024; Çalışkan, 2023b), and interior spaces (Çalışkan, 2023a).

Our study aims to extend this line of research by coupling 3D texturing with material selection using generative AI tools like DALLE-2 and ChatGPT; thus, our research also extends prior works that explored coupling these tasks together (Juan et al., 2021; Balali et al., 2020; Zhang et al., 2019; Huang, 1995) by leveraging generative AI. Lastly, our research explores how interior designers can interact and benefit from these generative AI tools in material selection and texturing.

This research aims to answer the following research questions:

- RQ#1: How can interior designers benefit from generative AI in texturing and material selection?
- RQ#2: What kinds of interactions can be derived from the interior designers' usage of generative AI tools for texturing and material selection?

We first developed a system prototype that integrates DALLE-2 and ChatGPT and closely mimics the interfaces of commonly used 3D modeling software. Through prompt engineering, the prototype leverages DALLE-2 to generate texture maps and ChatGPT to contextually suggest materials and colors designers can use for their objects in a 3D interior scene. We then evaluated the generative AI prototype by conducting an exploratory user study with 11 professional designers and students in texturing a given 3D scene according to a design brief.

To answer RQ#1, we evaluated how designers can benefit from generative AI by assessing the following aspects: task load designers experience when using the system and the extent to which the system provides creativity support. We assessed the participants' task load and the prototype's creativity support by administering the NASA Task Load Index (NASA-TLX) (Hart, 2006) and Creativity Support Index (CSI) (Cherry and Latulipe, 2014) questionnaires, respectively. We also conducted semi-structured interviews with them to gather insights on their experience using ChatGPT and DALLE-2 through the system. To answer RQ#2, we learn how the designers interacted with ChatGPT and DALLE-2 in the prototype by tracking and analyzing the instances they used them, the prompts they used in DALLE-2, and the queries they gave to ChatGPT.

Overall, we present the following contribution:

- The results of a user study on how professional designers and students interact with and benefit from DALLE-2 and ChatGPT in texturing and selecting materials.

2 Related work

2.1 Material selection and its challenges in interior design

When choosing materials, designers first consider if the material and its properties satisfy several functional criteria such as durability, maintenance, comfort, safety, versatility (Sadıklar and Tavşan, 2016; Zhang and Peng, 2015), sourcing (Alfuraty, 2020), sustainability (Zhang, 2019), and cost (Yi, 2011). On the other hand, they also consider the material's visual aesthetic (e.g., color, texture, pattern), as it affects the interior design's concept and the customer's visual perception of it (Alfuraty, 2020; Zhang and Peng, 2015). Moreover, they consider if the material harmonizes with other interior space aspects such as lighting, layout, other materials, and desired ambiance (Li, 2016; Zhang and Peng, 2015). Lastly, designers consider whether they can take advantage of the material's structural properties to create innovative and expressive designs (Yi, 2011; Li, 2016; Yuanyuan, 2019).

Designers also have several challenges in material selection. First, choosing a material that satisfies multiple criteria, such as having a low environmental impact, being low-maintenance, durable, and comfortable, is challenging (Alfuraty, 2020; Asbjørn Sorensen et al., 2016; Jahan et al., 2010; Karana et al., 2010). Furthermore, even if such a candidate is found, sourcing can be difficult, so designers must also consider choosing regionally produced materials (Larson, 2015; Thompson and Johansen, 2007). Designers also face other challenges when choosing sustainable materials. One challenge is that designers often have limited knowledge about the environmental impact of certain materials, according to Bettaieb et al. (2019). Additionally, it is difficult to determine their environmental impact since it is also based on factors such as the material's extraction, manufacturing, packaging, and installation, as noted by Thompson and Johansen (2007). According to two studies by Máté (2009; 2006), another challenge is that designers often struggle with trust issues when dealing with their suppliers. In one interview study, Máté found that 40% of designers expressed skepticism about the sustainability and quality of the materials claimed by their suppliers (Máté's, 2006). In another study, which administered a questionnaire to interior designers, only 20% of the respondents were confident that their suppliers provided accurate information on the environmental impact of their materials (Máté, 2009). Lastly, designers face a challenge with client preferences, as 40% of the respondents said that their clients prohibited using eco-materials in offices, according to Máté's (2006) interview study.

2.2 Intelligent systems in texture transfer and material selection

Developing intelligent systems that assist interior designers in texture transfer and material selection has been a long-standing research area. Texture transfer is the task of generating and applying textures to 3D models and scenes. Early systems like Material Memex (Jain et al., 2012) and Magic Decorator (Chen et al., 2015) automatically assign materials and colors to 3D objects and scenes using data-driven approaches. Material Memex assigns materials to objects by referring to a database of 3D multi-part objects and their material-part relations. Magic Decorator, similarly, specializes in interiors and uses a labeled image database of interior scenes to learn material-object relationships in the interior space. Moreover, it maintains overall color harmony by using a color compatibility model trained on a labeled dataset of color palettes. Succeeding data-driven systems (Zhu et al., 2018; Park et al., 2018; Park and Hyun, 2022) also learn from image and 3D databases, enabling designers to semantically texturize 3D scenes simply by inputting image examples. The emergence of such prior systems have made a significant impact in material texturing in interior design, performing faster than traditional methods (Chen et al., 2015) and creating textured scenes that are almost indistinguishable to ones made by human designers (Zhu et al., 2018; Chen et al., 2015; Park et al., 2018). With deep learning, other methods utilize deep neural networks for matching materials and colors semantically with 3D objects (Hu R. et al., 2022; Lin et al., 2018) and scenes (Yeh et al., 2022; Perroni-Scharf et al., 2022; Koh, 2023). The drawback, however, with these prior approaches is that they require a significant amount of effort in collecting, labeling, and even segmenting many images when creating the datasets. Moreover, these systems can perform only as well as the data they are trained on, and require expansion to improve their generalizability.

We thus look into large-scale generative AI models such as text-to-image generators and LLMs that have been trained on vast amounts of data to create a wide variety of human-like images and text, respectively, in a short timeframe (Cao et al., 2023; Fui-Hoon Nah et al., 2023). Text-to-image generators like StableDiffusion (Rombach et al., 2022) and DALLE-2 (Ramesh et al., 2022) create detailed images by using a diffusion model to progressively refine a noisy image to visually represent a textual description given by the user. These can used in generating texture maps from text, as shown by DreamTextures (Carson-Katri, 2022), a 3D software plugin that leverages StableDiffusion to directly create and apply texture maps onto 3D models. Relating to text-to-texture generation, studies have developed their own models, enabling seamless texturing of 3D objects (Richardson et al., 2023; Michel et al., 2022; Chen et al., 2023, 2022) and interior scenes (Jin et al., 2022) by simply typing in text prompts. Conversely, with LLMs, C2Ideas (Hou et al., 2024) is a system that uses a pre-trained LLM in harmoniously coloring interior scenes according to the user's design intent and preference. By using large-scale generative AI, these recent systems texturize and colorize 3D objects and scenes with better quality, speed, and efficiency, providing an opportunity for innovation in various fields, especially in interior design.

On the other hand, with material selection, expert systems help engineers and contractors select suitable materials by filtering and ranking candidate materials based on their relevance to multiple criteria like environmental and budget constraints (Castro-Lacouture et al., 2009; Rahman et al., 2012; Zarandi et al., 2011). While these are more catered toward engineers and contractors with more knowledge of materials' technical properties, these systems may not be familiar to designers. This gap often necessitates collaboration between designers and engineers during the later stages of the design process to realize their designs. To bridge this gap, other studies pair material selection with texturing in tandem (Juan et al., 2021; Balali et al., 2020; Zhang et al., 2019; Huang, 1995), aiming for designers to not only visualize and change materials but also view their technical aspects like estimated cost and environmental impact. Zhang et al. (2019) developed a virtual reality system that assists users in selecting suitable interior finishing materials based on functional criteria such as cost, maintenance, environmental impact, and aesthetic criteria like visual harmony and customer preference. The VR system of Balali et al. (2020) lets users select and change material finishings in interior scenes while seeing their costs in real time. This enables designers to involve clients during the early stages and easily determine if the desired materials satisfy their budget, which can prevent construction delays. However, like most data-driven approaches, their performance is only limited to the data that they have. For example, the expert system of Rahman et al. (2012) for roofing material selection does not consider the weather and fire resistance criteria, while the VR system of Balali et al. (2020) does not take into account properties related to the production method and sourcing of roofing materials.

Generative AI models, namely ChatGPT, have been shown to assist in material selection. Several studies have been conducted to explore the application of ChatGPT in material selection in architecture and interior design. In Rane et al.'s literature review (2023), engineers and architects can ask ChatGPT for optimal materials considering factors like resilience, sustainability, and budget. Moreover, it can serve as a construction support assistance by guiding material selection while also adhering to design specifications. Another paper by Rane (2024) suggests that ChatGPT can also be used to assess construction materials by accounting for their recyclability and toxicity, suggesting eco-friendly materials, and proposing novel materials by inputting material databases. Çalışkan (2023a) explored using ChatGPT in requirement elicitation of a hotel, with the model responding with material requirements for each interior space element, such as the flooring, walls, and ceilings. In our study, we are interested in combining 3D texturing and material selection, aiming to make design changes as early as the conceptualization stage; thus, our work aligns with previous works that combine such tasks (Juan et al., 2021; Balali et al., 2020; Zhang et al., 2019; Huang, 1995). Different from them, we turn to generative AI models like DALLE-2 and ChatGPT in facilitating these tasks. We also extend previous works on generative AI for texturing by considering technical aspects of the materials the textures approximate to. To explore this, we investigate the interior designers' usage of DALLE-2 combined with ChatGPT.

2.3 Human-AI co-creative tools in interior design

In the interior design domain, previous research has developed support tools to assist designers in designing interior spaces. In space planning, Merrell et al.'s interactive system (2011) suggests interior layouts by employing a density function that considers layout guidelines. Dreamrooms (Weingarten et al., 2019) optimizes furniture placement in a virtual reality environment through a generative process. In 3D modeling interior spaces, Karan et al. (2021)'s intelligent agent reconstructs the 3D environment of interior images and uses a Markov decision process to suggest optimal design decisions, while RoomDesigner (Zhao et al., 2023) creates 3D indoor scenes of furniture and performs tasks like indoor scene completion and swapping objects with visually compatible ones. With the advent of deep generative models like StableDiffusion, many previous works have leveraged these as tools to create images and 3D models in interior design. For example, in images, Chen and Shao (2023) developed a new loss function and trained StableDiffusion on a dataset of interior design images; the result is a diverse set of high-quality interior design images based on style and space functions. On the other hand, He et al. (2023) modified StableDiffusion using LoRA (Hu E. et al., 2022) and ControlNet (Zhang L. et al., 2023) to create a model that designers can use to create and edit images of interior design ideas, schematic drafts, and layout plans that can be used in their respective stages of the interior design workflow. Zhang H. et al. (2023) developed an interactive system that utilizes reinforcement learning to recommend interior design images based on the user's textual feedback. Works like 3DALL-E (Liu et al., 2022) and Jigsaw (Lin and Martelaro, 2023) are co-creative systems that utilize multiple generative AI models together; 3DALL-E (Liu et al., 2022) is a plug-in that utilizes GPT-3 (Brown et al., 2020) and DALL-E (Ramesh et al., 2020) to generate image references, which designers can model on in 3D modeling software, while Jigsaw (Lin and Martelaro, 2023) is a visual programming interface for generative AI models that designers can use to create images of designs from text and realize them into 3D. In line with this research, our work also investigates using multiple generative AI models but specifically focuses on helping designers texture 3D interior design scenes while estimating a suitable selection of materials when constructing the interior space.

3 System overview

To the best of our knowledge, current 3D modeling software such as AutoCAD or Sketchup lacks plugin support for developing conversational interfaces for ChatGPT. Because of this, we instead developed a prototype whose interface generally mimics that of 3D software. The prototype is a web application that is used to change and modify the material textures of objects in a given 3D scene. For this research, we use furniture as they can have various materials. Like common 3D modeling software, users can navigate the 3D scene, render, view a selected object's material details like its name and texture map, and save 3D scenes. Furthermore, the user can modify material properties such as opacity, texture map scale, and color. The user can also access a panel containing a design brief containing project details of the 3D scene being designed, such as its target market, location, and desired ambiance. The system uses DALLE-2 and ChatGPT, along with prompt engineering, to (1) generate texture maps and (2) suggest materials and color palettes. The system uses the DALLE-2 and ChatGPT models as they are, without any fine-tuning.

In this section, we describe the system's generative AI modules: the Material Generator and the Suggestion Chatbot. An overview of the system's interface and its modules can be seen in Figure 1. A list of all of the prompts used in the modules can be found in the Supplementary material.

3.1 Generative AI modules

3.1.1 Material generator

The material generator uses DALLE-2 and ChatGPT to create texture maps from an input material. Figure 2 shows an overview of the module. To use it, the designer types the material and

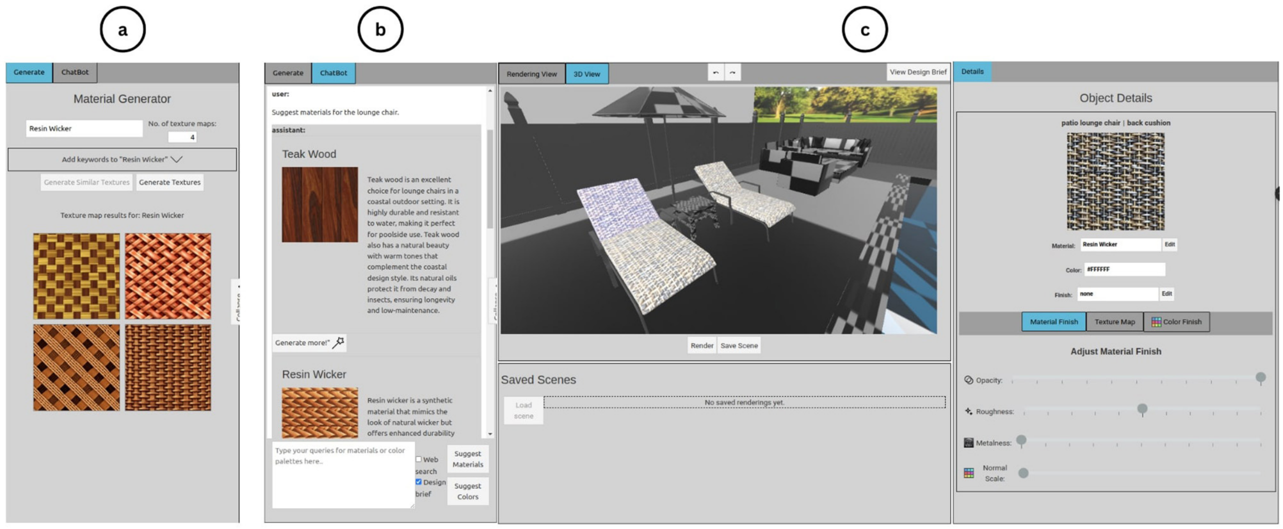

FIGURE 1
Overview of the prototype system interface. Its generative AI components are the Material Generator **(a)**, which is used to generate material texture maps, and the Suggestion Chatbot **(b)**, which suggests materials and colors for the design. The interface also features other functions that are common in 3D software like a 3D view, adjusting texture roughness, transparency, texture map scale, and color **(c)**.

chooses the number of texture maps they want to generate. After pressing the Generate Textures button, the material name is inserted into a preset prompt and inputted into the material generator to create texture maps. The designer can then apply a texture map to an object in the 3D scene by selecting it and clicking Apply Texture. If the designer wants to generate variations of a texture map, they can select it and then click on Generate Similar Textures. This uses DALLE-2 to generate texture maps similar to the selected texture. Additionally, the designer can add keywords to the prompt to create a texture map with a certain look. For example, if they want to create a wood texture map with a horizontal grain, they can add "horizontal grain" as a keyword. The designer can also leverage ChatGPT to automatically generate keywords based on the input material by clicking the Brainstorm Keywords button.

3.1.2 Suggestion chatbot

The suggestion chatbot uses ChatGPT and DALLE-2 to suggest materials and color palettes to the designer based on their queries, as shown in Figure 3. If the designer requests the chatbot to suggest materials, it returns their names, details on why they were suggested, and their image texture maps generated by DALLE-2. If the designer wants to generate more texture maps of a suggested material, they can click on "Generate More!", redirecting them to the material generator. On the other hand, if the designer requests the chatbot to suggest colors, it returns color palettes containing color hex codes and the reason why the color palette was suggested. The designer can save these color palettes and use them later when applying color to an object's material. When requesting to suggest materials or colors, the designer can check two boxes: Web Search and Design Brief. The Web Search checkbox enables the chatbot to search and use sources relevant to the user's query. The user can select this option if they are searching for materials and colors that are up to current trends since ChatGPT has a knowledge cutoff. The Design Brief checkbox lets the chatbot consider the design brief when suggesting materials and color palettes by inserting it into the query prompt. The user can use this option if they want the chatbot to request materials or colors in context with the design brief.

3.2 Technical implementation

When implementing the web application, we used Svelte and Three. JS for the front end and Flask and Python for the back end. We used the OpenAI API to access DALLE-2 and ChatGPT. To render the 3D scene, we used the Blender API. The 3D objects are manually loaded and placed into the scene.

4 Methods

We conducted a user study with professional designers and students to learn how interior designers interact with and can benefit from generative AI in texturing and material selection. In this user study, the participants were tasked to use the prototype to apply materials to an untextured outdoor patio.[1] We chose an outdoor patio for this task because patios and outdoor spaces, in general, require more careful material selection. This is because. apart from aesthetics and functionality, environmental conditions, including temperature (Djekic et al., 2018; Doulos

1 We retrieved and modified the 3D scene created by the user, *victorbied*, from the Blend Swap website. It is publicly available in the following link: https://www.blendswap.com/blend/18001.

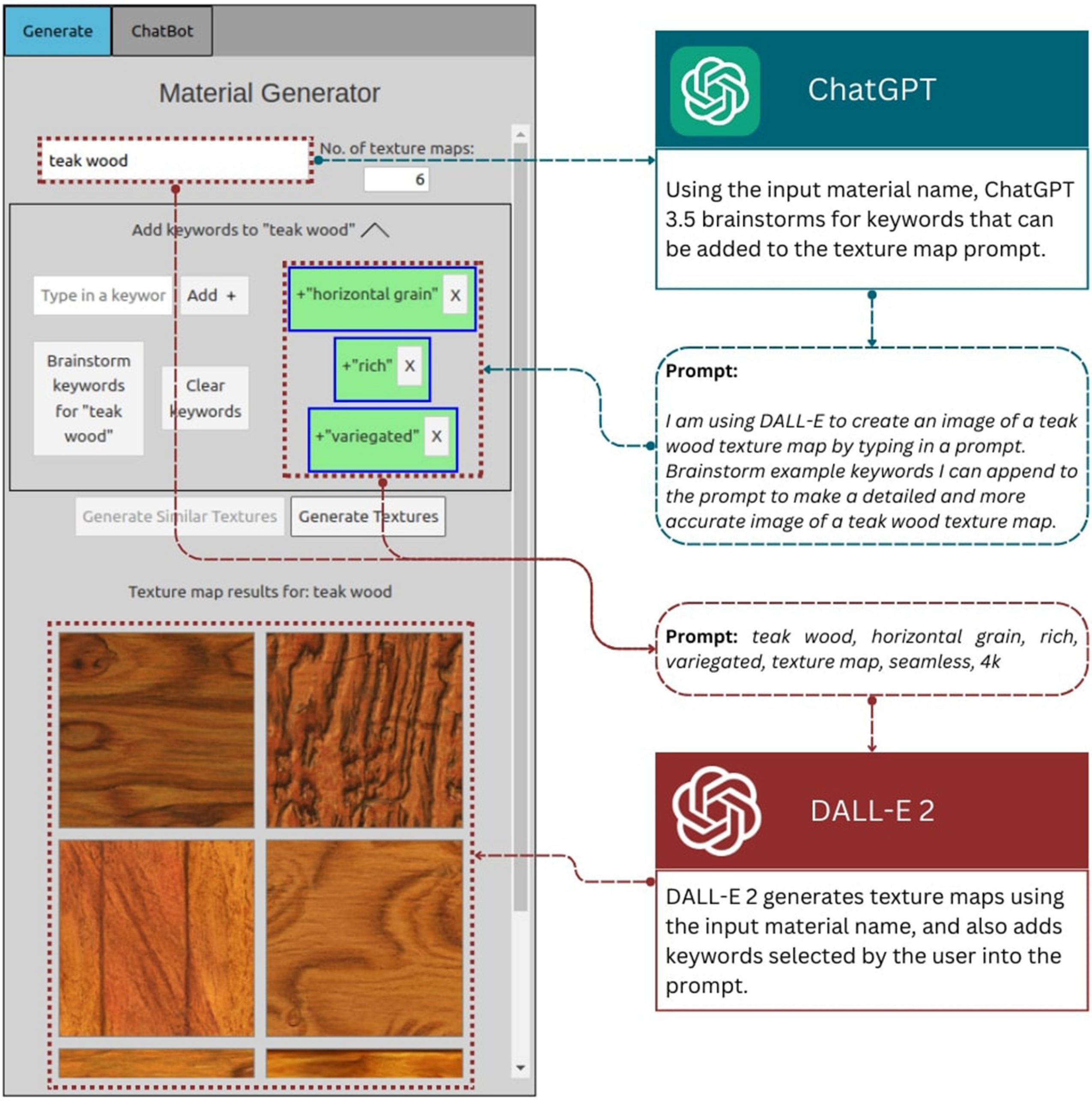

FIGURE 2
Overview of the material generator. It uses DALL-E 2 to generate texture maps from an input material, and ChatGPT to brainstorm keywords that the user can add to the prompt.

et al., 2004) and UV radiation (Andrady et al., 2019), also need to be considered when choosing materials for outdoor spaces. Thus, more effort is required to achieve comfortable outdoor spaces compared to indoor spaces (Kannamma and Sundaram, 2015). Therefore, choosing a patio for the task would be more challenging, and would help better assess how the generative AI tools can benefit designers by not only providing visually pleasing textures but also suggesting materials that are functionally and environmentally appropriate for the space.

To address RQ#1, which focuses on how the prototype's generative AI components, the Material Generator and Suggestion Chatbot, can benefit designers in texturing and selection, we measured the participants' task load and the system's creativity support by having them answer the NASA Task Load Index (NASA-TLX) and Creativity Support Index (CSI) questionnaires, respectively. We assessed task load because material selection is a task that can be mentally challenging due to considering multiple criteria (Godsey, 2012; Alfuraty, 2020) and limited knowledge of material properties (Bettaieb et al., 2019) and processes (Thompson

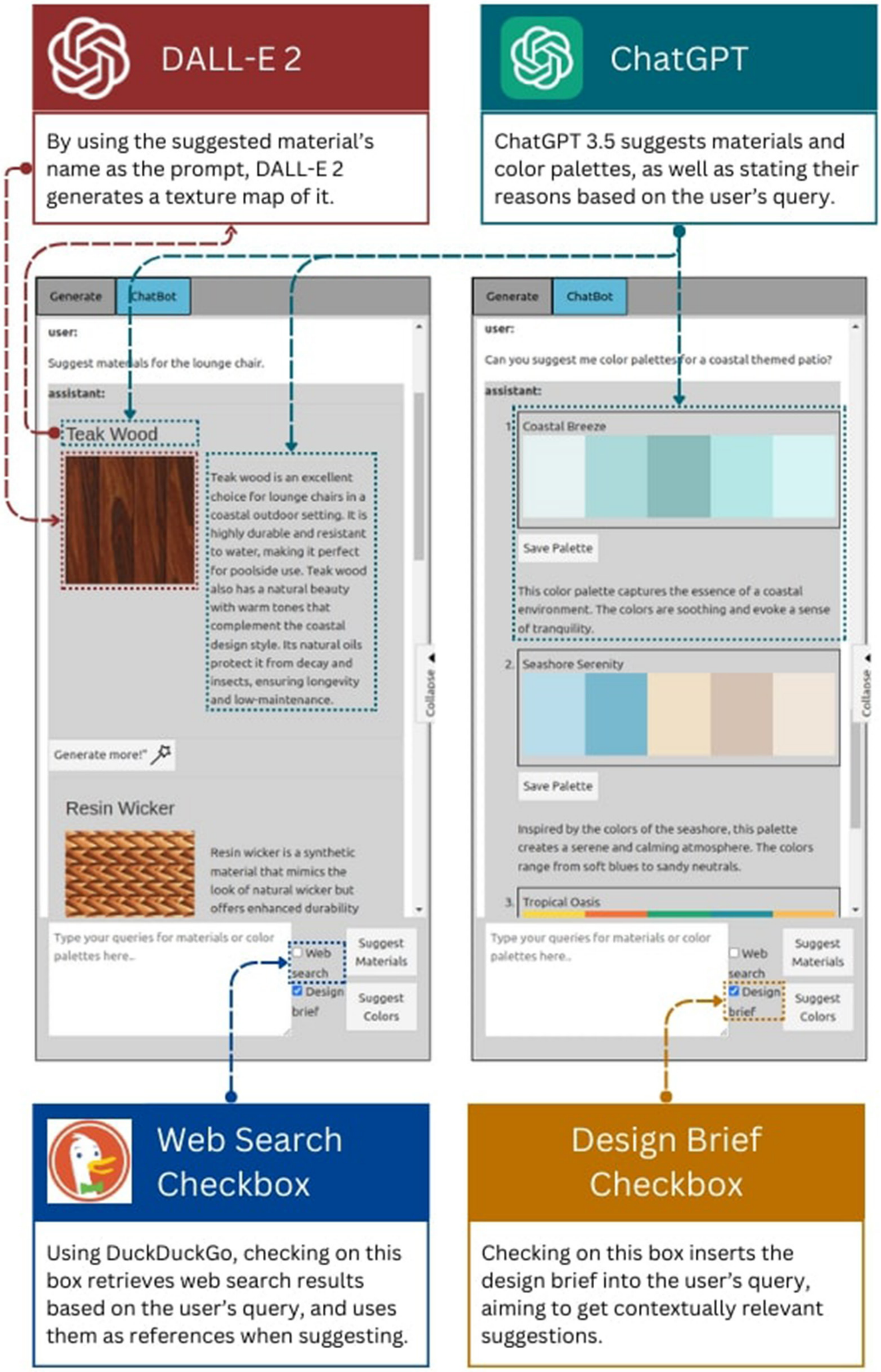

FIGURE 3
Overview of the Suggestion Chatbot, which uses ChatGPT 3.5 and DALL-E 2 to suggest material textures and color palettes based on the user's query. The left panel shows an example of the chatbot suggesting materials, while the right shows suggesting color palettes.

and Johansen, 2007), and selecting appropriate textures can also be a tedious and time-consuming task (Zhu et al., 2018). Thus, it is important to assess if the generative AI components help reduce task load. We chose NASA-TLX as our metric because it has been proven to be a reliable and flexible tool for assessing workload over various domains, as long as explicit instructions are provided to establish context (Hart, 2006), which we did when administering the questionnaire. We assessed creativity support using CSI, as it is also important to measure how well the system supports providing a wide range of material and texture map alternatives (evaluated by the Exploration dimension) based on the user's intent (Expressiveness). Additionally, it is important to evaluate the overall user experience (Immersion and Enjoyment) and user satisfaction with their output after using the system (Results Worth Effort). Apart from administering questionnaires, we also conducted semi-structured interviews to gain insights and qualitative feedback from the designers while using the system.

To address RQ#2, which focuses on how interior designers interact with DALLE-2 and ChatGPT, we tracked their usage instances during their sessions, their queries sent to the Suggestion Chatbot, and their texture prompts inputted in the Material Generator. We then analyzed this data to infer the types of prompts and queries the designers used and identify interaction patterns with the system when assigning material textures.

4.1 Participants

To test the prototype, we conducted a convenience sampling to recruit six professional designers and five interior design undergraduate students (one male and 10 females). We contacted a government design agency and a university student organization in the Philippines to recruit professional designers and design students, respectively. All participants are Filipino. Of the six professionals, four are interior designers, one is an architect, and one is an industrial designer. Moreover, two interior designers are professors at the same university as the students. The professionals have a range of 2–15 years of work experience and are proficient in material and finish selection, with a rating of an average of 4.2 on a scale from 1 to 5 (with 5 being an expert). Of the five students, four were third-year students, and one was second-year when the user study was conducted. The students are fairly knowledgeable in material and finish selection, rating an average of 3.6. All of the demographic details of the participants are shown in Table 1.

4.2 Study procedure

The study was conducted in person or remotely via Zoom, depending on the participants' availability. For the remote setup, the researcher took control of the system while the participant instructed the researcher. At the start of the session, the researcher briefed the participants, and the participants signed an informed consent form. Next, they watched a series of video tutorials on using the system and were given time to explore using it to texture a bedroom. After a break, the participants were given 30 minutes to texture the patio based on the provided design brief. After the task, they were instructed to complete the NASA-TLX and CSI questionnaires. Then, we conducted the semi-structured interviews with the participants. We performed a thematic analysis of the interview transcriptions to know how the generative AI tools in the system helped them texture and select materials, as well as issues encountered. Each session took about 2 hours, and the participants were each compensated with a cash reward.

5 Results

5.1 Taskload

The overall NASA-TLX score and scores per dimension of the participants, as well as the scores separately calculated from the professional designers and students, are shown in Table 2. We excluded the Physical Demand aspect from the NASA-TLX questionnaire because the study involved minimal physical activity; the participants sat down, typed, and clicked on a computer. Overall, the participants averaged a NASA-TLX score of 47.26 out of 100, indicating moderate task load levels while using the system for material selection and texturing. Furthermore, they also averaged between 46 to 50 in each of the task load dimensions, indicating moderate to moderately high values of workload in the dimensions.

Delving into the subgroups, the professionals averaged scores between 40 and 50 in temporal demand, frustration, and performance. This indicates that they felt rushed and experienced stress at moderate levels. They also felt they performed moderately successfully in their task. On the other hand, they averaged 63.33 in mental demand, indicating that they experienced high cognitive load when using the system. Also, their average of 51.67 in effort indicates that they had to put in moderately high effort. The students scored 34 in mental demand, meaning they did not need to exert a high cognitive load when using the system. They scored between 40 and 50 in temporal demand, effort, and performance. This indicates that they felt moderately rushed, had to exert a reasonable amount of effort, and felt moderately successful in their performance. However, they felt somewhat high levels of stress, averaging 54 in frustration.

To further observe the diversity in perceived task load among the participants, we show the distribution of the ratings in each dimension of task load made by the participants in Figure 4. In mental demand, five out of 11 of the participants found their task to be cognitively straining ($\geq$65/100). On the other hand, five participants experienced low mental demand ($\leq$ 40). Overall, their ratings fell at a median of 55, indicating that they experienced a moderately high mental load. This may be due to the participants' unfamiliarity with utilizing generative AI tools when selecting materials and their textures. In performance, however, five participants felt that with the generative AI tools, they accomplished their goal of selecting materials and textures ($\leq$40). Three participants felt that they underperformed ($\geq$65) in the task. Overall, the participants' ratings settled at a median of 50, indicating that they accomplished their goal to a moderate extent. In the effort dimension, eight participants felt they exerted a low ($\leq$ 40) to medium ($45 - 60$) amount of effort. The number of low-scoring participants is higher than the 3 participants who

TABLE 1 Overview and demographics of the participants in the user study.

ID	Sex	Occupation	Work experience (years)/ University year	Material selection Expertise (1–5)
P1	F	Architect	8 years	4
P2	F	Interior Designer	2 years	5
P3	F	Interior Designer	7 years	3
P4	F	Industrial Designer	3 years	5
P5	F	Int. Design Student	3rd year	3
P6	F	Int. Design Student	3rd year	3
P7	M	Interior Designer	15 years	4
P8	F	Int. Design Student	3rd year	4
P9	F	Int. Design Student	2nd year	4
P10	F	Int. Design Student	3rd year	4
P11	F	Interior Designer	5 years	4
$n = 11$	1 male 10 females	5 students 6 professionals	Work Exp Mean: 6.7 years Work Exp Range: 2–15 years	Student Mean: 3.6/5 Pro Mean: 4.2/5

TABLE 2 Average task load scores per dimension and overall NASA-TLX score of the design professionals and students.

	Mental demand	Temporal demand	Performance	Effort	Frustration	NASA-TLX score
All (σ)	50 (34.42)	46.82 (28.92)	42.27 (28.32)	47.27 (22.18)	49.55 (25.15)	47.36 (14.84)
95% CI	(30.45, 69.09)	(30.45, 62.73)	(26.36, 57.73)	(34.55, 59.55)	(34.46, 63.64)	(38.73, 55.09)
Professionals	63.33	46.6	42.5	51.67	45.83	51.39
Students	34	47	42	42	54	42.53

A lower value is better. We also show the standard deviations (σ) and bootstrapped 95% confidence intervals for the NASA-TLX score and each of the dimensions.

felt they exerted a high amount of effort ($\geq$ 65). Overall, the effort needed to use the prototype was at most manageable, which is also evident in the median of 45. In temporal demand, four participants felt rushed ($\geq$65), and four felt lower levels of time pressure ($\leq$40). Their ratings garnered a median of 55, meaning that the participants felt moderately high levels of time pressure. This may be due to the system's slowness in generating responses. Lastly, in frustration, four participants felt irritated or stressed ($\geq$65), while the rest perceived them at most medium levels ($\leq$60). Moreover, five felt moderately low levels of frustration ($\leq$40). Their ratings settled at a median of 55, indicating that the participants experienced moderately high levels of stress. Similar to the mental and temporal demand dimensions, this may be due to the system's slow response time and the challenge of using the generative AI tools. Overall, based on the distribution and medians of ratings, participants experienced moderately high levels of mental strain, time pressure, and frustration when using generative AI tools for material texturing. This means that there is room for improvement in making the system respond faster and more intuitive to use for designers in their workflow. Despite this, designers only exerted moderate amounts of effort in their tasks and felt that they had somewhat accomplished their goals.

While the means, medians, and rating distributions encompass the overall experiences of the participants, they alone do not fully convey the statistical reliability of the data. Thus, we calculated 95% confidence intervals (CIs) of the NASA-TLX score and its dimensions in Table 2 to estimated the range where the true NASA-TLX population mean scores of designers lie. Because we are dealing with a relatively small sample size, we performed bootstrapping (DiCiccio and Efron, 1996). The mean Mental Demand score is 50, with a 95% bootstrap confidence interval of $(30.45, 69.09)$, which means that the true mental demand score falls within this range. This interval is wide due to not only the small sample size but also the variability in participants' perception of the required cognitive effort. Similar can be said for that of temporal demand, frustration, and performance, which have confidence intervals of $(30.45, 62.73)$, $(34.46, 63.64)$, and $(26.36, 57.73)$, respectively. While their mean scores indicate that participants overall felt moderate time pressure and performed somewhat well with moderate stress levels, their wide confidence intervals reflect the high variability of the participants' perception of these dimensions. This strengthens the need to improve the system's speed and usability to ensure a more positive experience for all designers. On the other hand, a somewhat smaller confidence interval is evident in the effort dimension (Avg = 47.27), with a range of $(34.55, 59.55)$. This means that the participants exerted a medium amount of effort to use the prototype's generative AI tools. Lastly, the participants' mean NASA-TLX score has a bootstrap confidence interval of $(38.73, 55.09)$. This is considered to be relatively narrow and indicates a moderate level of agreement among the participants that they overall perceived a medium amount of task load. Additionally, the true NASA-TLX mean score would fall within a range that is moderately low to high.

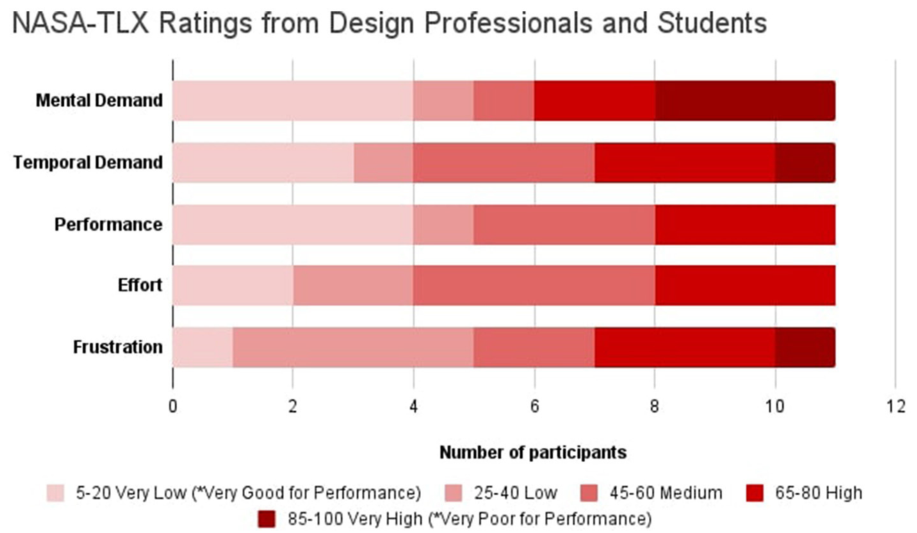

FIGURE 4
Distribution of the NASA-TLX ratings of the design professionals and students.

5.2 Creativity support

The average factor scores, factor counts from each dimension, and CSI score of the participants are in Table 3. The factor score indicates how well a tool supports a certain dimension in a creative task, with the maximum score being 20. The factor count indicates how important the dimension is in the task, with the maximum count being 5 (Cherry and Latulipe, 2014). In this study, the task pertains to selecting materials, finishes, and colors for a given 3D interior space. We excluded the Collaboration aspect of the CSI questionnaire since the system does not involve multiple users working together. Overall, participants averaged a CSI score of 72.82 out of 100, indicating a moderately high level of creativity support provided by the system.

Based on factor scores, the professionals averaged the highest in exploration (15.17 out of 20), meaning the system supported their exploration of different materials and colors. They scored moderate in enjoyment (14.17), indicating they were somewhat engaged in using the system. They also scored somewhat moderate in expressiveness (13.5) and immersion (13.5), meaning that the system somewhat helped them in expressing their intent when creating textures and querying, and the professionals were somewhat immersed. Their score in results worth effort (12.67) was the lowest, indicating that they felt the system required some effort and could be improved to make the interior scene more worthwhile in material texturing. Based on average factor counts, the professionals give importance to exploration (3.83 out of 5), followed by results worth effort (3.5) and expressiveness (3.17).

On the other hand, the students averaged the highest in exploration (17.8), followed by enjoyment (17.2). This means that they also found the system highly beneficial in helping them explore different materials and colors while also being engaged. They also averaged high in expressiveness (15), meaning the system helped them express their intent. They scored moderate in results worth effort (14.6) and lowest in immersion (13). This means that the students were also somewhat immersed in the system. Moreover, this can indicate that the outputs they received from the Material Generator and Suggestion Chatbot and their final design were somewhat worth the effort exerted. Like the professionals, the students prioritized exploration (4.2), followed by results worth effort (4), and then expressiveness (3.2).

To observe the diversity in how the participants perceived creativity support from the system, we show the rating distributions in Figure 5. In enjoyment, eight out of the 11 participants enjoyed the system ($\geq$ 15/20), yielding a median value of 16 out of 20. This indicates that the system provided a gratifying user experience for the participants. Similarly, in exploration, nine agreed that they could explore different materials and textures ($\geq$ 15), with a median of 17. In the expression dimension, five participants felt they could express their intent when using the generative AI tools ($\geq$ 15), with four participants in somewhat agreement ($12 - 14$), and two participants remaining neutral ($9 - 11$). Their median is 14. This means that while the tools were moderately effective in facilitating the participants' intents, there is still room for improvement. In immersion, six participants felt immersed ($\geq$ 15), while the rest of the participants either were neutral ($9 - 11$) or somewhat not ($6 - 8$). Their median value of 15, indicating that most experienced moderately high levels of immersion. It is also worth noting that their median is higher than their average of 13.27 from Table 3. This means that fewer participants gave much lower ratings; however, most participants gave high ratings. Given that five felt neutral or worse, immersion in the system can still be improved. Similarly, six participants perceived that their results were worth the effort ($\geq$ 15). On the other hand, one slightly agreed ($12 - 14$), three remained natural ($9 - 11$), and one somewhat disagreed ($6 - 8$). Overall, their median is 16, indicating that most felt it was worth the effort. Similar to immersion, their median is higher than their average of 13.55. This indicates that while most gave high ratings, few gave much lower ratings. Overall, most participants agreed that the system helped them explore options. While most participants could somewhat express their desired textures to generate or materials to search, this can be improved

TABLE 3 The average factor scores and average factor counts for each dimension and the average CSI score of the design professionals and students.

	Enjoyment		Exploration		Expressiveness		Immersion		Results worth effort		CSI score
	Score	Count	Score	Count	Score	Count	Score	Count	Score	Count	
All (σ)	15.55 (3.08)	1.64	16.36 (3.35)	4	14.18 (2.96)	3.36	13.27 (3.69)	1.36	13.55 (4.44)	3.55	72.82 (15.58)
95% CI	(13.82, 17.27)		(14.37, 18.09)		(12.45, 15.82)		(11.18, 15.36)		(11.0, 16.0)		(63.76, 81.19)
Professionals	14.17	1.83	15.17	3.83	13.5	3.5	13.5	1.5	12.67	3.17	68.11
Students	17.2	1.4	17.8	4.2	15	3.2	13	1.2	14.6	4	78.47

The scores for both groups are also shown separately. A higher value is better. We also show the standard deviations (σ) and bootstrapped 95% confidence intervals for the CSI score and each of the dimensions.

by better aligning the system with how they typically search for them. While the participants agreed they had an enjoyable user experience, immersion can still be improved by perhaps making the system respond faster. By improving on expression and immersion, the effort-results ratio can be improved.

We also computed confidence intervals to assess the CSI scores' variability and estimate their true values at 95% confidence. In enjoyment and exploration, participants averaged 15.55 and 16.36, which yielded CIs of (13.82, 17.27) and (14.37, 18.09), respectively. These are relatively narrow, meaning that their true scores lie between moderate to high, and that participants consistently had an enjoyable experience while being able to explore. In expressiveness, they averaged 14.18 with CIs of (12.45, 15.82). This indicates that the population's score would lie between moderately low and high. It also indicates that there is consistency among the participants in somewhat expressing their intent. On the other hand, participants averaged 13.27 and 13.54 in immersion and results worth effort, respectively, which are moderately low scores. Furthermore, their bootstrap confidence intervals are (11.18, 15.36) and (11.0, 16.0), respectively. Both CIs are wider, indicating more variability in the participants' immersion and their satisfaction with the results. With the participants' CSI score, the true population CSI score lies within (63.76, 81.19), which indicates moderate variability among the participants. On the other hand, it also indicates that the designer population's overall perception of the system's creativity support lies between moderate to high. Overall, the CIs reveal that participants generally enjoyed the generative AI prototype, positively rated its exploration support, and gave moderate scores regarding its support in expressiveness. This conclusion aligns with that from observing the rating distributions. The wider CIs in immersion and perceived effort-results ratio indicate needing to improving system usability.

5.3 Final designs and generated outputs

Figure 6 shows several final designs on the patio using the prototype. Participants used various textures for some elements in the patio. For the floor, P2 and P4 used wood decking material, while P4, P6, and P9 used stone materials like granite and sandstone. For other elements, they used similar materials. For the pool flooring, all participants opted for blue tiles, and for the sofa base, P3, P4, and P9 used wicker materials.

Some example texture maps from the Material Generator are shown in Figure 7. In many cases, the Material Generator generated textures of various patterns from general prompts like P1's "*stone flooring*." It also created textures that align with specific prompts, such as in generated textures from P7's "*white wood wash*" and P2's "*light blue fabric*." However, there were some visible artifacts, such as in P10's white rattan textures. Some textures did not align with the prompt, like in P8's textures, where there were dark-colored textures even if the prompt mentioned the keyword, "*light*."

Lastly, we show example responses made by the Suggestion Chatbot in Figure 8. In many cases, the Suggestion Chatbot gave detailed and various suggestions when responding to queries, as shown by P10 and P11. However, there are some suggestions where the accompanying texture map was not visually accurate (e.g., Cedar, Redwood).

5.4 Benefits in using the prototype's generative AI tools

During the interviews, design professionals and students mentioned how the prototype helped them select textures and colors for their 3D scene, as well as select materials overall for their assigned task. We present the following ways the designers benefited from the system:

5.4.1 Designers could search for texture maps and materials specific to their prompts (8/11)

Through prompts, designers found the generative AI tools convenient for searching texture maps and querying for specific materials. With the Material Generator, P1, P2, P5, and P6 mentioned that it was easy to search for readily available textures by simply typing in words like "*wood*."

> I can easily type and generate a wood material for me for this specific item.—P1

With the Suggestion Chatbot, P5, P6, P8, P9, P10, and P11 found it convenient to ask for specific materials based on criteria like cost-efficiency and eco-friendliness. Moreover, P5 and P8 mentioned that it could save them time searching on websites like Google.

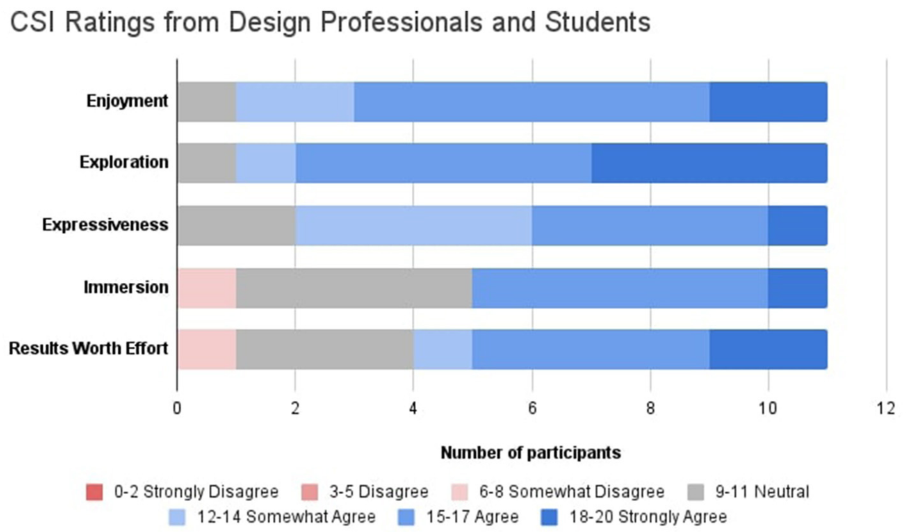

FIGURE 5
Distribution of the Creative Support Index (CSI) ratings of the design professionals and students.

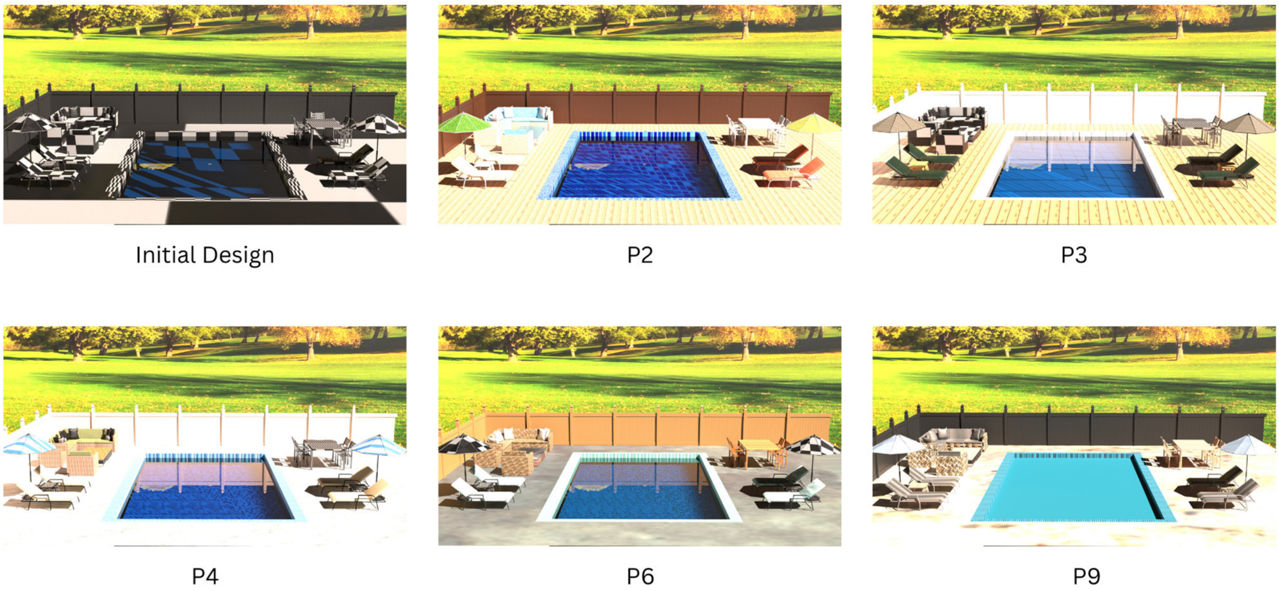

FIGURE 6
Example textured designs made by the participants. The top-left design is the initial untextured design of the patio. Some parts of the final designs were not textured, as the participants ran out of time.

> I would usually search on the internet what kind of materials I could use for this weather. I think with the chatbot, it would save me more time in researching what materials I should use.—P8

5.4.2 Designers received relevant suggestions in context to their project (7/11)

With the design brief box checked in the Suggestion Chatbot, P3, P4, P8, and P10, found the suggestions accurate and contextual to their assigned design brief. P10 says, "*I think it produced accurate color palette suggestions in relation to the [brief's] design style.*" Additionally, P3, P2, and P5 found checking the box convenient as it reminded them about their design brief, which they found too long to read. For example, P2 says, "*We tend to forget about the design brief and design problem provided by the client. So, this design brief [checkbox] is very helpful.*"

5.4.3 Designers received informative material suggestions (6/11)

P4, P11, and most students, namely P5, P6, P8, and P10, found the chatbot's suggestions convenient and helpful to include

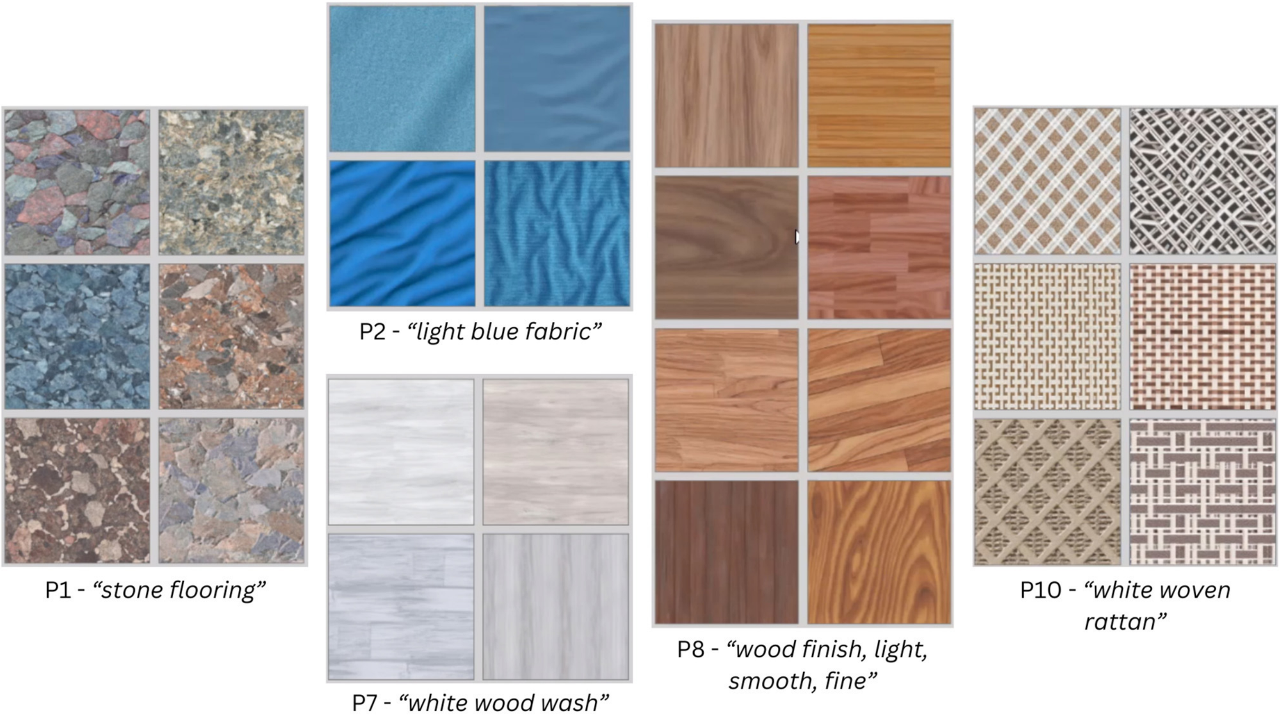

FIGURE 7
Example texture maps created by the Material Generator based on prompts from the participants.

descriptions of the materials and reasons why they were suggested. Furthermore, P8 mentioned that the suggestions helped ideate other materials, saying, "*The material I'm looking for may not be there, but it gives me an idea of what other materials I can use*".

> I did find them helpful because they also included descriptions of the materials and the properties that I would have searched in Google. So yeah, it's very convenient.—P10

5.4.4 Designers could explore various texture map and material options (5/11)

The Material Generator and Suggestion Chatbot helped designers explore a wide range of texture maps and material options, respectively. For example, with the Material Generator, P9 could explore textures beyond the options she was limited to in her software library and found it "*helpful to have an infinite amount of materials.*" For P3, P6, and P7, the Suggestion Chatbot could recommend ideas to them, especially if they could not think of materials or finishes that they could use.

> When there are many projects, and then your people are filled with tasks, they have no headspace. They have to keep designing. It doesn't matter to them if it's beautiful. It's now all about compliance. With that, I think [the chatbot] could help there. Like if they have questions, they could actually ask and then give an idea.—P7

5.5 Challenges and issues when using the prototype's generative AI tools

Conversely, the designers raised several issues and challenges when using the prototype's generative AI tools.

5.5.1 Generative AI tools were slow in responding (7/11)

A major issue most designers encountered was that the system was slow in generating textures and making suggestions, resulting in some designers not finishing on time. This common issue may also reflect the many participants perceiving medium to high levels of temporal demand in assessing task load. While the system was loading, P11, a professional, was "*still able to think faster than the system.*"

> It was kind of slow. I'm very impatient. So if it were on my laptop, I would have deleted it.—P9

5.5.2 Designers needed other essential 3D features (7/11)

Since the prototype was implemented as a web application and not integrated into existing 3D software, P2, P4, P5, P7, P8, P9, and P11 sought other features: adding and adjusting 3D objects and setting lighting. Adding and adjusting 3D objects was important for them as they wanted to add more furnishings, as well as adjust their positions and geometry; however, it was not included since

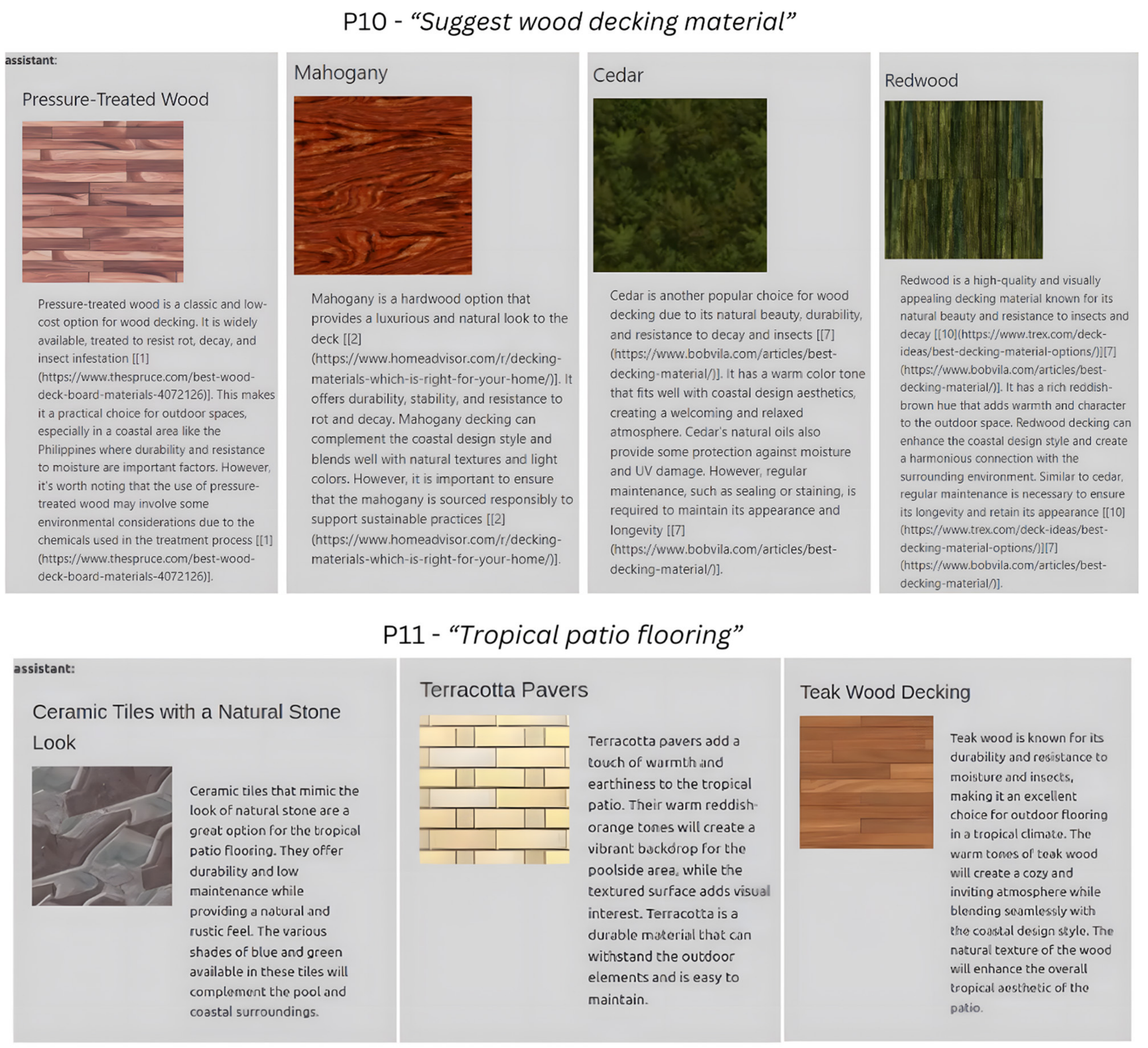

FIGURE 8
Example suggestions created by the Suggestion Chatbot based on queries from P10 and P11.

the system was solely focused on changing textures. For example, P1 felt limited with her material choices due to the patio chair's fixed shape, saying, "*[its shape is] already limiting me with the type of material I'll use for this design.*" Adjusting the lighting in the 3D scene was essential since it played a role in the material's look. Most designers also mentioned that the chatbot would be helpful if it could suggest lighting setups and furnishings. For example, P2 suggests, "*We can ask what specific lighting we can use to illuminate that space. We can ask what specific light fixture that we can use.*"

5.5.3 Designers were not confident in the suggestion chatbot's credibility (4/11)

P4, P9, P10, and P11 were unsure if the chatbot's suggestions were credible, with P4 being "*not sure if the bot knows the [interior design] standards.*" Being informed that ChatGPT had a knowledge cutoff, P9 wanted it to be more updated, as "*interior trends are changing very fast.*" P10 requested colors with whites, blues, and greens but received palettes that "*are a little bit too dark for that style.*" P11 suggested "*if the search can be more fine-tuned to sources like academic journals, which are more credible than web articles.*"

5.5.4 Designers struggled with using text as input (3/11)

At the start of the experimental session, some professional designers, P1, P4, and P7, found it difficult to prompt in the material generator and struggled to write the best prompt to get their desired texture maps. This also aligns with the participants' moderate score in expressiveness from CSI. They were more used to selecting pre-made texture map images.

I guess being a visual person, I'm not used to looking for adjectives to explain what I'm looking for exactly.—P4

5.5.5 Designers struggled with establishing visual harmony in textures and colors (2/11)

P1 and P4, both professionals, mentioned that only generating texture map images was insufficient. They preferred them already applied onto their intended 3D objects to see if they were applied seamlessly and harmonized with other objects in the scene. This may also be reflected by the moderately high mental demand score of the professionals in NASA-TLX. For P1, she was not satisfied with her final materials and colors because "*since I couldn't visualize, it was very difficult. So, the results were quite a mix of many things that don't work well together.*"

5.5.6 Accompanying texture maps did not match the suggested material (3/11)

P1, P8, and P11 mentioned that when receiving material suggestions, their texture maps did not visually match the suggested material. For example, when requesting materials for the umbrella, P8 says, "*there was like an actual picture of the umbrella, not the texture and material itself.*"

5.6 Designer interactions with generative AI

From the user study, we observed the designers' interactions with the prototype, especially on the Material Generator and Suggestion Chatbot, both of which use DALLE-2 and ChatGPT. We observed and analyzed the designers' interactions with the generative AI based on the following criteria: the number of Material Generator prompts, the number of Suggestion Chatbot queries, the types of prompts from the Material Generator, and types of queries from the Suggestion Chatbot. Lastly, we tracked and analyzed the sequence of all of these interactions with the prototype to identify potential interaction patterns from the designers.

5.6.1 Usage activity and patterns

The timeline in Figure 9 shows a complete visualization of all participants' usage of the prototype, including the Material Generator and Suggestion Chatbot.

Referring to the timeline, all participants followed a common approach in using the Material Generator to assign material textures to the elements in the space (e.g., flooring, pool flooring, chair cushions). They did this by first clicking on the target element, prompting the Material Generator to create and apply a texture, and then refining the texture by adjusting its scale, color, roughness, and rotation. With the Suggestion Chatbot, on the other hand, most participants used it by typing in their query, clicking on the target element, and then applying the texture map of the suggested material. Delving deeper, most participants exhibited certain approaches when using the generative AI tools for material texturing. We list down two ways the design professionals and students used the prototype's generative AI tools:

- Exploration, experimentation, and refinement: P2, P6, and P7 did not use the Suggestion Chatbot to query materials or colors, and heavily used the Material Generator in creating various textures for the space. With the generated textures, P2 and P7 applied several of them onto the furniture items and changed different colors, showing a trial-and-error process in finding the desired combination of color and texture. P2 added and brainstormed keywords to refine the texture she was looking for.
- Assisted creativity: P5, P8, P9, and P11 took on an assisted approach, frequently inquiring the Suggestion Chatbot on appropriate materials, and directly applying the textures of the suggested materials to the space. They also used the Material Generator in-tandem to further explore more texture maps of a suggested material.

Moreover, some designers also considered specific aspects while doing their tasks. These are namely:

- Lighting: While P1 and P9 were using both the Material Generator and Suggestion Chatbot, they frequently rendered the scene multiple times to see how the textures would look under lighting.
- Color themes: P3, P4, and P10, apart from inquiring materials, used the Suggestion Chatbot for inquiring color palettes and applied them to the elements in the space.

Overall, examining the participants' activities reveals two ways they used the generative AI tools for material texturing: 1) solely using the Material Generator to explore texture options and converging on the desired texture by adding keywords, and 2) first consulting with the Suggestion Chatbot on suitable materials and then exploring their representing textures using the Material Generator. Moreover, they also take into account how the materials will be diplayed under photorealistic lighting and add aesthetically pleasing colors.

5.6.2 Material generator prompts

The designers inputted a wide variety of prompts to the material generator to create texture maps. Most prompts were generic materials such as *"wood"* or *"cloth"*, and specific materials like *"rattan"* or *"sandstone"*. Rather than typing in materials, P1 and P8 specified finishes like *"powder coated"* and *"wood finish"*. P7 created patterns through prompts like *"blue white stripes"*. Designers like P2 and P11 typed in materials specific to a certain kind of flooring, like *"wood deck"* and *"pool tiles"*. Most participants specified colors in their prompts.

There were some moments, however, where participants did not get the kind of texture map they were looking for on the first try. As a result, they had to rewrite their prompt around one to two more times by adding their own keywords or those

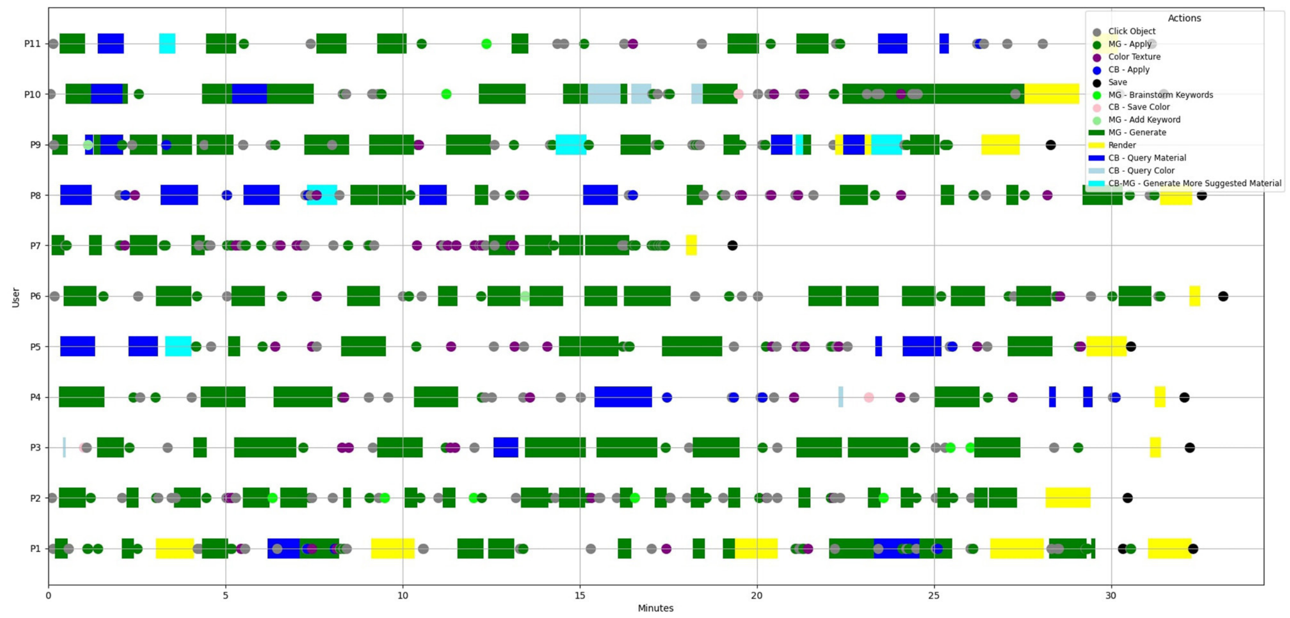

FIGURE 9
Timeline of usage activity of the design professionals and students with the prototype, including the Material Generator (MG) and Suggestion Chatbot (CB). Usage instances that were accidental were omitted.

brainstormed by the ChatGPT until they got the texture with their desired look. These keywords included colors, finishings (e.g., matte), specific materials, adjectives (e.g., clear, shiny), and even design styles (e.g., coastal). For example, from *"sandstone"*, P9 changed the prompt to *"sandstone, light-colored, beige, sand like"*, and P1 changed from *"weaved"* to *"weaved rattan"*. We found that participants re-prompted the most when trying to generate textures of glass. For example, P6 re-prompted by adding *"clear, transparent"*, and again by adding *"smooth"*. Moreover, we found that *"clear"* and *"smooth"* were common words that were used by participants (P2, P6, P10) when re-prompting for glass.

5.6.3 Suggestion chatbot queries

After analyzing the design professionals' and students' queries for materials and colors in the Suggestion Chatbot, we found three distinct queries. Most participants made *object-based queries*, meaning they asked the chatbot for materials for a certain object. For example, P5 typed, *"I want to search a material for the fence."* Participants also made *style-based queries*, asking for materials or colors suitable for a certain design style. For instance, P10 queried, *"Suggest colors for coastal design"*, while P11 typed, "*Coastal wood*." Lastly, participants made *characteristic-based queries*, asking for materials and colors with certain practical or style attributes. For example, P5 asked, *"What waterproof textures are good for the pillows?"*, while P3 queried, *"Suggest color palettes that involve monochromatic blues."* Overall, the designers queried the chatbot for materials and colors with various textual contexts, such as objects, design styles, and desired characteristics.

6 Discussion

6.1 RQ#1: How can interior designers benefit from generative AI in texturing and material selection?

First, based on interviews with the designers, we found that they can benefit from generative AI in quickly exploring various options of texture maps for their 3D design and materials for their design project. This is evident in their high Exploration score (Avg = 16.36) in creativity support. The finding also aligns with previous work on co-creative AI tools (Cai et al., 2023; Liu et al., 2022; Rane et al., 2023), which further supports generative AI's robustness in rapidly exploring design outputs. On top of previous work, we show that text-to-image generators like DALLE-2 cannot only be used in creating image references (Liu et al., 2022; He et al., 2023) or design inspirations (Chen and Shao, 2023; Zhang H. et al., 2023) but can also be used to explore various texture maps and patterns beyond the limits of material libraries, as mentioned by P9. With ChatGPT, on the other hand, designers can brainstorm materials for their projects, which can be useful if they feel mentally overwhelmed with other projects, as mentioned by P7.

Second, designers can search for textures and materials by prompting, which was mentioned by several participants. This is supported by their CSI scores in Expressiveness (Avg = 14.18) and Results Worth Effort (Avg = 13.55, Median = 16), which indicate that with prompting, designers could articulate their intentions to a reasonable extent, exerted moderate effort, and were somewhat satisfied with the generated outputs. This is also supported by their high Enjoyment score (Avg = 15.55), which indicates that they enjoyed using the system that mainly involves prompting.

Lastly, this is supplemented by their moderate Effort score (Avg = 47.27) from NASA-TLX, which also means that they only exerted a medium amount of effort. Through a chatbot, designers can express their intent by asking for specific materials based on criteria like sustainability and durability. Likewise, by using text-to-image generators, designers can easily streamline texture search which can save effort when searching for specific textures. However, it is also evident from the aforementioned scores that there is room for improvement. For instance, some designers struggled with prompting and had to re-prompt multiple times to get their desired texture. This has been a common issue for designers with generative AI, where they must express their visual intent with text (Hong et al., 2023). One common solution would be to fine-tune with datasets containing paired text-texture images. Moreover, we found that designers made various prompts, including specific materials, finishes, and patterns. These kinds of prompts can further be used as a basis for creating the datasets for fine-tuning. Another solution would be to use image modality, which has also been emphasized by previous works (Hong et al., 2023; Hou et al., 2024). Designers can begin with pre-made textures, as they are more used to selecting images from libraries. If they want to explore variations, they can input them to generate more variations. Designers still maintain their texturing workflow and human-made textures still have an important role, while they get to leverage the capability of generative AI. It is important to note that image generators should also create texture variations that are distinct categorically (Hong et al., 2023) for wider exploration. For example, if the designer wants to explore more basket-weaving textures, the generator should show different weaving types.

Third, most of the time, designers were able to receive suggestions that were generally in context to their project by inserting the design brief into the prompt, which was implemented in the system by having the users check the Chatbot's Design Brief checkbox. This is supported by their feedback, where they found it convenient to use due to the design brief's lengthiness. This is also somewhat evident in their moderate scores in Results Worth Effort from CSI (Avg = 13.55, Median = 16) and their moderate Effort score from NASA-TLX (Avg = 47.27), meaning that with the feature, they did not need to exert significant effort to ask relevant suggestions and were fairly content with what they received. With LLMs being able to input larger contexts, designers can insert their project specifications in text form and retrieve contextually relevant suggestions for their design apart from materials like furnishings, lighting setups, and accessories. However, there is also some room for improvement. Some designers raised concerns regarding the suggestions' credibility. Thus, the LLM should be fine-tuned to more credible and domain-specific sources like material databases, project data, and design guidelines (Rane et al., 2023).

Lastly, ChatGPT can provide informative suggestions, which is helpful for students. Apart from their feedback, this is supported by their low Mental Demand (Avg = 34) and moderately low Effort score (Avg = 42) from NASA-TLX, which can indicate that searching for suitable materials did not require exerting much mental strain, as the information is conveniently provided for them. This is also somewhat supported by their high Enjoyment score (Avg = 17.2) and moderate Results Worth Effort score (Avg = 14.6) from CSI. This means that they regularly used the Chatbot and were moderately satisfied with the material suggestions. With LLMs, Students can use them as tools for conveniently researching materials; however, as mentioned by P11, this should require fine-tuning them to credible academic sources. Moreover, it is still important that students practice their research skills; one way can be prompt engineering the LLM to make "half-responses" and encourage students to continue reading the cited sources to learn more about what they queried.

6.2 RQ#2: What kinds of interactions can be derived from the interior designers' usage of generative AI tools for texturing and material selection?

Based on how the designers used the generative AI tools, we found that most used them in the following ways: 1. Exploring, experimenting, and refining the textures with the Material Generator, and 2. Using the Suggestion Chatbot as a creative assistant. The first approach further supports that DALL-E is a valuable tool for interior designers in searching material textures for their work. By adding keywords, designers can narrow their options to find particular textures. This is reflected in their high Exploration score (Avg = 16.36) and moderate Expressiveness score (Avg = 14.18) from CSI. Designers not only leveraged DALLE-2 to explore but also experimented with how each of them would look on their target 3D object. This suggests that it is not only sufficient to just create texture maps, but it is also essential to preview how they will appear when applied to the target object when texturing 3D interior spaces. This would help designers better visualize when choosing the most suitable texture made by DALLE-2 and help them decide if other adjustments (e.g. scaling, setting roughness) are necessary.

The second approach suggests that designers use ChatGPT as an assistant in suggesting appropriate materials and color themes. This is also apparent in their scores in Results Worth Effort (Avg = 13.55, Median = 16), Enjoyment (Avg = 15.55), and Exploration (Avg = 16.36) in CSI, because these mean that the designers generally enjoyed using the system's generative AI tools and were able to explore different options, while being satisfied with their generated outputs to some extent. This is also supported by the students' low score in Mental Demand in task load, as it suggests that students (Avg = 34), who mostly fall in the second approach, did not feel mentally overwhelmed with the assistant. Having an AI assistant can lighten the burden of interior designers in choosing materials and colors, especially since designers face challenges such as hectic deadlines and idea exhaustion (Chu, 2003). By additionally fine-tuning them to reliable, project-specific, and organization-specific resources, LLMs can be useful tools to assist interior designers in material selection.

Moreover, we also found that designers gave importance to rendering the textures under lighting and adding color by inquiring from the Suggestion Chatbot. Lighting is important when texturing objects, as it affects materials' appearance (Salci, 2019; Waldram, 1954). Some designers had to frequently re-render the scene to visualize, which can be time-consuming. One way to address this is to also suggest suitable material settings when placing them under a certain lighting configuration or vice-versa. On the other hand, designers also queried the chatbot for colors to use. Similar to the second approach mentioned above, this can be helpful for them, especially when they are mentally overwhelmed with idea fatigue and deadlines; moreover, the chatbot can give more relevant colors through fine-tuning.

With DALLE-2, we found that the designers specified the following kinds of material prompts: generic materials, specific materials, finishes, and materials specific to interior design flooring. Based on this, apart from creating generic textures such as "wood" or "metal," we found that interior designers can use image generators for different purposes, whether it is creating a certain finish or creating a texture of a material that is local to a certain region. However, for both cases, this would require fine-tuning. When querying the Suggestion Chatbot, which mainly uses ChatGPT, we found that designers made various material queries based on a target object, design style, and attribute. Based on such queries, ChatGPT can be used by and benefit interior designers when brainstorming materials that adhere to certain design styles or desired interior space characteristics that are often mentioned in the design project specifications.

6.3 Comparing traditional and generative AI-based methods in texturing and material selection

We compare our proposed generative AI system that facilitates texture generation and material selection with their corresponding traditional methods in interior design. Using text-to-image generators and LLMs can offer several advantages over traditional methods, specifically in terms of workflow efficiency, exploring options, and contextual understanding.

First, text-to-image generators like DALLE-2 can make the texture selection workflow more efficient, saving time and labor. In texture selection, interior designers often obtain their textures from different websites, if they need to explore beyond their material libraries. This approach can be time-consuming and repetitive (Chen et al., 2024; Zhu et al., 2018). With text-to-image generators, designers can alternatively generate any arbitrary number of textures in a relatively short duration by simply prompting their desired material. This is evident in the participants' creativity support scores in enjoyment and expressiveness. Furthermore, the advantage of prompting is that designers can insert additional details into their target textures (e.g., colors, tints) by simply appending keywords into their prompts, allowing ease of tailored output textures. As mentioned in Section 6.1, the text-to-image generators can be further enhanced by fine-tuning them on paired text-texture image datasets to better match designer intent, and add more support for searching via reference texture input since designers are more visually oriented, as mentioned in the interviews.

Second, by using generative AI tools in their workflow, designers can better explore options for texture images and materials, which is clearly apparent in the participants' overall high Exploration score in creativity support. In texturing, as mentioned before, 3D interior design spaces need hundreds of textures (Chen et al., 2024), which can make exploring manually repetitive. Text-to-image generators can expedite this process, enabling users to create and explore endless options by prompting. Similar can be said for exploring different materials. In material selection, interior designers have thousands of available material options, each with their own advantages (Binggeli, 2008). Moreover, when dealing with clients, designers could also be tasked to collect materials and colors that align with the client's brand, even when the client does not have a clear identity yet (Brown and Farrelly, 2012). In these situations, interior designers can feel mentally overwhelmed. With LLMs, designers can ask them to brainstorm for material options, which is exhibited by P5, P8, and P9, who made frequent queries. By conversing with LLMs, designers can easily explore their options without feeling overwhelmed.

Third, in material selection, LLMs can be advantageous to use over traditional approaches when choosing contextually suitable materials. When choosing materials for their project, interior designers refer to a brief set by the client that includes their needs (Brown and Farrelly, 2012; Binggeli, 2008). Moreover, interior designers must also assess several aspects when selecting materials (Binggeli, 2008). For example, they have to check how durable or water-resistant the materials would be under the conditions of the project. Furthermore, they may also need to refer to codes and regulations, such as fire safety and sustainability codes, to check if the materials comply. As a result, considering many criteria is what makes material selection challenging (Bettaieb et al., 2019). LLMs can assist designers by suggesting materials in context to project specifications and safety requirements, which is done by adding them to their large context windows. Our prototype demonstrates a simplified version of this, in which participants appreciated based on their qualitative feedback, and is evident in their results worth effort score and effort score from CSI and NASA-TLX. Alternatively, methods like retrieval augmented generation (Lewis et al., 2020) can be done to refer to multiple documents that exceed the LLMs' context size.

6.4 Limitations

First, we performed convenient sampling to recruit a small sample size of 11 designers from the Philippines. Consequently, this may limit the generalizability of our findings to the broader interior design community. Second, most user study sessions (9/11) were conducted online through video conferencing, where we controlled the prototype while the participants gave instructions. As a result, this may impact the task load on the participants, creativity support, and overall user experience in using the prototype and the generative AI tools. Third, some participants experienced technical issues like system crashes, which impacted their user experience. Fourth, participants were only given 30 minutes for their task in the user study. We found that this amount of time was not enough, and some participants were not able to finish, mostly due to the system's slowness. Thus, more time should be allocated, or the system should be optimized to obtain a better assessment of the extent to which the system's generative AI tools can help interior designers. Fifth, participants were tasked with assigning materials to an outdoor patio, which may limit the study's findings only to these kinds of scenes and may not fully reflect on a wider range of other interior designs. Lastly, since the focus was on materials and textures, the system was implemented as a web application and lacked other needed 3D modeling functions, which participants sought.

7 Conclusion

Through a prototype, we explored using generative AI tools, DALLE-2 and ChatGPT, in assisting designers in material selection and texturing their 3D interior spaces based on a design brief as context. We investigated how generative AI tools can benefit interior designers in these tasks together in tandem and how they interact with such tools by having professionals and students texture a 3D patio scene with the prototype.

We found that participants generally perceived only moderate task load levels and moderately high creativity support from the system based on their confidence intervals. Specifically, in terms of task load, they only needed to exert moderate effort and were somewhat satisfied with their work. The system overall gave participants an enjoyable experience while supporting exploring materials and textures. These results also align with the participant's feedback on its benefits, where they appreciated being able to search and explore various options, as well as receive informative suggestions that are contextual to a general extent. On the other hand, results and confidence intervals from other dimensions of NASA-TLX and CSI show that participants have mixed experiences with the prototype's usability, including their immersive-ness, response time, and required cognitive effort. These also align with participant feedback, where they expressed concern with the prototype's slowness, credibility, and lack of multi-modal input. Thus we suggest design improvements such as fine-tuning with domain-specific datasets and text-to-image datasets and exploring reference texture image input.

When interacting with the generative AI tools, we found that designers use them in mainly two ways. The first is as a texture explorer, where designers refine their desired material by adding keywords, visualizing them on their target objects, and re-rendering the scene under photorealistic lighting. The second is as an assistant to guide them in texturing their interior spaces. With DALLE-2 in particular, we found that they made various text-to-texture prompts, intending to generate specific material textures and finishings. With ChatGPT, on the other hand, we found that they made queries specific to objects, design styles, and characteristics.

For future work, apart from fine-tuning the generative AI tools and improving their usability, we plan to explore how they can help in not only suggesting materials and textures but also in other aspects like furnishings, lighting setups, and accessories.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Ethics statement

Ethical approval was not required for the study involving humans in accordance with the local legislation and institutional requirements. The participants provided their written informed consent to participate in this study.

Author contributions

RG: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Visualization, Writing – original draft, Writing – review & editing. YS: Conceptualization, Funding acquisition, Resources, Supervision, Writing – review & editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's note

Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fcomp.2024.1493937/full#supplementary-material

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