Towards a Co-creative System for Creating, Suggesting, and Assessing Material Textures for 3D Renderings During Design Reviews in Industrial Design

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ABSTRACT

Material selection is an important task in industrial design as they affect several aspects of a product including its sensory characteristics and feasibility. This paper presents an early iteration of a co-creative system that uses generative AI to change, suggest, and provide feedback on a 3D rendering's materials. The system is aimed to be used during design review sessions to assist designers in quickly exploring alternatives, and converging on suitable materials before construction. We first interviewed industrial designers on how they assess materials in various deliverables (e.g., sketches, and 3D renderings) during design review sessions. Based on our findings, we then develop a prototype of the co-creative system for generating, suggesting, and providing feedback on a 3D rendering's material textures. We believe that using this system can assist designers in not only creating textures for their 3D renderings but also in providing material-aware feedback to create the product feasibly.

CCS CONCEPTS

• **Human-centered computing** → **Interactive systems and tools**; **User studies**; • **Computing methodologies** → **Texturing**.

KEYWORDS

generative AI, texture transfer, industrial design

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1 INTRODUCTION

In the early stages of the industrial design life-cycle, 3D renderings are one of the tools commonly used by industrial designers to quickly show a product's visual representation to other stakeholders such as clients, engineers, and manufacturers. When assessing 3D renderings during design review sessions, the product's choice of material is a critical aspect evaluated by other stakeholders, and changing the material can be done based on reasons such as the product's aesthetic, manufacturability, and material availability [1, 11, 13]. Depending on the reason for changing the material, design review sessions may repeat for several days or weeks, which contributes to the industrial design life-cycle being a complex and iterative process.

Advancements in generative AI [4, 8, 23] have significantly progressed over the past several years, especially in the task of texture transfer, where previous work enables semantic material texturing of 3D models [10, 28] and interior scenes [20, 30] using inputs such as images and text [5, 7, 19]. In industrial design, however, designers have to ensure that the product can be feasible to construct based on material textures applied to the 3D model. Commercial and academic works on industrial design support tools assist designers in creating aesthetic and feasible designs [6, 14, 17, 18, 25]; however, most of these tools are used in their workflows and not during design review sessions with other stakeholders.

In this paper, we propose a co-creative system that leverages generative AI to assist industrial designers in changing and suggesting materials for 3D renderings of a product, while also providing feedback on its feasibility based on the materials applied. We first conduct a formative interview study with industrial designers to know the aspects they and other stakeholders assess the materials used in a product's design deliverables during design review sessions, and the challenges when assessing materials. Next, we design and develop an initial prototype of the co-creative system for transferring images of material textures to a product's 3D rendering, suggesting materials, and providing feedback on assembling the product based on the materials currently applied. We envision that using this system can help industrial designers and stakeholders quickly change material textures in 3D product renderings, while also considering the product's feasibility during the early stages of the industrial design life-cycle in order to minimize product flaws.

Overall, we make the following contributions:

- We present preliminary results from a formative interview study with industrial designers on the rationales behind reviewing the materials used in design deliverables.
- We present an early design and implementation of a generative AI system that enables designers to quickly explore alternative materials in 3D renderings by generating, suggesting, and giving feedback on materials.

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2 RELATED WORK

2.1 Material Selection in Industrial Design

Choosing materials for a product is a challenging yet important task. This is because industrial designers and engineers choose materials based on a wide range of aspects including mechanical properties, material cost and availability, and sensory characteristics such as visual aesthetic and tactile feel [1, 11, 13]. With many factors to consider, previous research has devised methods for selecting materials. Inspired by the Double Diamond process [9], Van Bezooyen et al. [26] propose that designers first explore materials that satisfy marketing needs such as, and then converge on materials based on costs and manufacturing processes available. With a focus on sensory properties, Van Kesteren et al. [27] introduced a set of tools that help designers involve users in selecting materials. This includes a picture tool for designers to choose materials based on the look and personality of product examples selected by users and a material sample tool for users to choose materials based on their tactile properties. Relatedly, Ashby and Johnson [2] emphasize that the material's texture and color impact the product's personality which includes its aesthetic and perceptions evoked by the customer when viewing the product.

2.2 Industrial Design Support Tools

Research on support tools has also progressed with the goal of assisting designers in creating aesthetic and functional designs. In the industry, CAD software like Google Sketchup, Rhino, and Keyshot assist designers in 3D modeling and rendering; others like Autodesk Fusion360 and SolidWorks enable designers to simulate the model in withstanding mechanical forces and optimize their topology to satisfy manufacturing constraints. In academic research, sketch-based tools [6, 14, 24] and CAD-based tools [15, 18, 25] have been developed to improve the workflow of designers by also evaluating feasibility, ergonomic requirements, and manufacturing constraints. Forte [6] supports sketching while also optimizing them to handle specified mechanical load conditions. SketchChair [24] is another sketch-based tool for fabricating chairs that can also check ergonomics by simulating human figures sitting on it. Similarly, DreamSketch [14] is a sketching interface in 3D space that assists designers in assessing both ergonomics and mechanical durability. In CAD, Li et al. [15] and Schulz et al. [25] proposed systems that allow designers to explore 3D model options that meet specified mechanical and manufacturing requirements. Using generative AI, Liu et al. [17] propose 3DALL-E, a plugin for Fusion360 that uses GPT-3 [4] and DALL-E [22] to create image references that can be modeled on top of by designers. While most of these tools support industrial designers in their workflow in creating 3D models, our proposed system is intended to be used during design review sessions on 3D renderings, where designers and clients can quickly explore alternative material textures for their products.

2.3 Texture Transfer

Texture transfer has been a longstanding task in generating and transferring image textures between different types of data such as images and 3D models. Early works transfer textures from object images onto 3D models by extracting image texture patches [3, 28]. Yang et al. [29] propose a method that considers the properties of the material when fabricating the 3D model. Specifically, it reshapes the 3D model's geometry based on the material being applied. With the advent of deep learning, most previous work has also utilized neural networks in semantically transferring textures from images onto 3D models. For instance, given an input image of an object and a segmented 3D model of differing structures, Hu et al. [10] use an image translation network to extract colors and textures from the image, establish a part-to-part correspondence, and then use a material assignment network to semantically apply visually similar materials onto the 3D model. With a focus on interior scenes, PhotoScene [30] semantically transfers materials and scene lighting from images of interior rooms to 3D rooms while the work of Perroni-Scharf et al. [20] creates variants of an input 3D interior scene by changing its materials with perceptually similar ones. Lin et al. [16] train a convolutional neural network (CNN) to predict the type of material applied to parts of furniture models. They demonstrate applying this CNN in not only semantic texturing but also in the material-aware physical simulation of furniture and furniture part retrieval, tasks that can assess the mechanical durability and manufacturing, respectively, based on material properties. By taking advantage of CLIP [21], many studies have also devised methods for texturing 3D objects using text as input. For example, Text2Mesh [19] and TANGO [7] optimize the colors and topology of an input 3D model to match the verbal description of the texture. Similarly, Jin et al. [12] uses text input to semantically texture 3D interior scenes. With text-to-image models like StableDiffusion [23] being accessible, several tools like DreamTextures [5] have been incorporated into 3D modeling software to quickly generate texture maps and apply them to 3D models. Similarly, our proposed system uses StableDiffusion to generate and transfer textures; differently, by using GPT-3, our system also provides suggestions and feedback on the materials used in the 3D model in order to ensure that the product is feasible to make.

3 FORMATIVE STUDY

We recruited industrial designers online using email and social networking sites such as Facebook and LinkedIn. Interested participants were first required to answer a pre-interview questionnaire requesting their demographic details, and read and accept an informed consent form that explains the purpose of the interview study. Ten participants (5 males, and 5 females) were recruited. Eight of the participants shared their experiences as professionals, and one participant shared his experience as a university student. One participant (P4) shared her experience as both. All participants have worked on various products such as furniture, electronics, and appliances. The complete details of the participants are shown in Table 1.

All interviews were conducted individually and online using Zoom, where each interview lasted between 1 to 2 hours. At the start of the interview, we asked the participants for their details about their work or university course including job position, number of years of work experience, and projects previously worked on. Next, we asked them about the stages they undergo in the design process when creating a product, and the design deliverables that

Table 1: Details of the participants

Participant	Sex	Role	Work Exp. / Course Dur.	Projects
P1	M	Industrial Designer	1 year	Apparel, furniture, exhibits
P2	M	Industrial Designer	29 years	Mobile devices
P3	M	Industrial Designer	22 years	Furniture, Household appliances
P4	F	Graduate, Draftsman	4-year course, 2 years work exp.	Phone amplifier
P5	M	Industrial Designer	24 years	Household appliances
P6	M	Graduate	4-year course	Barstool, goggles
P7	F	Industrial Designer	2 years	Vending machine, bike tracker, mouse
P8	F	Industrial Designer	31 years	Furniture
P9	F	Industrial Designer	8 years	Interior rooms, exhibits
P10	F	Industrial Designer	2 years	Furniture, home decoration

are reviewed in each stage. Then, for each design deliverable, we ask them the following questions:

- Who are the stakeholders involved in reviewing the deliverable?
- In what aspects is the design being reviewed?
- What are the rationales behind reviewing the material of the deliverable?

The online interviews were then recorded and transcribed. In order to know the rationales behind assessing materials during review sessions, we conducted a thematic analysis with prior knowledge from the literature on the factors designers consider when selecting materials, which served as a framework for analyzing the transcripts.

3.1 Rationales in reviewing material choice

3.1.1 Product Aesthetics. A common rationale in reviewing the material and color of the product was its aesthetics, which was driven by factors such as market trends and user preference. For instance, when conducting a user study on choosing refrigerators of differing materials, P5 mentioned, "*Chrome is very popular. It gives a more durable and elegant impression of the product. For the high-end market, that's okay.*". When assessing the colors of a 3D model of a baby stroller, P7 shared that their client thought that "*the people who would be using the stroller would be the mothers. But then after the survey, the stroller could also be used for people who are into adventure. So there's a need to change color to more earth tones.*"

3.1.2 Material Durability. The material was also reviewed based on its durability which takes into account external factors such as environmental conditions. For example, P6 shared an anecdote about his professor critiquing the 3D rendering of another student because "*the wood that they tried to pitch on wasn't optimal for an outdoor setting*". On the other hand, when choosing an indoor flooring material for a store, P9 says that she avoids using carpet since "*it is hard to maintain in the long run*" and "*most stores accommodate a lot of customers*".

3.1.3 Availability and Manufacturing. Lastly, the material of the product is also critiqued based on its availability, and also the product's manufacturing. For example, P6 mentioned, "*My classmate tried to merge two different types of wood... but the critique of the professor is that the particular wood type is very difficult to merge together through means of maybe a dowel, or other connecting joints.*" Similarly, P4 overlooked assembling the speaker and stand components together [1], and struggled with connecting them due to their material properties (i.e., the speaker component is made up of coconut shells, and the stand component is made of metal).

> "The metal stand does not have a porous surface, nor does the coconut shell since it was sanded. So, my professor asked, "How would you glue it together? What adhesive will you use?" Because it is hard for the glue to stick to a non-porous surface. That's why here, [with the final prototype], the components are just taped together." (P4, student graduate)

With regard to availability, P10 shared that their client wanted to change the material for reasons like "*...[it] is no longer available. We want to get this material instead because it's wet or they can't source it in the area anymore.*"

4 SYSTEM OVERVIEW

Based on the aspects feedback is given to the material choice of products during design review sessions, we next develop an intelligent system that incorporates generative AI in generating, suggesting, and providing feedback on material textures in 3D renderings. In particular, it uses StableDiffusion [23] to generate material image textures and GPT-3 [4] in suggesting and providing feedback on materials. The system is comprised of three main modules for interaction: the generation module, the suggestion module, and the assembly feedback module. The system also tracks the displayed rendering's material information which comprises the names of the materials applied to each part of the product and also saves renderings. The user interface is shown in Figure 1, which shows a 3D rendering of a bedroom nightstand. The targeted products of this system are furniture and interior scenes, which are products that can have a wide variety of material choices.

4.1 Generation Module

The generation module facilitates creating material texture maps, and semantically applying them to the product's 3D rendering in order to quickly change the material of a product. In creating the

[1] To give more context, her project was to design a phone amplifier using coconut shells, where her planned manufacturers are coconut farmers in order to provide another opportunity for them to sell their harvest.

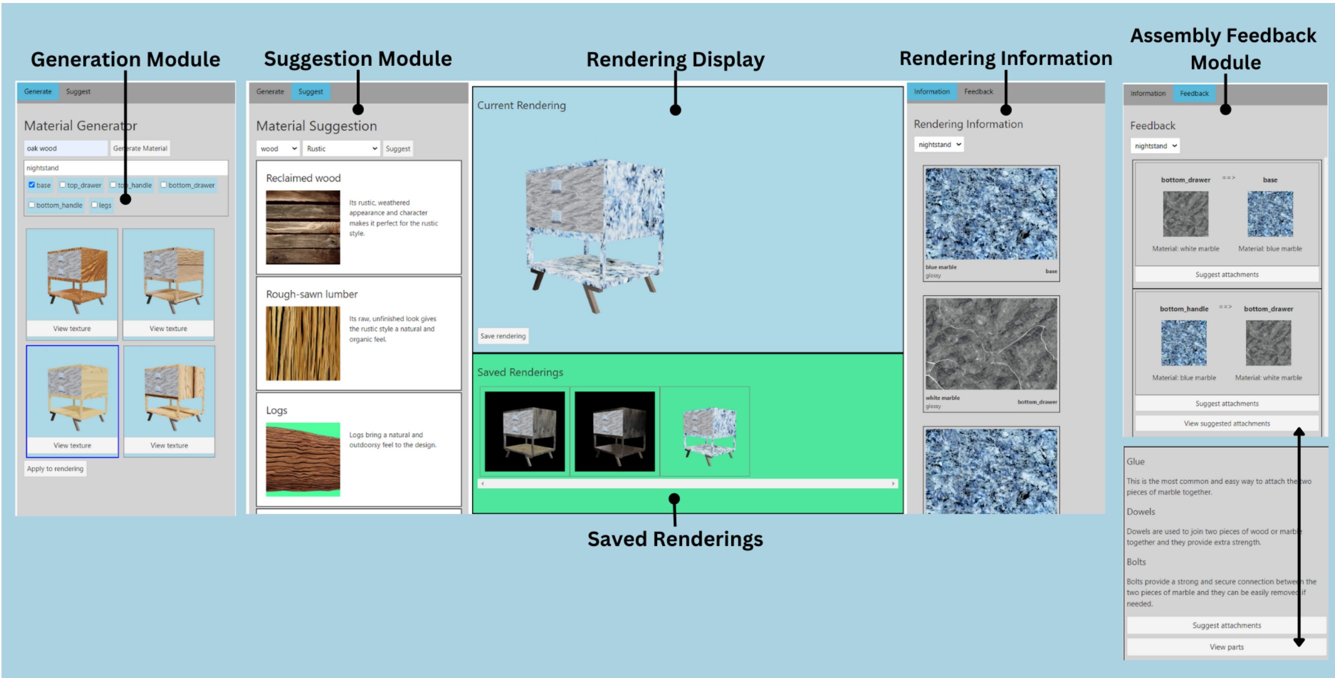

Figure 1: A screenshot of the user interface of the proposed system, which shows the generation of materials for a nightstand. Note that the modules and rendering information components are tabbed, so all of them are displayed in the figure.

texture maps, it uses StableDiffusion, a text-to-image generative model trained on billions of paired images and captions that allows users to arbitrarily create images by inputting textual prompts. In order to use the generation module, the user first types in the material they want to generate, and selects the parts of the product they want to apply the material onto. Next, the inputted material is appended to the following textual prompt, "*<MATERIAL NAME> texture map, 4k*" and fed into StableDiffusion to generate up to four image textures. Each generated texture is then mapped onto the selected parts, after which, candidate renderings with the material applied are shown to the user. The user can choose to select a candidate and update the current rendering accordingly or regenerate material textures.

4.2 Suggestion Module

The suggestion module facilitates recommending materials to the user by leveraging GPT-3. The current implementation suggests materials based on interior design styles such as the Scandinavian and Transitional interior design styles. The user must first specify in the drop-down the type of material they would like the module to suggest, and also the interior design style. Using the inputs, we retrieve suggestions from GPT-3 by using the following text prompt: "*"What examples of <MATERIAL TYPE> materials are of <STYLE> interior design style? For each example, give your reason. Separate the example and reason by a | . Return in bullet points."*" The last sentence in the prompt is added in order for the system to properly parse the text returned by the user when displaying the suggestions. The module then returns a list of suggested materials that are of the selected interior design style, where each material is accompanied by a reason that is also generated by GPT-3 and an image texture generated by StableDiffusion. The user can then use these suggestions when generating materials for the 3D rendering if they have a particular interior design style in mind.

4.3 Assembly Feedback Module

The goal of the co-creative system is not only to facilitate creating and suggesting materials but also to provide feedback on the 3D rendering based on the materials used. Currently, the module provides feedback on how the parts of the product can be assembled together, considering the materials applied to each part. For each pair of parts that are connected together, the following prompt is sent to GPT-3: " *"What can be used to attach a <PRODUCT NAME> <PART 1> made of <MATERIAL 1> to a <PRODUCT NAME> <PART 2> made of <MATERIAL 2>? Give <N> recommendations. For each recommendation, give your reason. Separate the recommendation and reason by a | . Return in bullet points."*" GPT-3 then returns a list of suggested attachments that can be used to attach the two parts together which are displayed to the user. As the designer generates and applies material textures to the rendering, this module aims to provide material-aware feedback on the attachments that can be used when assembling the product prototype or final product in the later stages of the design life cycle.

5 CONCLUSION AND FUTURE WORK

In this paper, we investigated incorporating generative AI methods [4, 23] into a co-creative system that facilitates material selection, a task in industrial design that is essential yet complex as it affects product aspects such as aesthetics and manufacturability [1, 11, 13]. We first conducted a formative interview study with industrial designers to gain practical knowledge on how feedback on the material is given during design review sessions. We then developed an early prototype of a generative AI co-creative system for exploring, suggesting, and giving feedback on the materials used in a product's 3D rendering that is aimed to be used during design review sessions.

The system is still a work in progress, and we are consulting with industrial designers for feedback on the system's functionality. In the future, we intend to incorporate their feedback to improve the system further iteratively. For instance, we plan to implement functions such as adding a color finish to the materials, a desired functionality mentioned by one of the experts we consulted. We will also conduct a user study to evaluate the system by having users change materials for 3D renderings of various products.

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