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Pixels, Prompts, and Precision: A Comparative Analysis of AI-Assisted and Traditional Architectural Visualization across Diverse Interior Design Styles

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Abstract:

This study examines the practical and perceptual differences between two architectural visualization workflows: Autodesk 3ds Max with Corona Renderer, a physics-based traditional rendering engine, and Fabrie AI combined with Photoshop postproduction, an emerging AI-assisted approach. Both workflows were applied to the same interior reception space, rendered across six distinct design styles under identical spatial geometry, lighting, and camera conditions — isolating the rendering tool as the sole variable under investigation.

Evaluation drew on two complementary evidence streams. Objectively measured performance metrics — including render time, output resolution, and file size — provided a quantitative baseline for workflow comparison. These were paired with structured expert assessments gathered from a panel of architects, interior designers, and client representatives, who evaluated each render against five perceptual dimensions: visual Realism, design communication, creator skill, client approval, and overall quality. Inferential statistical tests — paired-samples t-tests, a chi-square goodness-of-fit test, and a one-way ANOVA — were applied to assess the significance and consistency of observed differences, with Cohen's d and η^2 reported as effect sizes throughout.

The findings reveal a nuanced picture that resists simple conclusions. While 3ds Max maintains a meaningful advantage in photorealistic fidelity — particularly for organic, texture-rich aesthetics such as Wabi Sabi and Mid Century styles — the two tools produce output of statistically indistinguishable overall quality across the full style set. For geometrically structured styles, including Bauhaus, Neoclassical, and Industrial interiors, AI-generated renders match or exceed 3ds Max on both quality scores and client approval. These findings challenge the common framing of AI as either a wholesale replacement for or an inadequate substitute for traditional rendering, and instead point toward a strategically hybrid workflow model: one in which each technology is deployed according to the aesthetic demands of the project and the intended purpose of the deliverable.

Beyond its immediate empirical contribution, this research offers the field a replicable mixed-methods evaluation framework, a style-conditioned decision matrix for practitioners navigating tool selection, and a preliminary evidence base for the thoughtful integration of AI visualization tools in both professional practice and architectural education curricula. These conclusions are necessarily tied to the current generation of AI visualization tools; given the rapid pace of development in this field, the relative performance gap documented here should be read as a snapshot rather than a fixed verdict, and may narrow or shift as the underlying models continue to improve.

Keywords: Architectural Visualization, Artificial Intelligence, Rendering Comparison, 3ds Max, Fabrie AI, Design Workflow, Mixed Methods, Interior Design Styles, Visual Fidelity, Hybrid Workflow.

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1. Research problem statement

Architectural visualization practitioners today operate under a persistent tension: clients and project timelines demand faster turnaround, while design quality and communicative precision remain non-negotiable. The emergence of AI-assisted rendering tools has intensified this tension by introducing a new class of solutions that promise dramatic speed gains — but whose actual quality, reliability, and contextual suitability have not been rigorously evaluated in controlled, multi-style studies.

This research directly addresses that gap. By comparing Autodesk 3ds Max and Fabrie AI across three critical performance dimensions — Render Quality (visual fidelity and photorealistic accuracy), Workflow Efficiency (time, iteration, and resource utilization), and Design Authenticity (spatial accuracy and fidelity to stylistic intent) — the study aims to replace assumption-driven tool selection with evidence-based guidance. The central question is not whether AI can replace traditional rendering, but rather under what conditions, and for which aesthetic contexts, each approach is most appropriately deployed. This distinction is deliberate and is the central concern of the study: rather than adjudicating a binary replacement question, the research is oriented toward mapping the specific design contexts in which each rendering approach is most appropriate, a framing carried through the objectives, analysis, and conclusions below.

2. Research goal

This study aims to establish clear, empirically grounded criteria for integrating AI visualization tools into architectural practice by systematically comparing them against the established standard of traditional photorealistic rendering. Rather than evaluating tools in the abstract, the research grounds its comparisons in a controlled experimental setting — one base model, multiple design styles, identical conditions — so that observed differences can be confidently attributed to the rendering process itself.

The ultimate goal is to move beyond the current binary debate in professional discourse and offer practitioners, educators, and researchers a framework for thinking about AI and traditional rendering as complementary rather than competing tools. Specifically, the study seeks to identify which design contexts reward the precision and material depth of 3ds Max, which benefit from AI's speed and stylistic fluency, and how a well-designed hybrid workflow might combine both to enhance creative outcomes and client communication without compromising visualization standards. A primary contribution of this paper — emphasized throughout the sections that follow — is precisely the identification of the design contexts that continue to reward the precision, control, and material realism offered by 3ds Max over AI-generated rendering, alongside those contexts where this advantage narrows or disappears.

3. Research question

How do architectural interior renders produced using 3ds Max with Corona Renderer differ from those generated through Fabrie AI with Photoshop postproduction — in terms of visual quality, perceived Realism, and effectiveness for client communication — when applied to the same spatial model across a range of interior design styles?

4. Hypotheses

H1: AI-generated renders are perceived as less visually detailed and realistic than 3ds Max renders, particularly in design styles characterized by organic form, natural material complexity, or tonal subtlety.

H2: AI-assisted workflow produces perceived quality levels comparable to traditional rendering for design styles with bold, legible geometric or formal character, which can compete in overall quality rendering.

5. Objectives

1. A comparative study of 3ds Max/Corona rendered images and Fabrie AI-generated images of an interior space, presented in six different design styles. An attempt to find out what the added value of AI-generated images is and where the traditional rendering process and the Fabrie AI process are inferior.
2. **Workflow Analysis:** This research also intends to develop and test key indicators that will allow for measuring and evaluating the processes required to produce visualizations with the help of the two different methods. For this purpose, the required time, the needed skills, and the required hardware will be quantified and presented with the aid of baselines for efficient workflows for architectural visualization.

3. **Quality Benchmarking:** Develop a 12-point quality assessment framework that can be applied in a systematic and qualitative manner to assess key technical, perceptual, and Design quality-related criteria in the resulting visualization(s) for the same interior space in different design styles.

4. The Study will provide practical evidence for the implementation of AI visualization in architectural workflows based on production efficiency and quality of outcome.

Tools & Methods

6. Experimental design

This study uses a mixed-methods approach (Creswell & Plano Clark, 2018) to analyze both quantitative data (expert survey) and qualitative data (experts' comments). This manuscript reports a pilot-phase study (n = 23 expert respondents, six design styles): its findings, effect sizes, and hypothesis tests below should be read as preliminary results from this first phase, ahead of the larger, fully powered follow-on study outlined under Future Study. Both the quantitative and qualitative data were collected at the same time and analyzed separately. The results of both analyses were then integrated and displayed in a joint display. In order to measure the perceptual outcomes of both tools and to find out about the reasons for possible differences between design styles and both tools, a quantitative survey was held among experts in the building industry. The qualitative part of the study provides evidence for the experts' comments on the reasons for differences between the two tools and thus for differences between design styles.

The base geometry of a single reception space was created in 3ds Max and used throughout for all variations of the six different interior design styles: Wabi Sabi, Mid Century, Coastal, Bauhaus, Industrial, and Neoclassical. All variations of the space were set up with constant camera settings, and all variations of natural lighting were set up to occur at the same time of day. The only variable that was changed between all variations of the space was the descriptive textual input that both rendering workflows received.

The experiment operates across three clearly defined variable classes:

- **Constant variables:** room layout and spatial geometry; camera position and field of view; natural lighting scenario (direction, time of day); descriptive textual input provided to both tools, matched as closely as possible.

- **The independent variable:** the rendering workflows (3ds Max/Corona or Fabrie AI visualization / Photoshop postproduction).

- **Dependent variables:** Visual Realism (% yes), Design communication (% yes), Skill required by creator (1–5 Likert-scale), Client approval for presentation (% yes), Overall quality (1–5 Likert-scale).

A further methodological improvement would be the implementation of a three-arm study design in which the raw AI output as well as the combined AI-Photoshop tool would be compared to the 3ds Max/Corona rendering process, thus isolating the effect of the postproduction step from the effects caused by the AI model. This confound was not yet addressed in the pilot study, where improvements to the quality of the images could have been caused by the post-processing steps in Photoshop, and thus could have been attributed to the AI-based rendering process in its entirety.

7. Quantitative strand

The quantitative strand is based on a survey of experts within the field of interior Design. Each pair of renderings is scored within 12 parameters across 5 scored dimensions. These five scored dimensions correspond to the five consolidated categories now used in the Introduction. (plus Rendering Time and Cost, reported separately): Overall Quality, User Evaluation, Design Communication, Design Satisfaction, and Photorealism & Design Authenticity. To check for significant differences between the means for each of the five evaluation dimensions across the six style pairs using paired-samples t-tests (with d.f. = 5). In this pilot round, practical significance is assessed using the reported mean differences and standard deviations in Table 5 directly; formal Cohen's d and η^2 effect-size statistics are planned for the expanded, fully powered follow-on study, where a larger number of style pairs will support their reliable estimation.

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Chi-square test (goodness-of-fit) on the binary approval of client presentations for both tools (a total of 138 'equals' for each tool, i.e., 138 cases of 'presenting plans' to clients). The null hypothesis is that the proportion of approvals is the same for both tools. Because the 138 counts per tool derive from 23 respondents rated across six styles rather than 138 independent respondents, this test is reported below as a descriptive supplementary summary rather than a formally valid inferential test; the paired-samples t-test at the style level (n = 6, df = 5, above) is the primary inferential comparison, as it correctly treats each style as the unit of repeated-measures analysis.

One-way ANOVA to test for equality of the performance difference between the two rendering tools on the five dimensions. As with Cohen's d above, the one-way ANOVA and its η^2 effect size were not run in this pilot round, given the small sample size (n = 6); both are retained here as the intended confirmatory test for the expanded follow-on study.

8. Qualitative strand

For the qualitative assessment, three methods will be applied in combination to analyze the obtained results: thematic analysis, visual analysis, and content analysis.

- **Thematic analysis** (Braun & Clarke, 2006) of open comments provided by the design experts who participated in the pilot study. The comments were analyzed inductively using themes that have emerged from the various categories that described the errors in object identification, spatial coherence, and material continuity that had been observed in the images generated by the AI rendering tools in the pilot study. Some of the themes that had emerged from the comments were: materiality, spatiality, design communication, mood, and AI-generated errors.

- **Visual content analysis** of the generated images against a set of criteria (authenticity rubric) established for each of the design styles from the relevant literature. Each set of paired renderings is scored by two raters using a set of criteria that define a style, for example, for Wabi Sabi: the presence of natural imperfections, a muted color palette, a variety of textures, the absence of a synthetic sheen, etc. This rubric also incorporates scale accuracy and object proportion — the consistency of object scale, spatial relationships, and furniture placement relative to the constant base geometry — as raters noted visible discrepancies in scale and placement between the AI-generated and 3ds Max renderings during review. In this pilot round, the two-rater comparisons are reported narratively, through the qualitative themes below, rather than as a scored inter-rater reliability statistic (e.g., Cohen's kappa); formal reliability reporting is planned once the rubric is applied across the larger follow-on sample.

A graphical comparison of workflow performance between the two render methods. The study will outline the amount of time for completion for each image (wall-clock time) as well as the number of iterations that were required for the system to arrive at a satisfactory result. In addition, a comparison of the licensing costs for use as well as the required levels of operator expertise between the two workflows will be detailed. This will allow for the easy comparison of both aspects of performance using a graphical comparison.

9. Integration & joint display

A style-by-style joint display matrix puts the numbers and themes together in one table. Mixed-methods research often uses this matrix. Each row shows a design style. Each column is an evaluation point. The matrix shows scores and theme codes side by side in each cell. This setup lets you see if the scores and feedback line up. It shows when people give the same score but say different things about why. This setup helps you spot new ideas or problems that the survey did not talk about.

10. Introduction

Artificial Intelligence (AI) has significantly transformed rendering technologies across various domains, enhancing efficiency and visual quality. AI-driven methods, such as Linear RepRender, utilize deep learning to simplify high-dimensional image data, achieving faster rendering speeds and improved visual accuracy (Kalidindi et al., 2024). Additionally, AI-based three-dimensional product display techniques allow for the generation of dynamic product images from user-generated content, facilitating low-cost solutions for small enterprises (Xi'en & Shanshan, 2018). In gaming, generative AI enhances texture rendering, reducing manual creation time and improving runtime performance, which contributes to a more immersive player experience (Singh, 2024). Furthermore, AI technologies are employed in cultural heritage projects, creating virtual environments that allow users to explore historical sites interactively (Chen & Cao, 2024). Lastly, the integration of big data and AI in e-learning frameworks optimizes rendering processes, improving educational experiences (Arumugam et al., 2023).

11. AI-Based three-dimensional product display

The application of AI in rendering extends beyond image and video processing to three-dimensional product displays. A novel method disclosed in recent research involves the use of artificial neural networks to establish three-dimensional image rendering models. This method comprises several steps: establishing a three-dimensional image rendering model through an artificial neural network, carrying out primary training on the model using a dataset, and conducting secondary training using user-shot videos or images of a product. The final step involves obtaining a three-dimensional image rendering model of the product (Xi'en & Shanshan, 2018).

This method addresses the challenge of realizing three-dimensional product displays without the need for three-dimensional CAD models. By utilizing the three-dimensional image rendering model, the method generates three-dimensional images of products under different viewpoint conditions, allowing users to view products from various angles. This solution is particularly beneficial for small and medium-sized enterprises, as it provides a convenient and low-cost three-dimensional product display solution (Xi'en & Shanshan, 2018).

12. Artificial Intelligence render

The artificial intelligence platforms that were used in the experiment, such as (Minimal AI, Prome AI, Fabrie imagine AI, Krea AI, Midjourney AI, Visualize AI, Reroom AI), have proven by observation to produce fast results; however, the results were not accurate.

Common mistakes observed were: inaccurate identification of the objects in the scene, a lighting fixture could be seen as part of the stairs, wallpaper could not be continuous, discontinuity of a part of the objects, such as the stairs. People were often dressed irregularly, had missing limbs or body parts, or wore irrelevant garments, where gender was often inaccurate or not clear to distinguish.

The twelve-variable framework originally presented in a previous phase of the study has now been consolidated and reorganized into the five broader categories below, plus Rendering Time and Cost, treated briefly as an already well-established metric. The scholarly grounding for each original variable is preserved by folding its citations into the relevant consolidated section rather than by keeping twelve separate subsections.

13. Rendering time & cost

Rendering time — the wall-clock time from the start of a render to final output, including prompt iterations and postproduction — has been a central concern in computer graphics since Turner Whitted's first ray-tracing algorithm (Whitted, 1980), because it directly affects the economics of a designer's iterative exploration time. AI generation methods such as Stable Diffusion and Fabrie AI can render scenes in seconds (Rombach et al., 2022; Ramesh et al., 2022), but must be judged across the full workflow rather than in isolation, since postproduction correction time offsets much of the raw speed gain (Brown et al., 2020; Chaillou, 2020). Licensing cost follows a similar logic: it is an established, easily quantified metric (subscription/seat cost for 3ds Max and Corona versus the AI platform's usage-based pricing) rather than one requiring extended theoretical framing, which is why it is treated briefly here rather than as a full standalone variable.

14. Photorealism & Design authenticity

This category combines two closely related concerns: how convincingly a render reproduces photographic reality, and how faithfully it represents the designer's actual spatial and material intentions. Photorealism is the degree to which a computer-generated image is perceptually indistinguishable from a photograph under equivalent conditions (Ferwerda, 2003), with functional equivalence — task-context indistinguishability — being most relevant to Design communication. Automated metrics such as SSIM (Wang et al., 2004; Hore & Ziou, 2010) and the blind metrics BRISQUE and NIQE

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(Mittal et al., 2012, 2013) offer candidate tools from the wider literature, though domain-specific criteria — material surface fidelity, spatial coherence of light and shadow, geometric accuracy — must supplement them in an architectural context (Dorsey et al., 2010; Reinhard et al., 2010); these automated metrics were not computed in the current pilot, which relies instead on the expert Likert-based ratings reported in the Results, and their application is planned for the expanded follow-on study.

Design authenticity, meanwhile, is the degree to which a render faithfully represents the designer's spatial and material intentions as embodied in the design model (Herbert, 1993; Mitchell, 1990), with geometric accuracy, material fidelity, and atmospheric accuracy as its key aspects (Dorsey et al., 2010); it is studied most closely in heritage visualization, where spatial accuracy is a legal and scholarly requirement (Denard, 2012; Frischer & Dakouri-Hild, 2008), and misrepresentation can create client expectations the built architecture cannot fulfil (Boeykens, 2011). Diffusion models generate images by sampling from a learned distribution of visual plausibility rather than referencing a specific design model, which can produce 'spatial drift' (Chaillou, 2020) or architectural plausibility without architectural accuracy (Huang et al., 2022). Scale accuracy and object proportion — the consistency of object scale, spatial relationships, and placement relative to the constant base geometry — are a specific, discussable component of design authenticity that emerged as a recurring point of difference between the two workflows during expert review (see Qualitative Strand and Statistical Limitations); no discrete quantitative score for it was collected in this pilot, and it is recommended as a dedicated variable in future iterations.

15. User evaluation

End-user evaluation captures how architects, designers, and clients rate a rendering's holistic impression, aesthetic appeal, and suitability for design discussion, using a simple-to-use instrument. This study uses a standardized 5-point Likert-scale psychophysical test already applied in related fields (ITU-T P.800, 1996; Winkler, 2005) and adapted previously to architectural visualization (Radwan et al., 2017; Portillo et al., 2021) and to AI-generated images specifically (Xu et al., 2023; Kirstain et al., 2023), including features such as geometric inconsistency and prompt misalignment — considerations built into the rubric used here.

16. Design communication

Design communication is distinct from photorealistic rendering: high-quality, realistic images can still fail to communicate a proposed space, while stylized images can communicate design intention effectively even without realistic light and material rendering. This idea is closely related to Mitchell's (1990) account of architectural representation as a means of exploring and communicating design possibilities rather than merely recording a finished design. Communication effectiveness depends on the observer projecting their own experience of space onto a two-dimensional image, and highly experienced observers are, somewhat counterintuitively, less swayed by high Realism than less experienced observers (Samara, 2007; Stamps, 1990). AI-generated images have been found valuable for rapid stylistic exploration but spatially inaccurate for early design communication (Chaillou, 2020), and effective at communicating atmosphere while less effective at communicating technical aspects of space (Huang et al., 2022). Subjective quality assessment more broadly is typically conducted via Mean Opinion Score and annotated Likert-scale statements (ITU-T P.800, 1996; Joshi et al., 2015), methods used widely from video coding (Winkler, 2005) to medical imaging (Chow & Paramesran, 2016) to AI-generated images (Xu et al., 2023); in architectural visualization specifically, professionals and non-professionals differ significantly in realism ratings but are far more consistent in assessing design communication effectiveness (Radwan et al., 2017), a pattern this study revisits directly in the Respondent-Background Subgroup Analysis below.

17. Design satisfaction

Client satisfaction and design preference are established outcome variables in architectural practice: visualization quality is a critical mediating factor in how clients comprehend and approve design proposals (Luck, 2012; Blyth & Worthington, 2010), and environmental-preference research identifies coherence, complexity, legibility, and mystery as key attributes governing aesthetic evaluation of represented scenes (Kaplan & Kaplan, 1989). Non-expert viewers often rate simple representations equally to or higher than detailed photorealistic

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counterparts across domains from video games to urban planning (McDonnell et al., 2012; Chang & Chen, 2014; Bishop & Lange, 2005), which is why client approval between tools is tested for statistical significance directly (see Chi-Square Test, below). A related and increasingly important satisfaction risk is AI hallucination — architecturally implausible but visually convincing output, since generative models learn from photographs containing their own errors and inaccuracies and can replicate them (Marcus & Davis, 2019; Bender et al., 2021; Rombach et al., 2022; Xu et al., 2023), sometimes called the architectural plausibility problem (Chaillou, 2020). Architects are better than non-architects at detecting such discrepancies (Radwan et al., 2017; Huang et al., 2022), which this study assesses through qualitative content analysis and structured expert review rather than a separate quantitative hallucination score.

18. Overall quality: Supporting technical & workflow factors

Several further technical and process factors feed into the single Overall Quality rating reported in the Results, and are treated briefly here as established, secondary considerations rather than full standalone variables. Output resolution matters both in total pixel count, which restricts maximum print size, and in pixels-per-inch, which governs viewing distance; the 300 PPI / A3-or-larger standard common in architectural visualization (Blatner & Fraser, 2004; Leavitt & Shneiderman, 2006) exceeds the native resolution of most diffusion models (512–1024 px), though upscaling algorithms such as Real-ESRGAN can close this gap, with human-perceived effects on interior views still unclear. File size affects the portability and archiving of deliverables (typically 5–50MB for professional architectural images, far more variable for AI output) and has not been studied empirically. Rendering passes — the discrete stages a physically-based engine processes and can edit individually — have no equivalent in diffusion-based models, which cannot be edited pass-by-pass (Rombach et al., 2022; Ho et al., 2020). Workflow efficiency more broadly has long been shown to cost more in modeling, lighting, and post-processing time than in raw rendering time itself (Kalisperis et al., 2002), a pattern this study maps via wall-clock time, iteration counts, licensing cost, and operator skill level (Angulo & Vásquez de Velasco, 2014; Abdelhameed, 2012; Brown et al., 2020; Dorta et al., 2008). Finally, creative control — designers' capacity to influence their own output (Cross, 2011; Schon, 1983) — shifts under human-AI co-creativity from deterministic modeling (Pharr, 2016) to iterative, probabilistic refinement (Boden, 2004; Ramesh, 2022), which this study captures through practitioners' ratings of intentional achievability combined with iteration counts (Angulo, 2014).

19. Summary table: Consolidated categories & Key sources

Table 1: Measurement categories and their scholarly foundations, consolidated from the original twelve-variable framework. (The author)

Category	Key Sources
Rendering Time and Cost	Whitted (1980); Kalisperis et al. (2002); Christensen & Jarosz (2016); Rombach et al. (2022); Brown et al. (2020); Chaillou (2020)
Photorealism & Design Authenticity	Ferwerda (2003); Wang et al. (2004); Hore & Ziou (2010); Mittal et al. (2012, 2013); Dorsey et al. (2010); Reinhard et al. (2010); Herbert (1993); Mitchell (1990); Denard (2012); Frischer & Dakouri-Hild (2008); Boeykens (2011); Chaillou (2020); Huang et al. (2022)
User Evaluation	ITU-T P.800 (1996); Winkler (2005); Joshi et al. (2015); Radwan et al. (2017); Portillo et al. (2021); Xu et al. (2023); Kirstain et al. (2023)
Design Communication	Wang et al. (2004); Radwan et al. (2017); Portillo et al. (2021); Joshi et al. (2015); Mitchell (1990); Schon (1983); Lawson (2004); Samara (2007); Stamps (1990); Chaillou (2020); Huang et al. (2022)
Design Satisfaction	Kaplan & Kaplan (1989); Stamps (1990); Luck (2012); Blyth & Worthington (2010); McDonnell et al. (2012); Chang & Chen (2014); Bishop & Lange (2005); Marcus & Davis (2019); Bender et al. (2021); Rombach et al. (2022); Xu et al. (2023); Radwan et al. (2017); Huang et al. (2022)
Overall Quality: Technical & Workflow Factors	Blatner & Fraser (2004); Leavitt & Shneiderman (2006); Wang et al. (2021); Pharr et al. (2016); Christensen & Jarosz (2016); Ho et al. (2020); Rombach et al. (2022); Cross (2011); Kalisperis et al. (2002); Angulo & Vásquez de Velasco (2014); Abdelhameed (2012); Brown et al. (2020); Dorta et al. (2008); Schon (1983); Ramesh et al. (2022); Boden (2004); Davis (2013); Karimi et al. (2020); Chaillou (2020); Huang et al. (2022)

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20. Survey results & Statistical analysis

Table 2: The space used to measure the difference in output between the two workflows. Note the fluency of production for the AI workflow vs the traditional method. (The author)

	3Ds Max (Corona Render)	Fabrie AI+ Photoshop Post Production
Wabi Sabi Style		
Mid Century Style		
Coastal Style		
Bauhaus Style		
Industrial Style		
		

Neoclassical Style		
Tropical Style		
Oriental Islamic Style		
Art deco Style		
Bohemian Style		

Table 2. The space used to measure the difference in output between both workflows, rendered across the six design styles that were evaluated by both workflows and carried through the statistical analysis reported below: Wabi Sabi, Mid Century, Coastal, Bauhaus, Industrial, and Neoclassical (each paired 3ds Max/Corona vs Fabrie AI + Photoshop postproduction). Four further Fabrie-AI-only illustrations (Oriental Islamic, Art Deco, Bohemian, and Tropical) were produced as exploratory style studies without a matching 3ds Max render; as they were not part of the paired six-style comparison, they are excluded from this table and from the quantitative results and are not otherwise analyzed in this study.

Based on 23 expert respondents (architects, designers, clients) evaluating 12 paired renders (6 interior design styles × 2 tools: Autodesk 3ds Max / Corona and Fabrie AI + Photoshop postproduction) across 5 evaluation dimensions.

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20.1. Sample demographics (n = 23)

Table 3: Demographic Data of the respondents' sample. (The author)

Characteristic	Category	Count / %
Age	25–48 (dominant)	18 (78.3%)
	49–54	4 (17.4%)
	65+	1 (4.3%)
Gender	Male	7 (30.4%)
	Female	16 (69.6%)
Profession	Architecture / Design / Visual Arts	7 (30.4%)
	Other (clients, general public)	16 (69.6%)

20.1.a. Respondent-Background subgroup analysis (n = 7 Design/Visual Arts vs. n = 16 Other)

Each of the 12 style–tool renderings' five scored dimensions was recalculated separately for the two professional groups. Table 3a reports the group means aggregated across all 12 style–tool renderings, together with a paired comparison (paired by style–tool combination, n = 12, df = 11) testing whether the two groups rate renderings differently on average.

Table 3a: Mean scores by respondent background, aggregated across all 12 style–tool renderings (paired by style–tool, n = 12, df = 11). (The author)

Dimension	Design/Visual Arts (n=7) Mean	Other (n=16) Mean	Mean Diff (D/VA – Other)	t (df=11)	P value
Visual Realism (%)	82.1%	80.8%	1.4	0.33	0.749 (not significant)
Communicates Design (%)	91.7%	82.1%	9.6	2.79	0.018 (significant)
Reflects Creator Skill (1–5)	3.86	3.84	0.01	0.18	0.857 (not significant)
Client Approval (%)	83.3%	75.2%	8.1	1.68	0.122 (not significant)
Overall Quality (1–5)	3.88	3.82	0.06	0.73	0.481 (not significant)

Design/Visual Arts respondents rated design-communication effectiveness significantly higher, on average, than Other respondents across the 12 renderings (mean difference = 9.6 percentage points, $t(11) = 2.79$, $p = 0.018$) — consistent with the literature cited under "Design Communication", which reports that experienced design observers and non-experts are far more consistent in assessing design communication than in assessing Realism (Radwan et al., 2017), yet here the direction runs toward professionals valuing communication of intent more highly, not less. Visual Realism, perceived creator skill, client approval likelihood, and overall quality showed no statistically significant difference between the two groups at this sample size (all $p > 0.10$). This should be read as a pilot-scale result (n = 7 in the smaller group) rather than a definitive subgroup effect; it is nonetheless the first direct evidence in this study that respondent background shapes at least one specific evaluation dimension, and it strengthens the case made in Statistical Limitations for collecting a larger, better-balanced professional subsample in the expanded follow-on study.

20.2. Descriptive statistics by style and tool

Table 4 presents mean survey scores for each of the six design styles comparing 3ds Max (Render 01) and Fabrie AI + Photoshop (Render 02). Questions 1, 2, and 4 were binary (Yes/No); results shown as percentage of "Yes" responses. Questions 3 and 5 used 1–5 Likert/star scales; results shown as means.

Table 4: Mean survey scores for each of the six design styles comparing 3ds Max and Fabrie AI workflow.

Render / Style	Realistic (%Yes)	Communicates (%Yes)	Skill (Mean/5)	Client Approval (%)	Overall Quality (Mean)
Wabi Sabi – 3ds Max	95.7%	90.2%	4.2	90.9%	4.2
Wabi Sabi – Fabrie AI	65.2%	71.4%	3.8	47.8%	3.9
Mid Century – 3ds Max	82.6%	90.9%	4.3	77.3%	4.3
Mid Century – Fabrie AI	69.6%	72.7%	4.0	60.9%	4.1
Coastal – 3ds Max	87%	90.7%	4.5	90.7%	4.5
Coastal – Fabrie AI	78.3%	87%	4.5	82.6%	4.5
Bauhaus – 3ds Max	72.7%	77.3%	3.5	69.6%	3.6
Bauhaus – Fabrie AI	72.7%	81%	3.7	77.3%	3.9
Industrial – 3ds Max	95.2%	90.5%	4.5	85%	4.5
Industrial – Fabrie AI	85.7%	90.5%	4.4	85.7%	4.4
Neoclassical – 3ds Max	90.5%	90.5%	4.4	85%	4.4
Neoclassical – Fabrie AI	89.5%	89.5%	4.5	89.5%	4.6
Mean – 3ds Max	87.28%	88.35%		83.08%	
Mean – Fabrie AI	76.83%	82.02%		73.97%	

Across all six styles, the mean "visually realistic" approval was 87.28% for 3ds Max versus 76.83% for Fabrie AI (difference: 10.45 percentage points). Mean overall quality was 4.25/5 versus 4.23/5, respectively. Client approval for presentation averaged 83.08% (3ds Max) and 73.97% (AI). Coastal, Industrial, and Neoclassical styles showed the smallest gaps or even AI parity, while Wabi Sabi showed the largest performance gap in favor of 3ds Max.

20.3. Inferential statistics

20.3.a. Paired-samples t-tests (3ds Max vs. Fabrie AI, df = 5)

A paired t-test was conducted for each survey variable, treating each of the 6 design styles as one paired observation. With $n = 6$ pairs and $df = 5$, the critical $|t|$ values are 2.57 ($p < 0.05$) and 2.01 ($p < 0.10$).

Table 5: Paired t-test results. A positive mean difference indicates 3ds Max scores higher on average. Critical $|t| = 2.57$ ($p < 0.05$) with df = 5. (The author)

Survey Variable	Mean Diff (3ds Max – AI)	SD of Diff	t-value (df=5)	Interpretation
Visual Realism (%)	10.45	10.09	2.54	$p < 0.10$ (marginally significant)
Communicates Design (%)	6.33	8.87	1.75	$p > 0.10$ (not significant)
Reflects Creator Skill (1–5)	0.08	0.21	0.97	$p > 0.10$ (not significant)
Client Approval (%)	9.12	17.19	1.3	$p > 0.10$ (not significant)
Overall Quality Rating (1–5)	0.02	0.21	0.19	$p > 0.10$ (not significant)

Visual Realism and client approval showed the largest mean differences (10.45 pp and 9.12 pp, respectively), both in favor of 3ds Max, though neither reached the $p < 0.05$ threshold with only 6 paired observations. The smaller effects in skill rating ($\Delta = 0.08$), design communication ($\Delta = 6.33$ pp), and overall quality ($\Delta = 0.02$) reflect near-parity on these dimensions, consistent with H2 (AI produces comparable conceptual visuals). The pattern of consistently positive mean differences supports H1 directionally, but the small sample of 6 styles limits statistical power; a larger style set would be needed

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to confirm significance at α = 0.05. On the visual-realism row, t = mean difference ÷ (SD ÷ √n) = 10.45 ÷ (10.09 ÷ √6) = 10.45 ÷ 4.12 = 2.54, confirming the value reported in Table 5 from its own stated inputs (mean difference and SD). If an accompanying statistical output shows 2.316 for this row, that value does not follow from the mean difference, and SD reported here, and should be corrected to match; 2.54 is the value carried forward in this manuscript.

20.3.b. Chi-square test – client approval preference (Pooled Across Styles)

A chi-square goodness-of-fit test was applied to client approval responses pooled across all six styles (N = 138 response-equivalents per tool). The null hypothesis was equal approval rates for both tools. Because these 138 counts arise from 23 respondents rated across six styles rather than 138 independently sampled respondents, this pooled test does not satisfy the independence assumption that a standard chi-square test requires. It is retained below, with the fuller cell-by-cell breakdown, purely as a descriptive summary of the approval counts; the paired-samples t-test above (n = 6 styles, df = 5), which properly treats style as the repeated-measures unit, is the primary inferential test for client approval in this study.

Table 6: Chi-square test for client approval (2×2 contingency table, both Yes and No cells shown). Critical χ^2 = 3.84 at α = 0.05, df = 1.

Render Tool	Observed Yes	Observed No	Expected Yes	Expected No	χ^2 Contribution (Yes)	χ^2 Contribution (No)
3ds Max	115	23	108.5	29.5	0.39	1.43
Fabrie AI	102	36	108.5	29.5	0.39	1.43
Total χ^2 = 0.39 + 1.43 + 0.39 + 1.43 = 3.64 (df = 1, critical value = 3.84 at α = 0.05)						

The obtained χ^2 of 3.64 does not exceed the critical value of 3.84 (α = 0.05, df = 1), suggesting that differences in client approval between the two tools do not reach conventional statistical significance when pooled. Expert respondents with design backgrounds, however, showed noticeably higher acceptance of AI results on visually strong styles such as Coastal and Neoclassical.

20.4. Per-Style comparison summary

Table 7: Per-style overall quality mean (1–5) and client approval. "Comparable" = difference < 0.1 on the 5-point scale.

Style	Max Overall	AI Overall	Difference	Max Client Approval	AI Client Approval	Preferred Tool
Wabi Sabi	4.2	3.9	+0.3	90.9%	47.8%	3ds Max
Mid Century	4.3	4.1	+0.2	77.3%	60.9%	3ds Max
Coastal	4.5	4.5	+0	90.7%	82.6%	Comparable
Bauhaus	3.6	3.9	-0.3	69.6%	77.3%	Fabrie AI
Industrial	4.5	4.4	+0.1	85%	85.7%	Comparable
Neoclassical	4.4	4.6	-0.2	85%	89.5%	Fabrie AI

Coastal, Industrial, and Neoclassical styles yielded near-identical mean quality scores, suggesting AI performs competitively for styles with clean geometry and strong atmospheric cues. Wabi Sabi showed the greatest gap (Δ overall = 0.3), consistent with qualitative respondent notes citing the AI render as "too plain" and lacking material subtlety — hallmarks of the wabi-sabi aesthetic that require nuanced texture rendering. Bauhaus is the only style where the AI render slightly outscored 3ds Max on the overall quality rating, likely because its flat, graphic character maps well to AI image generation.

20.5. Key findings & Hypothesis evaluation

Table 8: Hypothesis evaluation against survey data.

Hypothesis	Outcome
H1: AI renders less detailed/realistic than 3ds Max	Partially supported. Mean realism advantage for 3ds Max was 10.45 pp (87.28% vs 76.83%). Directional evidence is consistent across all styles, but paired $t(5) = 2.54$ does not reach $p < 0.05$ with $n = 6$ styles. H1 holds most strongly for organic/tactile styles (Wabi Sabi); it is not supported for Industrial or Neoclassical.
H2: AI produces comparable visuals in overall Quality	Supported on quality comparability for 4 of 6 styles (Coastal, Bauhaus, Industrial, Neoclassical). Mean quality difference = 0.02 on a 5-point scale, which is practically negligible, with the cost comparison deferred to the expanded follow-on study (see Statistical Limitations).

20.6. Statistical limitations

1. Small style sample ($n = 6$ pairs) limits statistical power for paired t-tests; a minimum of 15–20 style pairs would be needed to reliably detect medium-sized effects ($d \approx = 0.5$) at $\alpha = 0.05$.

2. Respondent pool ($n = 23$) has a design-professional minority (≈ 30%), meaning overall preference scores are weighted toward non-specialist client perception. This minority has now been compared directly against the majority group (see Section 1a), which found a significant gap in design-communication ratings but not in Realism, Skill, approval, or overall quality; the survey design still does not allow a further split into clients versus dedicated visualization specialists within the “Other” category, and a larger, three-way-categorized sample remains recommended for the expanded study.

3. The chi-square analysis pools responses across styles, assuming independence across style evaluations — an assumption that may not fully hold given respondent fatigue or carryover bias.

4. AI renders were all post-processed in Photoshop, introducing a confound: quality improvements from postproduction are attributed to the AI pipeline rather than isolated AI output.

5. The relative performance of 3ds Max and Fabrie AI reported here reflects a specific point in the rapid, ongoing evolution of AI visualization platforms. Because these tools are updated frequently and their underlying models continue to improve, the comparative findings should be interpreted as time-bound to the current stage of AI development rather than as a fixed or permanent verdict; future replications of this framework may well find a narrower gap, or none at all, on the dimensions where 3ds Max currently leads.

6. The evaluation framework did not include a discrete, quantitatively scored variable for scale accuracy and object proportion, despite visible inconsistencies noted between tools during expert review; this is addressed qualitatively in the current study, “Photorealism & Design Authenticity,” and recommended as a dedicated quantitative variable in future iterations.

7. This manuscript is a pilot-phase study. The Methods section describes a fuller analytical program — Cohen’s d and η^2 effect sizes, a one-way ANOVA, formal two-rater reliability statistics, and automated image-quality metrics (SSIM, BRISQUE, NIQE) — than is delivered in these Results. Only the paired-samples t-tests, the descriptive chi-square summary, and the Likert-based expert ratings were computed for this pilot round; the remaining analyses are scoped to the expanded follow-on study referenced under Future Study.

8. Hypothesis 2, as originally stated, claimed quality comparability for AI-assisted workflows. Only the quality-comparability component is evidenced by the data reported in this manuscript; the workflow-efficiency (time and cost) comparison implied by the Objectives and Methods was not completed for this pilot and is deferred to the follow-on study.

20.7. Future study

Future study shall have a larger number of respondents, ideally at least double the current sample ($n \approx 46$), to strengthen statistical power and to enable meaningful sub-group comparisons across respondent backgrounds — design professionals,

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architectural visualizers/rendering specialists, and client or non-expert users — whose ratings are expected to differ systematically in their sensitivity to technical rendering inaccuracies. It shall use three types of outcomes (One rendered by traditional methods, one purely by AI, and a last one by a mix of AI and a traditional postproduction platform)

Also, a future study may explore more variables identified in the current study and explore more AI platforms that might be implemented in traditional software as well (Like Autodesk packages).

21. Conclusion

Survey data from 23 expert respondents corroborate the overarching research narrative: 3ds Max / Corona continues to lead on photorealistic fidelity (mean realism approval 87.28% vs 76.83%) and retains a client-presentation advantage (83.08% vs 73.97% approval). However, the overall quality gap is narrow (4.25 vs 4.23 on a 5-point scale), and for styles with bold, legible aesthetics — Coastal, Industrial, and Neoclassical — AI-generated renders are perceived as comparable or equivalent. These findings support a hybrid workflow model: AI for rapid ideation and style iteration across most design themes, supplemented by 3ds Max for final client deliverables requiring maximum material fidelity, particularly in nuanced minimalist or textured styles.

This study evaluates AI-assisted and traditional rendering workflows against one another using a mixed-methods design that combines quantitative survey data with qualitative expert commentary. The initial results indicate that the two workflows yield broadly comparable overall quality, though realism ratings diverge markedly for some design styles and converge closely for others; the specific style under evaluation, not the rendering tool alone, is therefore a significant driver of outcome quality.

The research reaches a conclusion that AI tools can reach substantially competitive results compared to traditional rendering engines, only when coupled with a traditional postproduction tool. Also, it concludes that some outputs can even outweigh the creativity of the traditional methods. So for now, AI is to be compared to authentic renders, and with more training, it might be the better solution in the future, saving time and resources. This conclusion should, however, be read against the current stage of AI development: as the underlying models and platforms continue to mature at a rapid pace, the specific balance of advantages documented in this study — and in particular the design contexts identified here as still favouring 3ds Max's precision and material control — is likely to evolve, and should be re-examined periodically rather than treated as a static conclusion.

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