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Exploringthe Potential of Artificial Intelligence as a Tool for Architectural Design: A Perception Study Using Gaudí'sWorks

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Abstract: This study undertakes a comprehensive investigation into the comparison of designs between the acclaimed architect Antoni Gaudí and those produced by an artificial intelligence (AI) system. We evaluated the designs using five main metrics: Authenticity, Attractiveness, Creativity, Harmony, and overall Preference. The findings underline the superiority of Gaudí's designs in terms of Authenticity and Harmony, testifying to the unique aesthetic appeal of human-created designs. On the other hand, AI-generated designs demonstrate significant potential, exhibiting competitive results in the categories of Attractiveness and Creativity. In some cases, they even surpass Gaudí's designs in terms of overall Preference. However, it is clear that AI faces challenges in replicating the distinctive aspects of human design styles, pointing to the innate subjectivity inherent to design evaluations. These findings shed light on the role AI could play as a tool in architectural design, offering diverse design solutions and driving innovation. Despite this, the study also emphasizes the difficulties AI faces in capturing the unique facets of human design styles and the intrinsic subjectivity in design evaluations.

Keywords: AI-generated image; architectural design; Gaudí; stable diffusion; perception

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1. Introduction

The advent of artificial intelligence (AI) has triggered significant transformations across various disciplines, thanks to its computational capabilities that enhance traditional methodologies and foster innovative approaches. Architecture stands out as one of the fields where the transformative potential of AI is being leveraged, ranging from the conceptualization to the execution of designs [1]. The integration of advanced AI techniques such as Generative Adversarial Networks (GANs) [2], Latent Diffusion Models (LDMs) [3], and Segment Anything Models (SAMs) [4] into architectural software underscores the scope of AI's application in this domain. These techniques enable AI to generate a diverse array of design alternatives, optimize structural components, and even emulate the stylistic subtleties of esteemed architects [5].

In addition to its role in design generation, AI is progressively recognized as a transformative educational tool in architecture. Beyond traditional classroom methods, AI offers an enriched learning experience, with its capacity to visualize unbuilt designs and understand design principles [6,7].

The work of Antoni Gaudí, celebrated for his unique blend of originality, harmony, and creativity, provides an intriguing case for examining the potential of AI in architectural design and education [8–10]. This research aims to scrutinize the relationship between Gaudí's designs and those generated by AI, exploring not only AI's capacity to replicate Gaudí's style but also its potential as a creative design and educational tool.

In this study, we first explore the role of AI as an innovative design tool in generating alternative solutions in the field of architecture. We then discuss the potential of AI in architectural education. Following this, we delve into the assessment of the aesthetic value of AI-generated architectural design. After the literature review, we perform an empirical analysis using Gaudí's work as a reference to assess the potential of AI in replicating his style. In conclusion, we discuss the implications of integrating AI into architectural design and education, highlighting the aesthetic considerations. Our research aims to contribute to the discourse by providing a systematic exploration and evaluation of the role of AI in architecture.

2. Literature Review

2.1. AI as a Creative Design Tool for Generating Alternatives

Artificial intelligence (AI) has progressively become a fundamental part of architectural design, pushing the envelope of what is possible and transforming traditional design methodologies into innovative, future-facing ones [11]. As the computational power continues to advance, we are witnessing a paradigm shift where machine learning has become a pivotal tool in architecture [12,13]. Previously, the integration of machine learning into architectural design tools was limited due to the complex and creative nature of design tasks. However, with the rise and integration of more advanced machine learning models, such as transformer models, into design workflows, this barrier is gradually being overcome [14].

Artificial neural networks, drawing inspiration from biological neural networks [15,16], have been key players in transforming the design space. By training these networks on specific examples, known as the training set, in the form of input parameters and corresponding output values, they learn and iterate on design solutions [17]. Some cases, which employed neural networks to generate innovative design alternatives in architectural planning, demonstrate how AI can broaden the creative possibilities [18].

Moreover, the concept of swarm intelligence, as elucidated by Bonabeau, Dorigo, and Theraulaz [19], has seen a transition from being a phenomenon observed in natural systems to a technique applied in artificial systems, specifically architectural design. It emulates collective behaviors observed in nature, such as bird flocking or insect swarming, and has been harnessed to produce complex spatial forms [20,21]. Swarm intelligence can be leveraged to optimize energy usage in building design, offering an approach that harmonizes design aesthetics with sustainability.

In the more recent years, AI models such as Generative Adversarial Networks (GANs) and Latent Diffusion Models (LDMs) have further expanded the horizon of creative possibilities [22]. These generative AI models, which leverage vast databases for initial learning, have an inherent level of decoding uncertainty. This can lead to the generation of diverse (see Figure 1), unconventional patterns and solutions, pushing the boundaries of conventional design thinking.

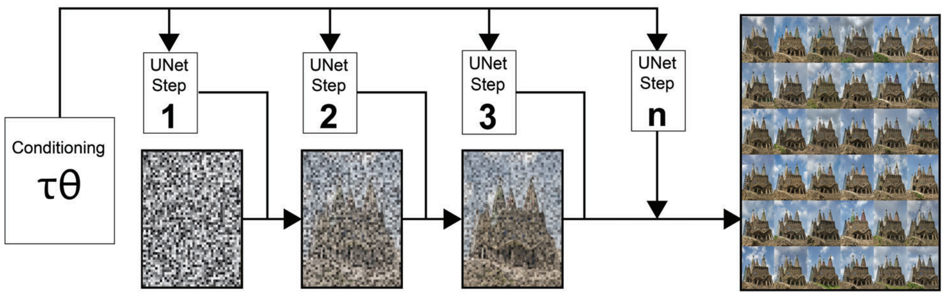

Figure 1. Due to the characteristics of Latent Diffusion Models, it is possible to generate diverse results.

The advent of AI has laid the groundwork for a revolution in architectural design by offering an entirely new realm of possibilities and paths for exploration. The integration of automated design systems not only streamlines the design process but also bolsters the role of conceptual thinking in crafting solutions [11]. Yet, the human element in the process—the role of the architect—remains indispensable. Architects bring a critical perspective in selecting the most suitable solution from a multitude of scenarios generated by AI, ensuring the blend of creativity and functionality in the final design [11].

2.2. Potential of AI in Architectural Education

The utilization of artificial intelligence (AI) in architectural design and education has made substantial progress, transitioning from rudimentary design tools to powerful instruments capable of generating innovative design solutions, optimizing existing designs, and playing a pivotal role in education [23,24]. These advancements have pervaded all facets of architectural education, including technical, theoretical, representation, and design studio modules.

Technically, the impact of AI is manifested in the use of building information modeling (BIM) and parametric design software, tools proficient in generating 3D spatial data to enhance the design and construction process [25]. Meanwhile, the application of machine learning (ML) requires customization for each project, with data collection, preprocessing, and computational power being crucial elements [23].

In theory-based courses, the employment of AI, particularly in collecting, storing, and analyzing massive amounts of textual data, significantly alleviates the students' workload [26]. This aligns with Negroponte's research suggesting that machines can learn architectural design via sampling and evaluation, bypassing the need for pre-encoding rules, offering unique opportunities for architectural education [27].

Moreover, deep learning (DL) models, with the support of big data, have demonstrated the capacity to tackle architectural design problems [28]. Remarkably, Generative Adversarial Networks (GANs) have been applied to create architectural layouts, generating an abundance of architectural floor plans even without a vast quantity of image data [18,29].

In representation modules, digital technologies such as Virtual Reality (VR), Augmented Reality (AR), and 3D printing have revolutionized spatial perception and design presentations [7]. AI, employed as a creative design tool, is starting to transform the communication process between architects and clients. For instance, AI image generation tools such as DALL-E can swiftly articulate architects' design intentions, reducing the architects' workload, and stimulating new creative thinking. In addition, novel AI technologies such as Generative Adversarial Networks (GANs), Latent Diffusion Models (LDMs), and Any Segment Models (SAM) are beginning to be incorporated into specific software tools. Tools such as Stable Diffusion V.5, Midjourney V5.1, and Photoshop 2023 (Beta) are being integrated into design studio workflows, with some studios even starting to train their algorithm models [30–32]. This rapid visual communication bears immense potential in architectural education as it fosters more effective communication between students and teachers during the design stages.

Design studios, viewed as the core of architectural education, serve as a confluence of theoretical and technical knowledge. Here, AI assumes a crucial role in data processing, research object indexing, environmental analysis, and suggesting design proposals through building performance analysis tools [7]. Innovative tools such as the Nuncias chatbot have been integrated into architectural education to aid in enhancing the verbal definition of designs [33].

However, the application of AI in architectural design and education is not devoid of challenges. Deep learning models and extensive datasets cannot mimic human ways of thinking, such as "common sense", i.e., the ability to generalize, create, and simulate abstract information [28]. Thus, the progression of AI needs to coincide with enhancements in educational models and strategies to adapt to the rapid technological advancements and cultivate designers capable of effectively utilizing these tools [24].

The integration of AI in architectural design and education equips students and designers with potent tools to explore novel design methods and optimize existing designs. Nonetheless, to effectively incorporate AI, appropriate educational models and strategies need to be developed to adjust to the rapid technological advancements.

2.3. Assessment of Aesthetic Value in AI-Generated Architectural Design

The rapid application of artificial intelligence in architectural design is catalyzing significant changes, including the rise of many innovative design approaches and practices. Nonetheless, this progress ushers in a new challenge: how can we objectively assess the aesthetic value of design schemes produced by AI? This challenge necessitates the application of diverse architectural aesthetics theories and studies, which hold a crucial role in the training of AI, particularly in reinforcement learning with human feedback (RLHF) [34].

Evaluating the aesthetic value of architectural design is a complex task encompassing multiple dimensions. It is also important to acknowledge that architecture, although primarily captivating through visual expression, is a multisensory experience incorporating elements such as touch, sound, and even smell. This awareness of the multisensory nature of architecture aligns with the Enlightenment period's emphasis on prioritizing the senses of sight and hearing over the senses of smell, touch, and taste [35,36]. Contemporary theories, as proposed by Bille and Sørensen, suggest a further extension of this awareness, highlighting the atmospheric elements, processes, and practices in architectural design [37].

Mehaffy, Gorichanaz, and Lavdas offer comprehensive discussions on architectural form, user experience, and sociocultural aspects, which furnish invaluable insights into understanding and evaluating the function of AI in architectural design [38,39]. Simultaneously, aesthetic evaluation straddles both subjectivity and objectivity. Fechner's endeavor to quantify aesthetics with numerical scales provides a potential approach to aesthetic assessment. Recent studies from neuroscientists such as Sussman reveal that our judgments about beauty are largely influenced by our perceptual mechanisms [40]. This concurs with Christopher Alexander's notion of "Quality Without A Name" and Buras's "beauty scale" theory, both stressing the importance of quick perception in aesthetic evaluation [41,42].

The efficacy of using a beauty scale for evaluation can reach 80–90% in rating consistency, suggesting that it can serve as an efficient instrument to predict and comprehend people's aesthetic experience of architectural design, and achieve consensus in the design and execution process [43].

Assessing the aesthetic value of AI-generated architectural design requires contemplating human perceptual experience, subjective feelings, memory, social and cultural demands, and aesthetic responses from a neuroscientific perspective. Among these, human intuitive responses and perceptual experiences play a pivotal role in the evaluation. In assessing the architectural image generation ability of AI, subjective scales can be employed for experimentation.

3. Methods

3.1. Preparation of Architectural Visuals

3.1.1. Selection and Preparation of Gaudí's Manuscripts

Gaudí's Crypt of Colonia Güell was purposefully selected as the focus of this investigation, owing to its historical significance and incorporation of Gaudí's pioneering architectural paradigms. From the available manuscripts [44], two panoramic views and two detailed images from the south facade of the Güell Crypt were meticulously selected [45] (see Figure 2). This choice was based on the acknowledgment that Gaudí's later works, such as the Güell Crypt, closely mirror the architectural style and techniques seen in his completed buildings, facilitating a more accurate basis for comparison with authentic images of his built works [46].

The construction of the Crypt of Colonia Güell started in 1908 under the commission of Eusebi Güell, who provided Gaudí with unencumbered creative freedom [8]. The ambitious plan entailed a church with two naves, distinctive towers, and a central dome reaching 40 m in height. However, due to financial constraints, only the lower nave was completed, leading to its familiar nickname as the "crypt". Despite its unfinished state, the Crypt of Colonia Güell represents the zenith of Gaudí's architectural innovations, embodying his unique design principles and techniques [46].

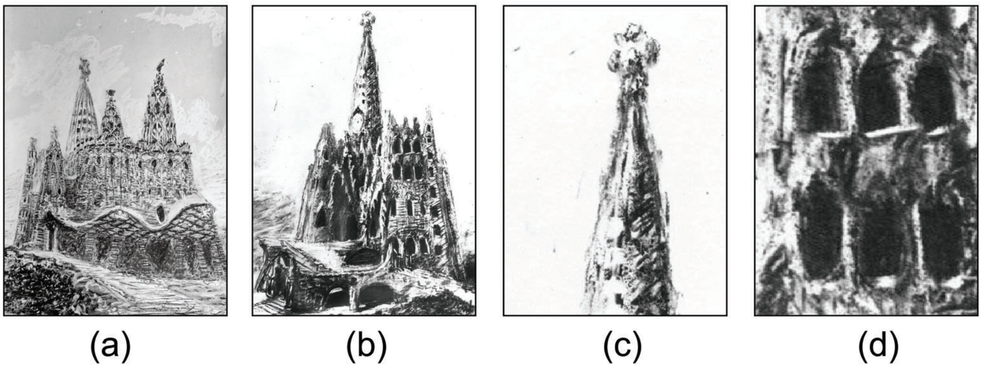

Figure 2. (**a**) East façade Güell Crypt (1910). (**b**) South façade Güell Crypt (1910). (**c**) Tower detail crop from south façade Güell Crypt. (**d**) Window detail crop from south façade Güell Crypt.

For the digital reconstruction of Gaudí's manuscripts, a thorough digitization process was conducted. Recognizing the necessity for preprocessing the manuscripts for optimal input into the Stable Diffusion algorithm, a blend of the Depth and Canny edge detection methods was adopted [47].

3.1.2. Creation of AI-Generated Images

The creation of AI-generated images involved the application of advanced deep learning and computer vision technologies. The process consisted of three key steps: 1—data acquisition, 2—model training, and 3—prediction (see Figure 3).

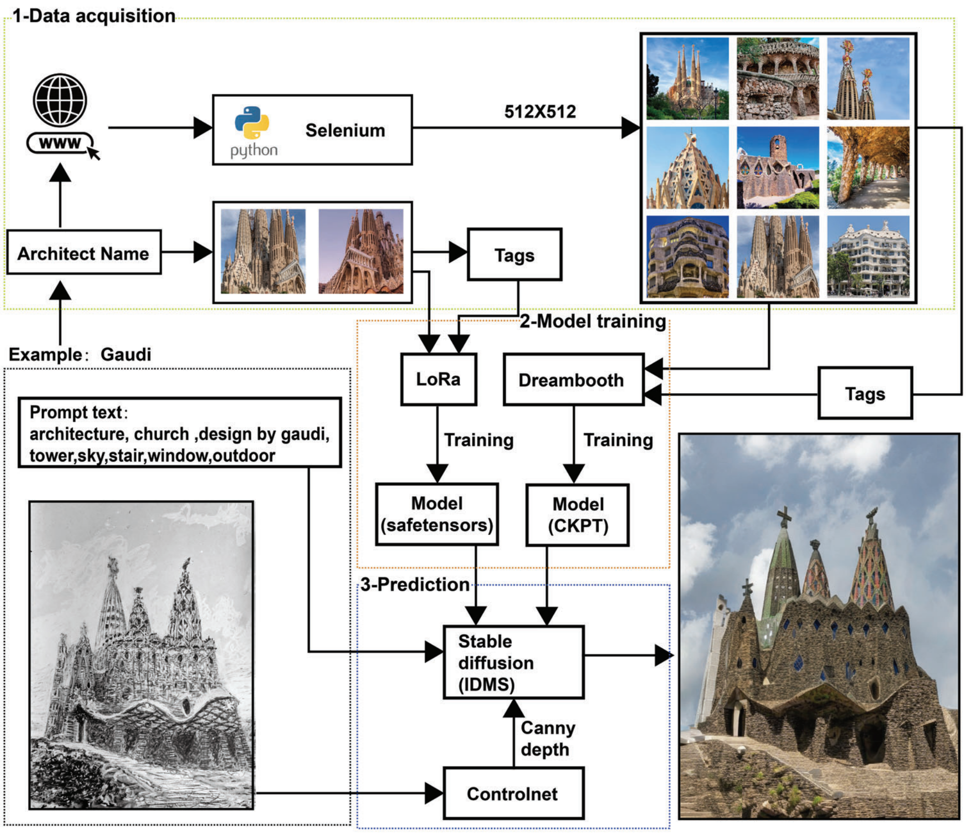

Figure 3. Text and Architectural Manuscript-Conditioned Image Generation Framework (consisting of three key steps: (1) data acquisition, (2) model training, and (3) prediction).

In the data acquisition phase, a dataset of 3000 images was collected using Python web scraping tools. To ensure data quality, a deduplication tool was employed to eliminate visually similar images. The images were then automatically cropped to a standard size of 512 × 512 pixels by identifying their central regions. Textual tags associated with the images were extracted using Deepbooru, and manual verification was conducted to ensure tag accuracy.

The subsequent model training phase was divided into two distinct methods for more effective learning. The first method involved training the Dreambooth AI model [48] on the initially collected and processed dataset of 3000 images. The training was performed over 30,000 steps, with a meticulously set learning rate of 0.00005 to ensure a balance between learning speed and performance. The loss function, which is an indicator of how well the model's prediction aligns with the actual result, gradually converged from an initial value of 0.168 to 0.078, indicating successful learning. However, after experimentation, it was determined that the model checkpoint at the 12,000th step, named Model A, yielded results superior to those at the final step.

In addition to the general training method, a targeted approach was also utilized. This method trained specific architectural elements, such as towers and windows, individually using the LoRA (low-rank adaptation of large language) model [49]. This method aimed to capture unique styles with a smaller set of representative images. Ten images were used for each element, and the training was carried out over 10 epochs, with each epoch consisting of 20 iterations. This resulted in a total of 2000 steps. The learning rate for this process was set to a lower value of 0.00001 to accommodate for the detailed and specific nature of the learning. The performance and weight variations of the LoRA models were monitored and evaluated using an XY-axis graph, allowing for the selection of the most suitable model, named Model B, based on the specific requirements (see Figure 4).

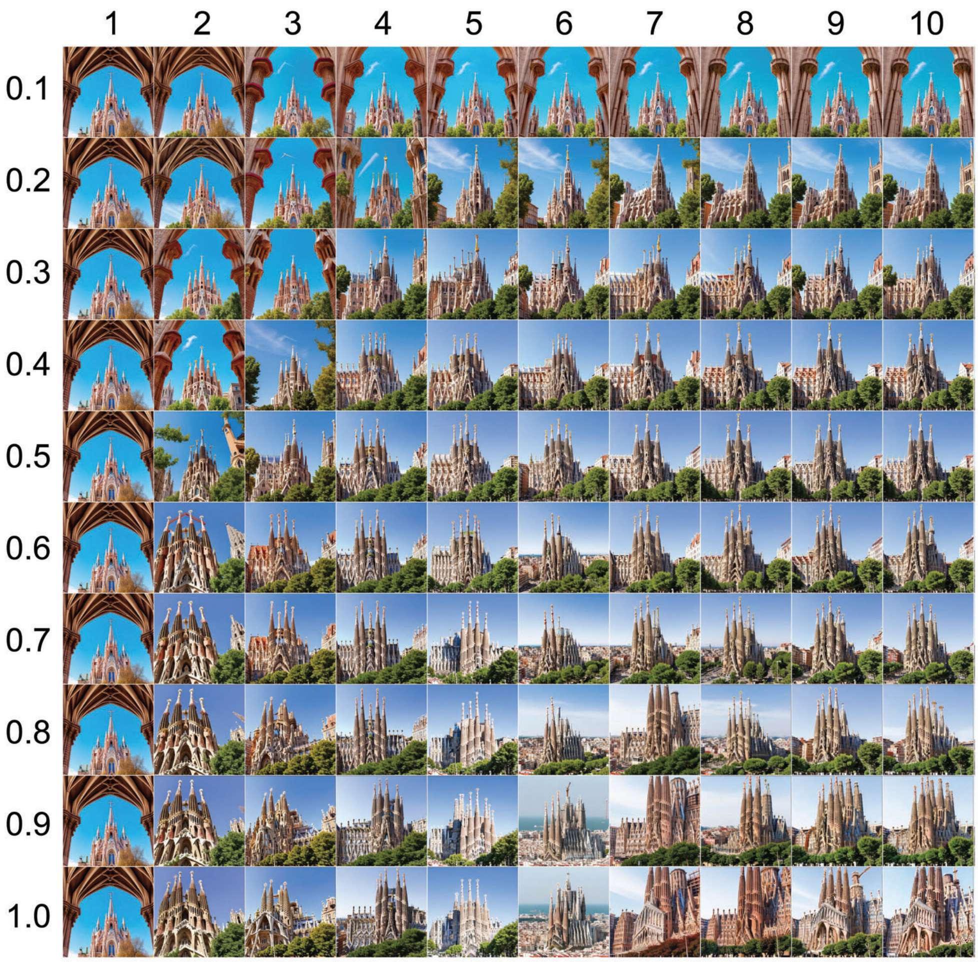

Figure 4. Model Performance and Weight Variation during LoRa Training (Epoch' (X-axis, 1–10) denotes training times. 'Model Weight' (Y-axis, 0.1–1) indicates feature importance).

During the prediction phase, the trained Model A and Model B were integrated into the Stable Diffusion (LDMs Algorithms) platform. The weights of Model B were adjusted as needed. In this phase, the preprocessed canny and depth images from Gaudí's manuscripts were fed into the model, along with the corresponding textual prompts. The output generated a set of AI-generated images that accurately represented Gaudí's architectural designs. Multiple runs were conducted to account for the unpredictable nature of denoising outcomes, ensuring the generation of consistent and sensible predictions.

3.2. Design and Execution of the Comparative Study

3.2.1. Participant Selection and Recruitment

We involved participants aged 19 to 40 years in the study, all of whom were university students from various academic fields. The majority of the participants (62%) were from non-architectural fields, while the remaining 38% were studying architecture. This demographic was chosen because of their significant engagement with technology and potential to influence the future of architecture and AI applications. We intentionally did not limit participants to those studying architectural or design-related fields, aiming to encapsulate diverse aesthetic preferences and emotional responses across the broader public. Regarding gender identification, we adhered to the Sex and Gender Equity in Research (SAGER) guidelines, which recommend against the collection of such information unless necessary for the research, recognizing that gender is not binary and its disclosure may be sensitive for some individuals—such as those transitioning. This decision reflects our commitment to fostering an inclusive, respectful, and ethical research environment. This approach helped ensure our findings are not influenced by potential gender biases and reflect a gender-neutral assessment of emotional responses and aesthetic preferences. Our research focuses on individual experiences and perspectives, aligning with current understanding in research that seeks to avoid overgeneralization or assumptions based on demographic categories, such as gender [50].

Upon a thorough screening process for completeness and consistency, we included a total of 990 responses in our final analysis. Through this methodology, we sought to capture a broad and comprehensive understanding of public perceptions and emotional responses to AI-generated architectural designs.

3.2.2. Image Presentation

In our perception-focused study, we utilized a set of carefully curated images for evaluation purposes. This set comprised four authentic representations of Gaudí's architectural works and four AI-generated counterparts, which were selected based on their stylistic resemblance to Gaudí's signature design aesthetics. The principal aim of this selection strategy was to ensure the validity and fairness of the subsequent comparative analysis.

For ease of reference during the evaluation process, the selected images were assigned unique identifiers: (a) Gaudí Façade View (GFV) image 1, (b) AI Façade View (AFV) image 1, (c) Gaudí Detail View (GDV) image 2, (d) AI Detail View (ADV) image 2, (e) Gaudí Façade View (GFV) image 3, (f) AI Façade View (AFV) image 3, (g) Gaudí Detail View (GDV) image 4, and (h) AI Detail View (ADV) image 4 (see Figure 5).

To ensure an unbiased evaluation, the presentation of the images was randomized and devoid of any contextual information. This strategy aimed at eliminating potential influences of background knowledge on participants' judgments, enabling them to focus exclusively on the architectural aesthetics depicted in the images.

The evaluative task required participants to assess and compare Gaudí's real architectural designs against their AI-generated counterparts. This facilitated an in-depth examination of participants' aesthetic preferences, as well as their perceptions of the AI's proficiency in emulating Gaudí's distinctive style.

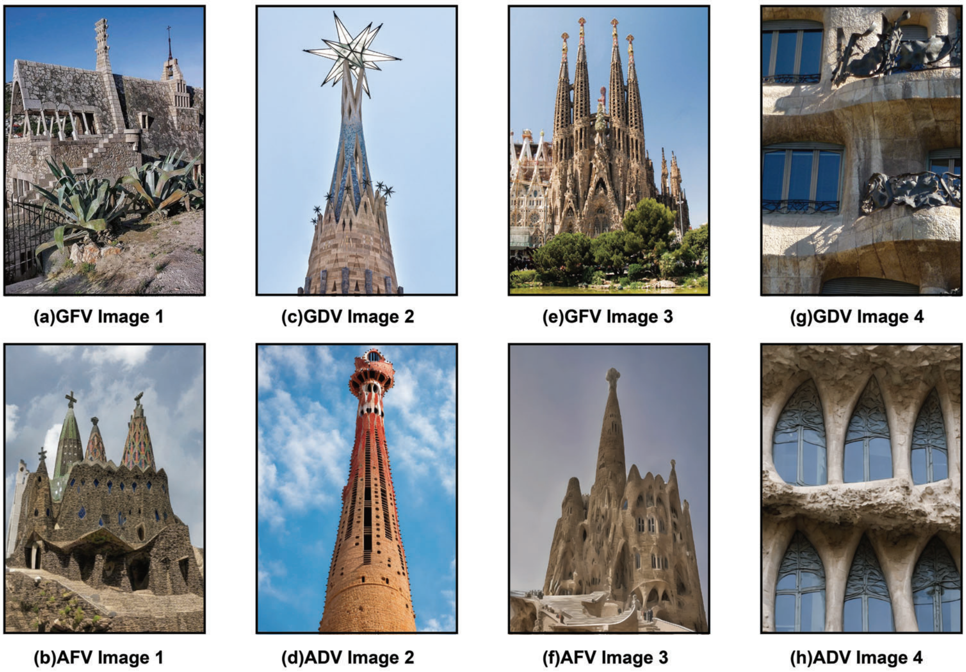

Figure 5. (**a**) Gaudí Façade View (GFV) image 1. (**b**) AI Façade View (AFV) image 1. (**c**) Gaudí Detail View (GDV) image 2. (**d**) AI Detail View (ADV) image 2. (**e**) Gaudí Façade View (GFV) image 3. (**f**) AI Façade View (AFV) image 3. (**g**) Gaudí Detail View (GDV) image 4. (**h**) AI Detail View (ADV) image 4.

3.2.3. Theoretical Framework and Methodology

The theoretical framework for this study builds upon a multidisciplinary perspective integrating insights from the neuroscience of aesthetics, artificial intelligence (AI), and architectural design. We employ the model proposed by Chatterjee and Vartanian [51], which includes perceptual processing, cognitive processing, and emotional responses, and extends it with an assessment of creativity—an essential aspect of AI's application in architectural design [52,53].

Our methodology involves a rating scale to measure these four dimensions in relation to AI-generated architectural designs:

1. Perceptual Processing:Participants' assessment of the designs' authenticity and attractiveness [54,55].
2. Cognitive Processing: Evaluation of the designs' harmony or cohesion [56].
3. Emotional Responses: Participants' emotional responses to the designs [57].
4. Creativity: Participants' assessment of the novelty and innovativeness of the designs [52,53].

This framework and methodology aim to quantitatively assess the aesthetic value of AI-generated designs, highlighting the interplay of perceptual, cognitive, emotional, and creative aspects in appreciating architectural aesthetics.

By quantifying each dimension, we could conduct a comprehensive analysis of participants' emotional responses, providing a more precise evaluation of the effectiveness of AI in emulating Gaudí's architectural style, meeting aesthetic preferences, and replicating key design elements.

3.2.4. Data Analysis

In this study, a comprehensive assessment of the data distribution for each dimension's ratings was conducted through normality tests. These tests are critical for determining the appropriate statistical analyses to apply and are widely used in the field of data science [58].

In the context of our data, the determination of the data distribution informs the choice of statistical tests. For dimensions with data following a normal distribution, we leveraged parametric tests, specifically independent *t*-tests. These tests, commonly used in hypothesis testing, are designed to compare mean ratings between different conditions or groups [59]. This strategy enabled us to ascertain the statistical significance of the observed differences and to estimate the corresponding effect sizes.

However, for data that violated the assumptions of normality, non-parametric tests were employed, such as the Mann–Whitney U test. Non-parametric tests have been shown to be robust against deviations from normality, making them a reliable alternative for evaluating significance and effect sizes when data deviate from normal distribution [60].

The selection of the most suitable statistical methods based on the data distribution helped to ensure the robustness and validity of the *p*-values and effect sizes generated. This, in turn, provided a solid foundation for drawing conclusions from the data analysis.

4. Results

In our thorough analysis of Gaudí and AI design evaluations across various views, we have meticulously calculated the mean, standard deviation, and median values for each metric (see Table 1). Our findings, outlined below, provide valuable insights into the comparative performances and perceptions of Gaudí's and AI's designs.

1. Analysis of Means: The mean scores, representing the average evaluation for each view, exhibit notable variability. Interestingly, 'Gaudí Attractiveness' and 'Gaudí Preference' consistently score higher on average, suggesting a potential preference for Gaudí's designs or their perceived attractiveness. Conversely, 'AI Authenticity' exhibits lower mean scores, indicating a less favorable perception of the AI's authenticity in its designs.
2. Standard Deviations Insight: The relatively high standard deviations across all categories signify a substantial diversity in scores. This considerable range of values points towards diverse opinions among evaluators, indicating a rich spectrum of perspectives on both Gaudí's and AI's designs.
3. Medians and Their Interpretation: Noteworthy is the higher median values compared to mean values in numerous categories. This discrepancy suggests the presence of a skew in the distribution of scores, possibly influenced by a number of lower-end values.
4. Comparing Gaudí and AI: When we juxtapose the mean scores for Gaudí and AI, the former tends to outperform the latter in most categories. This could be indicative of a broader appreciation or regard for Gaudí's work over AI's within our sample.
5. Comparison Across Views: Furthermore, different views reveal distinct patterns in scores. 'Façade View 1' and 'Façade View 3' garner higher mean scores in general, while 'Detail View 4' lags behind. This discrepancy may suggest a more favorable reception or better performance of facade views over detailed views.

In the following sections, we delve deeper into these intriguing findings and conduct a comprehensive difference analysis on each of the five evaluation metrics: Authenticity, Attractiveness, Creativity, Harmony, and Preference. This rigorous analysis aims to better understand the nuanced differences and implications of Gaudí's and AI's performance on these metrics. As we proceed with this exploration and comparative study, we will uncover more intricate details regarding the design evaluations of Gaudí's and AI's work (see Figure 6).

Table 1. Statistical Analysis of Gaudí and AI Views.

View	Metric	Gaudí				
		Authenticity	**Attractiveness**	**Creativity**	**Harmony**	**Preference**
Façade View 1	Mean	7.20	6.77	6.65	6.66	6.63
	Standard Deviation	1.97	2.04	2.11	2.11	2.25
	Median	7.50	7.05	7.05	7.00	7.10
Detail View 2	Mean	5.92	7.61	7.35	6.45	7.33
	Standard Deviation	2.59	1.96	1.98	2.20	2.10
	Median	6.60	8.10	7.80	6.90	7.90
Façade View 3	Mean	7.03	7.50	7.48	7.10	7.51
	Standard Deviation	2.18	1.83	1.90	2.03	1.97
	Median	7.50	7.80	7.80	7.50	8.00
Detail View 4	Mean	6.62	6.21	5.71	5.86	5.64
	Standard Deviation	2.29	2.27	2.43	2.35	2.57
	Median	7.10	6.60	6.00	6.20	5.95
View	**Metric**	**AI**				
		Authenticity	**Attractiveness**	**Creativity**	**Harmony**	**Preference**
Façade View 1	Mean	6.01	7.24	6.66	6.20	6.55
	Standard Deviation	2.33	1.92	2.17	2.24	2.39
	Median	6.50	7.60	7.00	6.55	7.00
Detail View 2	Mean	6.15	7.13	6.57	6.01	6.35
	Standard Deviation	2.41	2.05	2.26	2.33	2.45
	Median	6.75	7.60	7.00	6.40	7.00
Façade View 3	Mean	5.78	6.96	6.55	6.27	6.55
	Standard Deviation	2.48	2.07	2.32	2.33	2.44
	Median	6.40	7.40	7.00	6.70	7.00
Detail View 4	Mean	6.22	6.50	5.80	5.85	5.74
	Standard Deviation	2.34	2.21	2.43	2.42	2.63
	Median	6.80	7.00	6.20	6.30	6.20

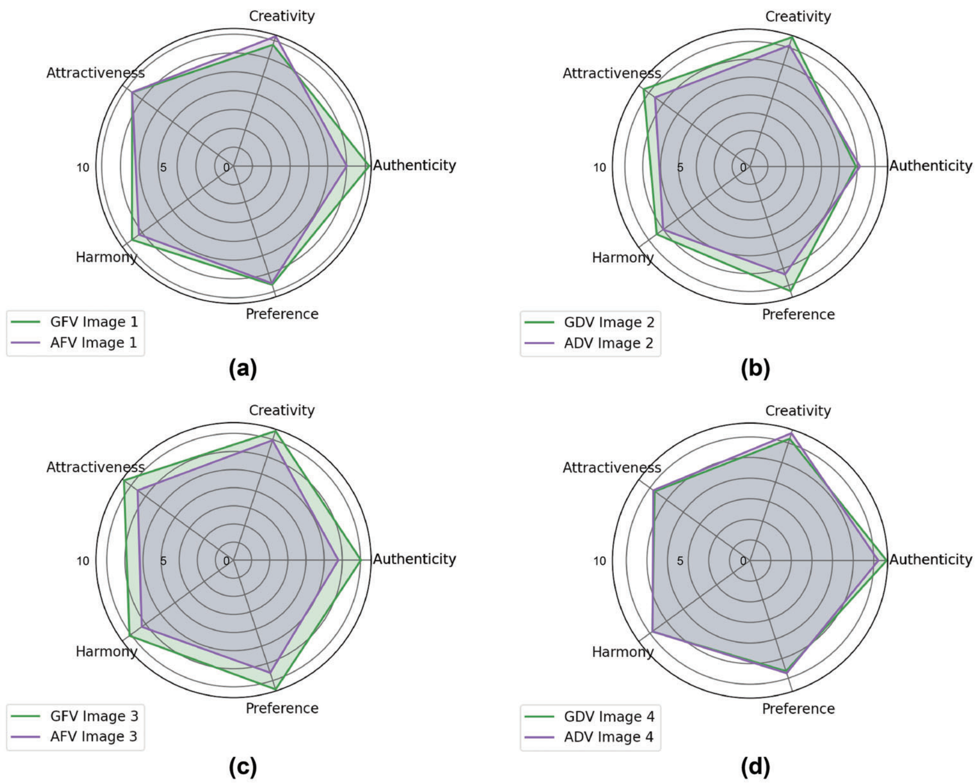

Figure 6. (**a**) Gaudí Full View (GFV) image 1 vs. AI Full View (AFV) image 1: Comparative Analysis of Five Metrics. (**b**) Gaudí Detail View (GDV) image 2 vs. AI Detail View (ADV) image 2: Comparative Analysis of Five Metrics. (**c**) Gaudí Full View (GFV) image 3 vs. AI Full View (AFV) image 3: Comparative Analysis of Five Metrics. (**d**) Gaudí Detail View (GDV) image 4 vs. AI Detail View (ADV) image 4: Comparative Analysis of Five Metrics.

This section may be divided by subheadings. It should provide a concise and precise description of the experimental results, their interpretation, as well as the experimental conclusions that can be drawn.

4.1. Authenticity

The analysis of Authenticity scores for various Gaudí and AI design views reveals statistically significant differences (see Figure 7). The disparity between Gaudí's and AI's Façade View 1 is statistically significant (p-value: 5.12×10^{-33}) with a negligible effect size (3.61×10^{-4}), implying that while the difference is statistically meaningful, its practical impact is minimal. A similar pattern is observed in Façade View 3 (p-value: 3.66×10^{-31}, effect size: 3.82×10^{-4}) and Detail View 4 (p-value: 3.64×10^{-5}, effect size: 1.77×10^{-4}). In contrast, Detail View 2 exhibits no significant difference (p-value: 0.082, effect size: -6.08×10^{-5}). Therefore, despite statistical differences in Authenticity scores between Gaudí's and AI's designs across most views, these differences are not practically substantial.

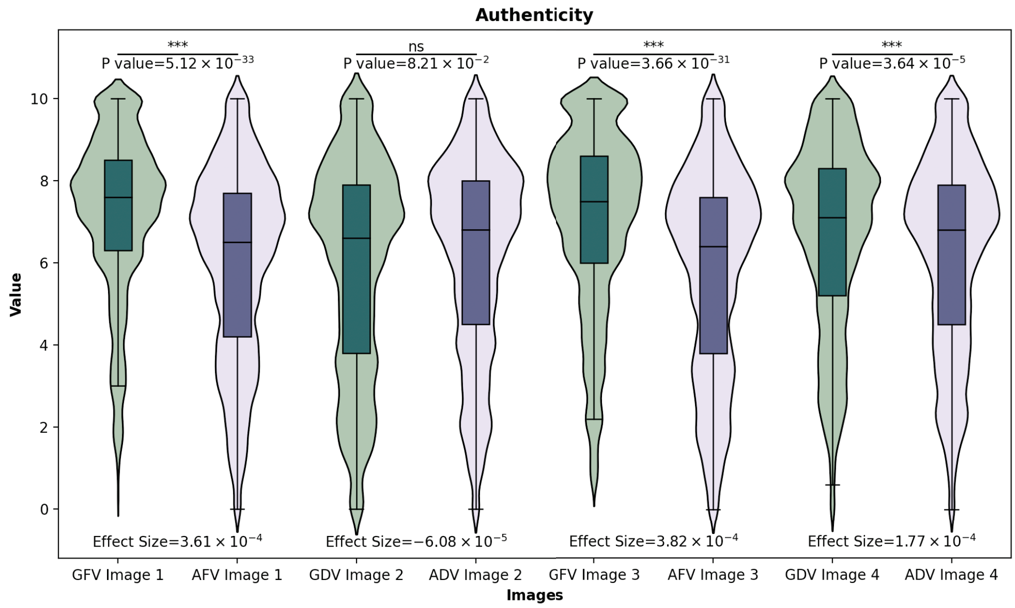

Figure 7. Comparative Analysis of Authenticity: Violin Plot and Box Plot for Gaudí vs. AI Images. ***, p Value < 0.001; ns, not significant.

4.2. Attractiveness

In examining the Attractiveness metric across various views, significant differences emerge in certain cases (see Figure 8). The comparison between Gaudí's and AI's Façade View 1 shows no significant difference (p-value: 0.835, effect size: -4.44×10^{-5}), implying near-equivalent attractiveness ratings for both designs. On the contrary, Detail View 2 and Façade View 3 reveal statistically significant differences (p-values: 1.01×10^{-16} and 5.32×10^{-20}, respectively) with small effect sizes (2.56×10^{-4} and 2.79×10^{-4}, respectively), indicating that while these differences are statistically valid, their real-world influence might be minor. Finally, in Detail View 4, no substantial difference in attractiveness is detected (p-value: 0.362, effect size: 3.10×10^{-6}). Thus, for Attractiveness, statistically significant differences between Gaudí's and AI's designs only occur in certain views and their practical implications remain marginal.

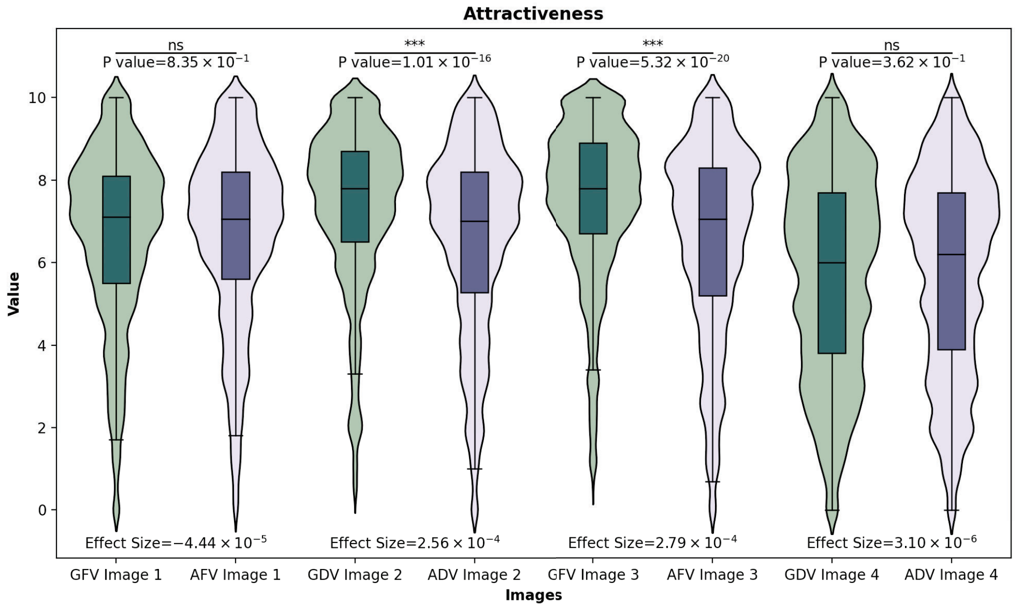

Figure 8. Comparative Analysis of Attractiveness: Violin Plot and Box Plot for Gaudí vs. AI Images. ***, *p* Value < 0.001; ns, not significant.

4.3. Creativity

For the Creativity metric, significant differences are observed in all views when comparing Gaudí's and AI's designs (see Figure 9). The Gaudí and AI Façade View 1 and Detail View 4 demonstrate a significant difference (*p*-values: 4.97×10^{-8} and 0.0034, respectively), with negative effect sizes (-2.25×10^{-4} and -9.81×10^{-5}, respectively), suggesting that the AI's design was rated less creative in these views. Contrastingly, in Detail View 2 and Façade View 3, the data reveals a significant difference (*p*-values: 1.79×10^{-9} and 5.72×10^{-9}, respectively), with positive effect sizes (2.40×10^{-4} and 2.15×10^{-4}, respectively), implying that the evaluators rated Gaudí's designs as more creative. In summary, for Creativity, there are statistically significant differences across all views, with the degree of impact varying based on the specific view.

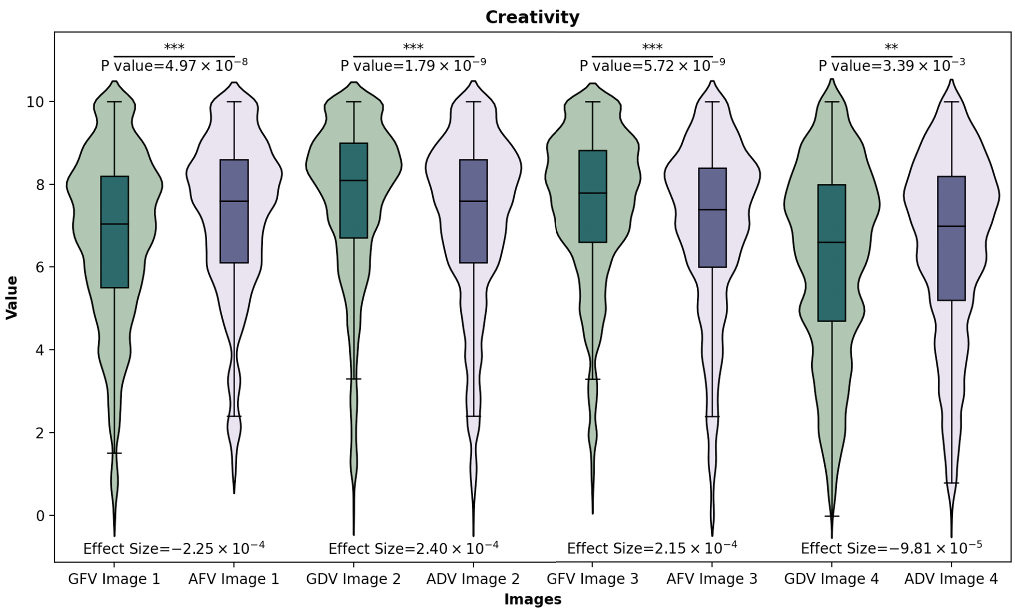

Figure 9. Comparative Analysis of Creativity: Violin Plot and Box Plot for Gaudí vs. AI Images. **, *p* Value < 0.01; ***, *p* Value < 0.001.

4.4. Harmony

For the Harmony metric, the analysis indicates significant differences across all views, with varying degrees of impact when comparing Gaudí's designs and those generated by the AI (see Figure 10). The Façade View 1, Detail View 2, and Façade View 3 demonstrate significant differences between Gaudí and AI, with p-values of 2.46×10^{-6}, 2.44×10^{-5}, and $2.47 \times 10-16$, respectively. The effect sizes in these cases are 1.27×10^{-4}, 1.36×10^{-4}, and 2.55×10^{-4}, respectively, suggesting that Gaudí's designs were rated more harmonious in these views. In contrast, Detail View 4 shows no significant difference (p-value: 0.8972) with a small effect size (4.13×10^{-5}), indicating that the evaluators did not perceive a substantial difference in terms of harmony between Gaudí's and the AI's design for this view. Therefore, in terms of Harmony, there are significant differences across the majority of views, but the impact depends on the specific view.

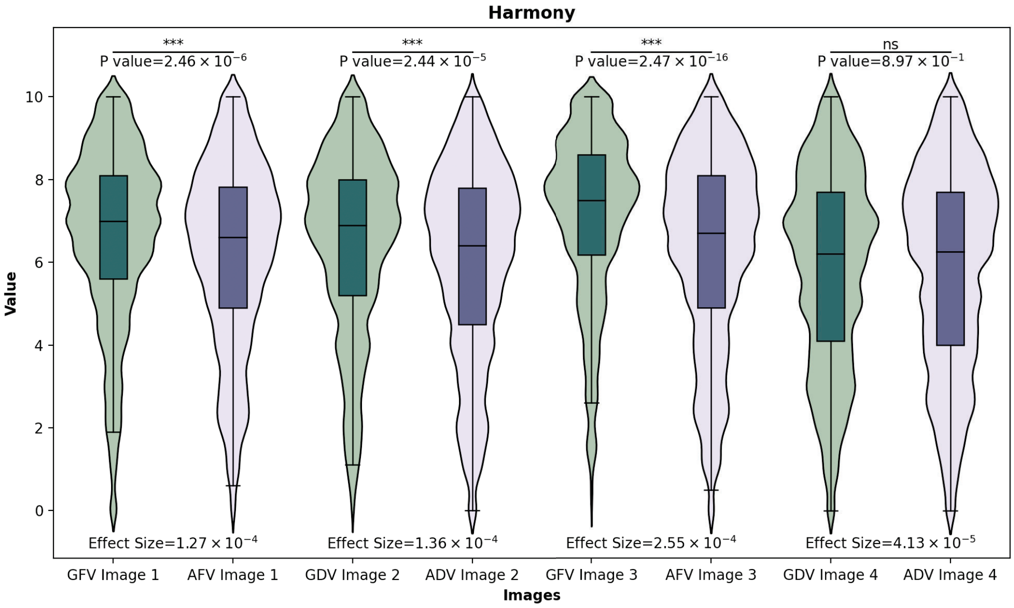

Figure 10. Comparative Analysis of Harmony: Violin Plot and Box Plot for Gaudí vs. AI Images. ***, p Value < 0.001; ns, not significant.

4.5. Preference

The Preference metric exhibits varied results across the different views (see Figure 11). For Façade View 1, no significant difference was discernible between Gaudí's and AI's designs (p-value: 0.7467) with an almost negligible effect size (1.14×10^{-5}), suggesting a similar preference for both. Conversely, Detail View 2 and Façade View 3 show highly significant differences with p-values of 1.63×10^{-21} and 3.56×10^{-19}, respectively. Their effect sizes are 3.14×10^{-4} and 2.92×10^{-4}, respectively, indicating a stronger preference for Gaudí's designs. Detail View 4, however, does not exhibit a significant difference (p-value: 0.3416), with a small negative effect size (-3.51×10^{-5}), suggesting an approximately equal preference for both Gaudí's and AI's designs in this view. Thus, in terms of Preference, results vary depending on the specific view, with Gaudí's designs generally favored in Detail View 2 and Façade View 3.

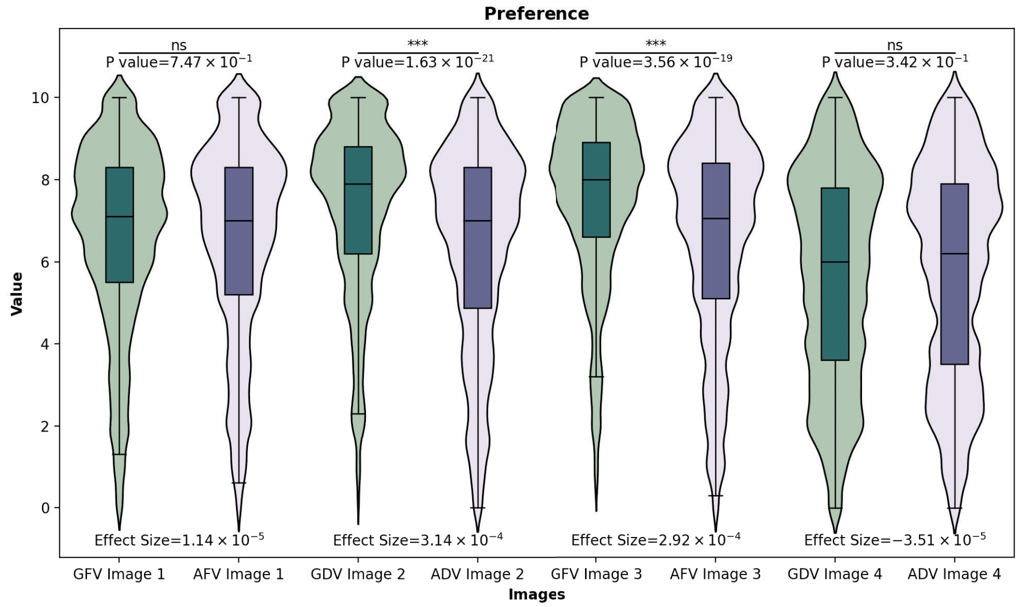

Figure 11. Comparative Analysis of Preference: Violin Plot and Box Plot for Gaudí vs. AI Images. ***, p Value < 0.001; ns, not significant.

5. Discussion

The in-depth analysis of the evaluation metrics in this study provides a complex understanding of the comparative effectiveness of Gaudí's designs and AI-generated designs. The results contribute significantly to existing research, revealing implications for architectural education and AI's design capabilities [38].

Gaudí's designs exhibited superior scores in Authenticity and Harmony across various images. This outcome aligns with the existing literature that emphasizes the importance of a distinctive stylistic signature and the coherence of an artistic vision in architectural works [61]. This bolsters the argument for a stronger focus on cultivating personal design languages in architectural education, and also illustrates the challenges AI systems face in replicating these complex, human-centric elements of design [62].

Interestingly, AI-generated designs demonstrated competitive performance in Attractiveness, Creativity, and Preference for certain images. This echoes recent research underscoring AI's potential for aesthetic and creative applications. However, the considerable standard deviations in evaluations highlight the subjectivity inherent in design evaluations and the diversity in individual aesthetic preferences. Understanding what underpins these individual differences is an intriguing avenue for future research and can inform efforts to personalize AI design algorithms.

This study underscores the promising potential of AI in the architectural domain, serving both as an educational tool and a creative design tool. In an educational context, AI can present a unique avenue for visualizing incomplete architectural masterpieces, thereby enhancing students' understanding of architectural design principles and history. The system's ability to generate a variety of designs and styles could stimulate students' exploration of diverse architectural concepts, fostering creativity, critical thinking, and innovative problem-solving.

Despite these potential benefits, we recognize that our study did not directly test these AI tools within an educational setting. Furthermore, we acknowledge the potential limitations associated with focusing primarily on visual aesthetics in our study due to the nature of the AI system's designs and Gaudí's works being presented in a visual medium. This focus, while essential for initial impressions and broad aesthetic appeal, may overlook other sensory experiences integral to a comprehensive architectural experience. Future studies could consider incorporating additional sensory modalities for a more holistic understanding. Therefore, we advocate for further research to apply these tools in educational environments and rigorously assess their impacts on student learning and engagement. Our propositions are based on the capabilities of the AI system, and we envision that the integration of AI in architectural education can open up new, exciting avenues for teaching and learning. Moreover, acknowledging the limitations in our study is essential. One limitation is the use of the Likert scale survey, which measures attitudes explicitly. This method may not fully capture implicit biases or influences, such as cultural influences on emotional evaluation. As the literature suggests, implicit biases can significantly influence the evaluation of aesthetic and creative outputs, often subtly shaping the results [63]. To mitigate such influences, researchers could consider adopting indirect measurement methods such as the Implicit Association Test (IAT), which has been found effective in identifying implicit biases in various fields [64].

The risk of reductionism is indeed present if there is a lack of investigation into the social class cultural influence in emotional evaluation since culture teaches us how to feel. This shortcoming limits our understanding of whether this method would produce consistent results across diverse audiences. Future research should consider incorporating cultural context into the evaluation process, as has been suggested by cultural sociologists [65].

Moreover, our study involved participants who were university students, but not specifically students of architecture. This limitation may affect the depth and specificity of responses, particularly in aspects related to architectural understanding and appreciation. However, the inclusion of a more diverse student population can provide a broader perspective on the aesthetic appreciation of architectural designs. Nonetheless, future research could benefit from including both architecture students and non-students to gain a more comprehensive understanding of AI's potential in architectural design and education.

6. Conclusions

In conclusion, this study highlights the significant potential of AI as a design tool in the field of architectural design. AI exhibits competitive performance in terms of Attractiveness and Creativity and in some instances surpasses human designs in overall Preference. Nevertheless, our study also underlines the existing limitations of AI in replicating the unique attributes of human designs, specifically in terms of Authenticity and Harmony.

The results of our study underscore the subjectivity inherent in design evaluations, suggesting that individual aesthetic preferences play a significant role in the perception of designs. This stresses the need for a more personalized approach in the development and utilization of AI design tools to cater to diverse aesthetic tastes.

Future research, therefore, should focus on exploring individual differences in perception and on adapting AI design algorithms accordingly. Through this approach, AI can truly become a beneficial tool in architectural design, capable of generating diverse and innovative design solutions. Despite its current limitations, the potential for AI in the field of architectural design is substantial and its exploration is worthwhile.

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