A conceptual visualization illustrating the architectural and spatial transition from contemporary technology retail spaces to AI-driven future interior projections of 2070.

Evaluating AI-driven predictions for the interior design of 2070 technology stores

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Abstract: This study explores the role of AI-powered predictions in shaping the interior design of technology stores projected for the year 2070, with a particular focus on emerging retail trends and the integration of artificial intelligence into architectural design processes. The research sought to understand not only how AI systems generate design proposals, but also how these outputs align with established professional standards. To achieve this, a structured survey was conducted with a group of architects and interior designers. Participants were asked to evaluate AI-generated visualizations, assessing their compliance with standard design criteria. The collected expert evaluations were then systematically compared with parallel assessments produced by ChatGPT 4.0, creating a basis for measuring similarities, differences, and potential biases between human and AI perspectives. Critical design parameters were carefully analyzed, including floor durability, the effective use of display areas, integration of advanced technology into spatial solutions, circulation efficiency, and considerations of user comfort and well-being. The results demonstrate clear differences between human and AI assessments, alongside notable professional divergences among human evaluators. While AI showed notable strength in areas such as technology integration and circulation optimization, human professionals identified significant weaknesses in other domains, particularly regarding customer orientation systems, signage clarity, and the organization of checkout areas. Furthermore, comparative analyses between professional groups revealed that architects placed a significantly higher emphasis on material diversity and circulation efficiency compared to interior designers, highlighting a professional prioritization of structural and flow-related parameters. A Bland-Altman analysis further revealed a systematic bias, showing that AI-generated evaluations were approximately 9% more positive compared to those of human experts. This suggests that AI tends to adopt a more optimistic lens, whereas human experts approach the same criteria with a more cautious and conservative stance. The study emphasizes the necessity of integrating human expertise into AI-driven design processes, both to ensure methodological rigor and to uphold ethical responsibility. Ultimately, by combining computational efficiency with human judgment, this research contributes to the development of more innovative, resilient, and human-centered design strategies for future retail environments.

Keywords: AI-driven design forecasting; artificial intelligence in architecture; future retail design; human-centered design; technology store interiors.

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1. Introduction

Spatial configurations are continuously reshaped by technological advancements, which have also transformed retail environments across different historical periods. From ancient agoras to contemporary commercial settings, retail spaces have evolved significantly, with smart systems increasingly shaping their structure and function. Today, the retail industry is undergoing a wave of innovation, with projections indicating that AI could influence over $340 billion in global retail spending by 2025 (Statista, 2023a). The rapid proliferation of digital culture in the early 21st century, driven by technological developments, particularly in digitalization and AI, necessitates a more comprehensive understanding of how these changes will shape the future of retail design (Yıldız, 2023).

Technological transformation not only affects the physical structure of retail spaces but also alters consumer behavior. Brands utilize AI systems in mobile shopping to analyze preferences and personalize experiences, converting stores into interactive and experiential environments (Shankar & Venkatesh, 2018). This shift requires architectural design to adapt to the digital age and propose future-oriented, sustainable, and innovative solutions (Yıldız, 2023). The integration of AI and machine learning (ML) into other sectors, such as education, offers relevant insights. In education, these tools enhance pedagogy, customize learning, and improve outcomes (Abuhassna et al., 2024), suggesting potential parallels for transforming retail.

AI-driven personalization and adaptive spatial strategies are increasingly central to retail, enabling layouts and interactions responsive to consumer needs (Kumar et al., 2024). Cross-disciplinary research highlights the potential of AI applications across domains, encouraging architectural innovation. These transformations position AI as a pivotal tool in shaping the interior environments of future retail spaces, particularly in technology-focused stores.

Against this backdrop, the year 2070 is selected as a strategic milestone for forecasting retail space evolution. This timeframe allows for speculative analysis of how AI may influence spatial configurations, consumer engagement, and integrated technologies. Projections anticipate a future shaped by advanced AI, automation, immersive systems, and sustainable practices (Statista, 2023b; Bizuayehu, 2024; Kok, 2025). The selection of this temporal horizon is strategically grounded in the projected maturity of transformative technologies, such as 6G/7G ultra-fast connectivity, advanced neural-link interfaces, and the emergence of programmable matter, which are anticipated to fundamentally redefine physical retail environments. These innovations are expected to shift store interiors from static spaces to hyper-interactive, immersive servicescapes where physical and digital realities are seamlessly integrated, necessitating long-term architectural foresight. This study addresses a critical research gap by evaluating AI-generated predictions for technology store interiors through expert and AI-based assessments, positioning AI not only as a design tool but also as a foresight instrument with measurable limitations in socio-spatial interpretation.

While technological forecasting has informed policy and organizational strategy (Grewal et al., 2019), limited research exists on AI's specific capacity to forecast retail store design. This study aims to bridge that gap by integrating AI-driven insights with human-centered evaluation, offering a structured framework for retailers and designers seeking to leverage AI for strategic and experiential advancements. By combining technological forecasting with design ethics, the study underscores the importance of maintaining human oversight in the face of AI's growing influence.

2. Literature review

2.1 Artificial intelligence and architectural design

Artificial Intelligence (AI), defined in 1955 as a scientific discipline aiming to create intelligent machines, has evolved from laboratory experiments into a transformative force across sectors including medicine, law, finance, fashion, art, and education (Keleş, 2007; Gümüş, 2019). Through algorithms capable of processing various data types text, image, and sound AI systems have achieved complex cognitive capabilities, enhancing decision-making and pattern recognition (Deveci, 2022).

Advancements in machine learning, particularly deep learning, have significantly expanded AI's application scope since its early developments in natural language processing during the 1950s–60s (Hoşer & Köymen, 2023). These technological milestones have established AI as a valuable asset in architectural design, where it is now used for generating floor plans, façades, and other spatial components (Yıldırım & Demirarslan, 2020), accelerating workflows and expanding formal possibilities.

AI's generative potential is also evident in creative disciplines. Neural network-based tools like "Deep Dream" simulate imagination by completing missing image data or generating novel visual outputs, broadening the landscape of artistic experimentation

(Babilik et al., 2019). Furthermore, professional projects in the field have demonstrated how AI can be used to visualize speculative and futuristic urban concepts, pushing the boundaries of traditional architectural forecasting (Holland, 2022; Ibrahim, 2022). These applications underscore AI's role not only in technical problem-solving but also in aesthetic innovation.

In architecture and interior design, text-to-image AI systems enable users to produce original visuals from textual input. These systems, powered by machine learning, allow for expressive freedom and automated generative outputs (Yıldırım & Demirarslan, 2021). The growing accessibility of such tools has positioned AI as a potent contributor to the design process (Fernandez, 2022).

As AI enhances flexibility and speed in creative workflows, it holds the potential to reshape the boundaries of artistic and architectural production. Moving beyond its role as a technical assistant, AI increasingly functions as a co-creator, augmenting human imagination in generative design processes.

Having outlined AI's influence on architectural practice, the next section focuses on how technological transformation has redefined the retail sector and consumer experiences.

2.2 Technological developments in the retail sector

Retail has been integral to human commerce since antiquity, with marketplaces such as forums and agoras serving as primary commercial hubs. With industrialization and globalization, retail spaces became more specialized and consumption-oriented, shaped by cultural and economic exchange (Yıldız, 2023). The Industrial Revolution catalyzed further transformations, giving rise to organized, product-focused retail environments. Since the 19th century, technological advances and sociocultural shifts have continued to reshape the structure and function of retail settings (Celal, 2006).

In contemporary society, shopping has evolved into a key social activity. With digital transformation and AI integration, traditional brick-and-mortar retail has expanded to include online platforms, mobile commerce, and smart store models. These developments demonstrate that retail is undergoing continuous redefinition, driven by the imperative to enhance customer engagement. Emerging technologies such as augmented reality, interactive displays, and intelligent tagging are now central to experiential retail strategies.

The ubiquity of technology in daily life, particularly among younger consumers, has prompted technology retailers to continually update store design and functionality (Leblebicioğlu & Uslu, 2017). These stores provide access to a broad range of digital devices essential to modern lifestyles, including smartphones, computers, cameras, and gaming consoles (Tek & Orel, 2008; as cited in Leblebicioğlu & Uslu, 2017). As product lifespans shorten and competition intensifies, retail strategies must be agile and adaptable (Polat, 2009).

Key spatial elements in store interiors include flooring, lighting, color schemes, product placement, checkout areas, signage, and layout configurations. Effective design captures attention and facilitates navigation and decision-making (Dunne & Lusch, 1999; Özgören, 2013; Gül, 2022). To understand the evolving nature of retail spaces, it is essential to ground the discussion in fundamental theoretical frameworks. Retail interior design is deeply rooted in environmental psychology, specifically the Stimulus-Organism-Response (S-O-R) model proposed by Mehrabian and Russell (1974). This model suggests that environmental stimuli (S) such as lighting, layout, and materials influence the internal emotional state of the consumer (O), which in turn dictates their behavioral response (R). Building upon this, Bitner's (1992) Servicescape framework emphasizes that the physical environment is a 'silent service provider' that shapes customer perceptions and social interactions. In the context of 2070 technology stores, these theories remain vital; as AI generates futuristic aesthetics, the core human-centric need for spatial coherence, emotional comfort, and intuitive navigation (atmospherics) continues to be the benchmark for successful design (Kotler, 1973). Flexibility in layout is crucial, with wayfinding systems supporting intuitive customer flow (Levy & Weitz, 2009). Store plans generally follow one of four models: grid, circular, spine, or free-flow layouts (Pekpostalcı, 2015). Ergonomic considerations such as circulation widths that accommodate diverse users are essential for accessibility and comfort (Mesher, 2013).

Technological enhancements in interior design such as AR interfaces, digital payment systems, and immersive displays support interactive and efficient customer experiences (Alemdar, 2010). Components like lighting and ventilation are integrated into ceiling structures, while durable flooring materials such as terrazzo or wood support long-term aesthetic and functional goals (Mesher, 2013).

Lighting plays a key role in shaping atmosphere and product visibility. High-intensity lighting draws customer attention, while energy-efficient LED solutions address sustainability concerns (Hussain & Ali, 2015). Strategic lighting design can guide customer focus and enhance spatial perception.

Retail design is increasingly aligned with smart systems that automate inventory recognition, monitor customer movement, and streamline payments. Future stores may eliminate traditional checkout areas altogether (Shankar, 2018). AI-powered robots are also being implemented to support product selection and in-store guidance (Gülşen, 2019).

Overall, contemporary retail design integrates brand identity, user experience, and technological functionality, underscoring the sector's responsiveness to rapid technological evolution (Shankar, 2018).

2.3 Prediction models for future store designs

The year 2070 is anticipated to mark a period of rapid technological advancement and societal change, presenting both opportunities and uncertainties in architectural forecasting. Complex interplays between technology, culture, and environmental concerns challenge the predictability of future design trends. However, current innovations and consumer insights suggest likely directions for the evolution of retail environments.

According to Blue Yonder (2022), future retail spaces will feature smart systems designed to enhance the customer experience. Findings from PwC's 2021 Consumer Insights Research in Turkey support this trend: 46% of participants emphasized the need for improved automated payment systems (e.g., QR codes), 45% requested in-store navigation tools, and 36% favored personalized messaging (PwC, 2021). Additionally, 68% of consumers valued the ability to physically experience products, underscoring the role of brick-and-mortar stores as immersive experience centers (Önder, 2022). This aligns with projections that future stores will adopt showroom-like formats, incorporating AR and VR technologies (Chew, n.d.).

Health and sustainability will also shape future retail design. Air quality and green building standards are expected to gain importance (Macomber & Allen, 2020), while population growth and urban density will drive vertical development. These conditions may lead to more compact yet efficient store configurations or multilevel retail formats (Archisoup, 2024).

Adaptability will be critical. Modular construction and advanced materials will enable flexible spatial configurations, allowing stores to respond dynamically to shifting consumer demands. Such flexibility will extend to interior layouts, product displays, and overall spatial organization (Archisoup, 2024).

Emerging technologies such as programmable matter which can alter shape, density, and color in response to stimuli may redefine how interiors are configured. Holographic surfaces are expected to gain traction, offering interactive displays controlled through gestures or neural inputs (Future Business Tech, 2022).

Voice assistants and smart digital price tags are also projected to become widespread. These tools enhance automation, enable real-time price updates, and facilitate personalized in-store interactions (Üçge, 2015; Lazarevich, 2017). AI-powered voice assistants can help customers locate products and access information, further improving the efficiency and appeal of physical shopping environments.

Collectively, these developments suggest that AI and emerging technologies will play an increasingly central role in shaping the functionality, adaptability, and experiential quality of future retail spaces.

2.4 Artificial intelligence and customer experience

Technological advancements in retail affect not only spatial design but also consumer behavior. Many brands now employ AI systems to analyze consumer preferences and personalize shopping experiences, transforming stores into interactive environments rather than mere points of sale (Shankar & Venkatesh, 2018). These systems enhance decision-making, product placement, and engagement, fostering greater customer satisfaction.

The implementation of adaptive AI methodologies originally developed in educational contexts has inspired similar strategies in retail, enabling personalized interactions and optimized spatial configurations based on user behavior (Kumar et al., 2024). AI technologies can track browsing patterns, predict needs, and recommend products, offering a dynamic, data-driven retail experience.

Today's store designs increasingly integrate brand identity, customer experience, and advanced technologies, reflecting a shift toward highly responsive, user-centered environments (Shankar, 2018). In this transformation, tools such as voice assistants and smart digital price tags are becoming prevalent. These technologies support automation and improve transparency by enabling real-time updates and contextual guidance (Üçge, 2015; Lazarevich, 2017). Voice assistants help users navigate stores, locate items, and access product information, enhancing convenience and autonomy.

Evaluation data from this study indicate that circulation space is considered a critical design factor. A high average success rate (87%) in this criterion demonstrates the importance of movement fluidity and accessibility in both current and future retail spaces. Similarly, technology integration achieved a high success rate (85%), signaling the anticipated dominance of digital and AI-driven systems in upcoming store models.

Design elements like augmented and virtual reality are expected to play a growing role in enhancing spatial interaction and experience. The combination of circulation fluidity, tech-enhanced environments, and human well-being reflects a forward-looking approach to customer-centered design.

In sum, AI-supported retail design is projected to create more fluid, adaptive, and engaging store environments by 2070. Designers and architects must respond to this shift by developing innovative, sustainable strategies that balance technological capabilities with human-centered values.

2.5 Conceptual framework and research gap

This literature review underscores the expanding role of AI across architecture, retail, and customer experience (Abuhassna et al., 2024; Kumar et al., 2024). AI enhances design workflows, enables personalized interactions, and fosters innovation (Yıldırım & Demirarslan, 2020; Samsul et al., 2023). However, a notable research gap exists in its application to forecasting and shaping future retail interiors especially in technology stores (Yıldız, 2023). These environments, shaped by rapid innovation, demand agile foresight yet risk overlooking human-centered considerations.

The conceptual grounding of retail interior design within this study is further strengthened by established environmental psychology models. Specifically, the Stimulus-Organism-Response (S-O-R) framework provides a theoretical basis for understanding how environmental cues such as lighting (q4), material diversity (q5), and circulation fluidity (q8) act as stimuli that shape professional perceptions and subsequent evaluative responses (Shankar & Venkatesh, 2018). Furthermore, Bitner's Servicescape theory is integrated to assess how the physical and technological environment of future stores influences spatial interaction, accessibility (q12), and human well-being (q14) (Shankar, 2018). These models help bridge the gap between AI's technical outputs and the human-centered sensory experience required in high-tech retail settings (Kok, 2025; Statista, 2023b).

The necessity of this theoretical expansion is further supported by professional industry reports, which highlight a growing consumer demand for technologically integrated and efficient retail spaces. For instance, projections indicate that AI could influence over $340 billion in global retail spending by 2025 (Statista, 2023a). Additionally, research by PwC (2021) in Turkey reveals that consumers increasingly expect automated payment systems (46%) and in-store navigation tools (45%), while Blue Yonder (2022) emphasizes the evolution of stores into immersive, omni-channel experience centers (PwC, 2021; Blue Yonder, 2022). These professional insights provide a contemporary anchor for the study's speculative foresight.

Existing studies typically address:

- **AI in architectural design,** emphasizing automation and generative creativity (Yıldırım & Demirarslan, 2020; Babilik et al., 2019);
- **Technological transformation in retail,** focusing on evolving consumer behaviors and spatial strategies (Shankar & Venkatesh, 2018; Celal, 2006);
- **Prediction models,** highlighting their use in strategic planning (Grewal et al., 2019; Haefner et al., 2023; Nahar, 2024);
- **AI-driven customer experience,** particularly through adaptive personalization (Kumar et al., 2024; Cerebro, 2018);
- **Educational bibliometric analyses,** offering interdisciplinary models for integrating AI and ML (Samsul, et al., 2023; Abuhassna et al., 2024).

Despite these contributions, few studies comprehensively explore how AI-generated projections can inform future technology store designs by integrating both spatial and experiential criteria (Abuhassna et al., 2024; Kumar et al., 2024). This research addresses that gap by: evaluating AI-driven visual predictions for 2070 technology store interiors; comparing them with current design standards and expert expectations; and assessing AI's capacity to propose innovative, user-centered spatial solutions.

The study adopts a conceptual framework built on three interconnected domains:

- Technological integration in spatial design (Shankar, 2018; Yıldırım & Demirarslan, 2020);

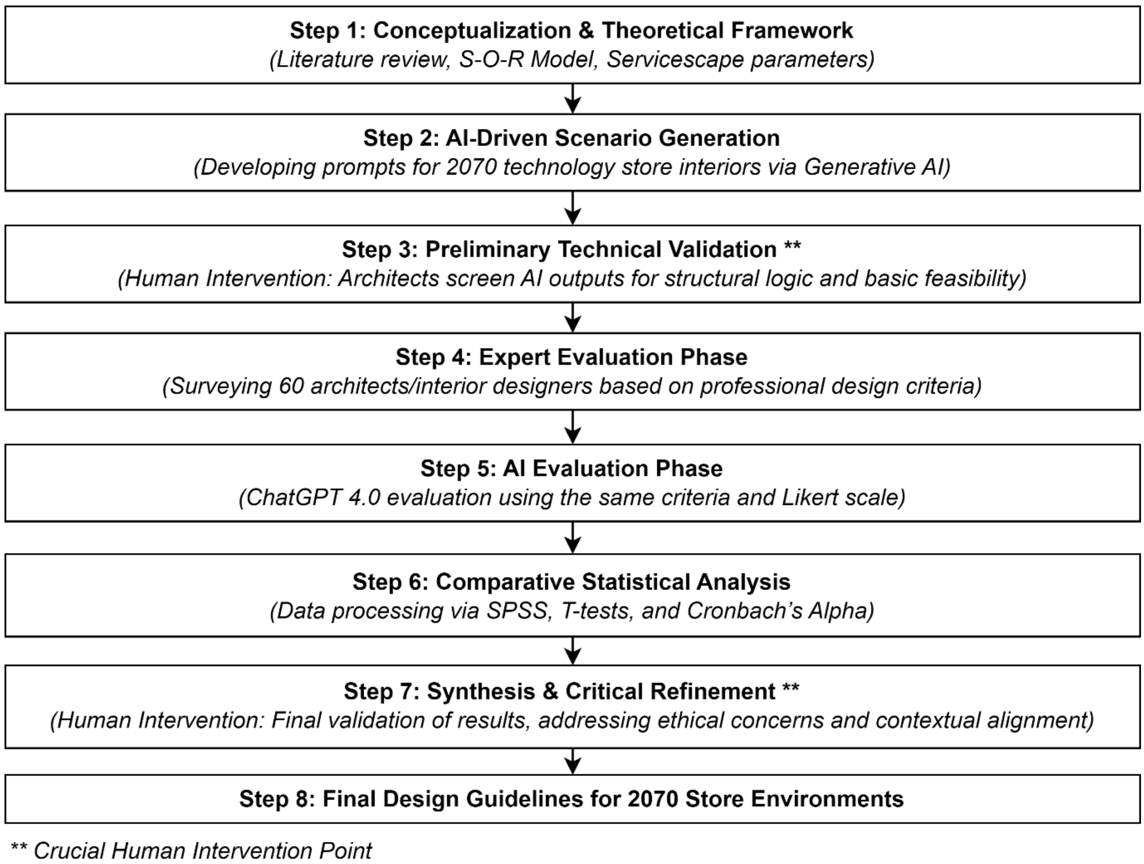

Figure 1 | Proposed AI-Human Collaborative Research and Design Process.

- Consumer-centered experience within retail environments, analyzed through the lens of S-O-R and Servicescape theories to assess the impact of speculative design on user-spatial interactions (Shankar & Venkatesh, 2018; Shankar, 2018);

- AI's predictive design capability, highlighting both potential and limitations (Statista, 2023a,b; Kok, 2025).

3. Methodology

This study adopts a mixed-methods approach to evaluate AI-generated interior designs for future technology stores. It integrates quantitative survey data from design professionals with qualitative assessments produced by ChatGPT 4.0. The methodology consists of three main stages: (1) generating visuals using AI prompts, (2) collecting expert evaluations via a structured survey, and (3) conducting parallel assessments using ChatGPT 4.0, followed by comprehensive data analysis. To clarify the systematic approach of this study, the integrated workflow incorporating both AI-driven generation and strategic human intervention points is illustrated in Figure 1. This model highlights the critical stages where professional expertise is required to validate AI outputs technically and ethically.

3.1 Defining prompts and generating visuals

To visualize interior environments of future technology stores, this study utilized the Playground v2.5 model via the Playground AI platform, selected for its balance between creative control, accessibility, and visual fidelity. Compared to alternatives such as Midjourney and DALL·E, Playground AI offered greater flexibility for iterative experimentation within the scope of speculative design research.

Prompt construction was informed by a targeted synthesis of literature review findings and the study's conceptual framework. To encourage generative breadth and avoid over-specification, prompts were deliberately kept concise. The primary prompt was: "An electronics store interior from the year 2070... 8k resolution, photo-realistic concept, holographic interior, futuristic visions, rendered in unreal engine, cyberpunk, adorned with interactive touch screens, digitalized space, future devices, quantum computers, and biotechnology devices". The images were generated using a square (1:1) aspect ratio and a 50% guidance scale; from a pool of over 100 trials, the five visuals that best represented the research criteria were selected for further analysis. These specific technical and aesthetic descriptors were prioritized to ensure high visual fidelity and thematic consistency. Furthermore, no negative prompts were used during the image generation process to allow the AI model to interpret the instructions without predefined exclusions.

Through iterative experimentation, numerous trials were conducted to achieve ideal visuals that accurately reflect future scenarios. From this extensive dataset, five visuals were selected using a representative sampling approach. The primary criteria for selection focused on the images' capacity to represent key design elements of 2070 technology stores, including spatial layout, technology integration, and product display arrangements. Special attention was given to "visual readability," ensuring that critical evaluation parameters such as internal organization, customer circulation, and the integration of technological components were clearly discernible for expert assessment.

To mirror the diversity found in contemporary retail concepts and avoid homogeneity, the selection also aimed to present a variety of store typologies, ensuring the five visuals offered distinct speculative spatial imaginaries rather than a uniform aesthetic. This selection ensured that different spatial configurations were represented while preventing "survey fatigue" among participants, thereby maintaining the reliability of the expert evaluations. The image generation process served not only as a methodological foundation for empirical testing but also as a form of visual forecasting, translating textual projections into spatial imaginaries. By integrating prompt engineering with AI-based generation tools, the study bridges speculative design with empirical assessment. (Figure 2).

3.2 Survey design and data collection

A 14-question survey was prepared based on the visuals generated with the support of artificial intelligence. The survey instrument was developed by the authors by synthesizing contemporary store design criteria with future-oriented retail projections identified in the literature. The development of this scale followed a systematic three-stage process to ensure its scientific rigor.

In the first stage (Item Generation), the evaluation criteria were derived from core design principles defined in retail and interior design literature, specifically focusing on product display layouts, circulation areas, lighting usage, material selection, ergonomics, accessibility, and user experience. For metrics concerning spatial organization and user movement, Neufert's architectural standards were utilized as a primary reference. Furthermore, emerging themes in the future of technology retailing such as advanced technology integration, experience-oriented spatial configurations, flexibility, and modularity were incorporated into the framework to bridge current standards with speculative foresight.

In the second stage (Content Validity), the draft items were reviewed by a panel of three senior architects each with over 15 years of experience to verify that the criteria accurately reflected the critical spatial and technological requirements of future technology stores. Based on their feedback, the wording of questions related to "technology integration" (q7) and "customer guidance" (q10) was refined to better encompass speculative design elements.

In the third stage (Pilot Testing), the survey was pre-tested with a small group of five design professionals to evaluate the clarity and comprehensibility of the questions. This pilot phase confirmed that the criteria were unambiguous and that the 5-point Likert scale was appropriate for capturing nuanced expert judgments. The subsequent high internal consistency (Cronbach's alpha = 0.88) achieved in the final administration further confirms the reliability of this refined 14-item scale.

The survey was conducted with 60 participants, comprising 38 architects and 22 interior designers. A hybrid data collection approach was used, combining online platforms with in-person sessions to facilitate clear communication regarding the speculative design context. These professionals were selected for their specific expertise in retail and technology integration, with professional experience ranging from 5 to 20 years across various practices. Detailed distribution of the sample and their experience levels are presented in Table 2.

The choice of 60 experts was guided by the principle of 'information power' and professional representation. In specialized research of this type, expert panels are typically smaller than general consumer surveys due to the high level of technical expertise required. Following the recommendations of Roscoe (1975), a sample size between 30 and 500 is considered appropriate for behavioral research. Furthermore, as established by Cochran (1977), a sample of 60 provides a high level of precision for evaluations involving specialized professional populations, ensuring the findings remain statistically robust and

Figure 2 | Visuals generated in the Playground AI platform.

Table 1 | Evaluation of visuals based on the criteria presented in the survey.

Evaluated Criterion	Theoretical Information Shared with Participants
q1. Floor durability	"The floor material in store design should be durable."
q2. Success in using walls and central elements for display areas	"Walls and central elements are used for product display."
q3. Success in using ceiling lighting and ventilation components	"Ceiling designs include necessary electronic and mechanical components such as lighting and ventilation."
q4. Success in using intense and emphasized lighting	"Intense lighting is important for attracting customers' attention and highlighting products."
q5. Material diversity	"Material use varies according to the concept."
q6. Compliance with human ergonomics	"Store arrangements should comply with human ergonomics."
q7. Level of technology integration	"Given the expectation that advanced technologies will be part of future retail design, technology integration should be successfully incorporated into interiors."
q8. Width and fluidity of circulation areas	"Circulation areas should be wide enough for two people to pass comfortably, whether standing or in a wheelchair."
q9. Use of payment points	"Payment areas should be designed in today's stores. However, it is predicted that checkout points may disappear in the future as payment processes become automated."
q10. Success in customer guidance	"Informative signage is important for customer guidance in current stores. However, it is anticipated that alternative methods to signage may emerge in the future."
q11. Suitability for product experience	"In today's stores, spaces where customers can directly experience products should be designed. In the future, it is expected that these experience areas will become more prominent."
q12. Accessibility in design	"Shopping spaces should be accessible."
q13. Flexibility and modularity in design	"Store designs should be flexible and adaptable."
q14. Consideration of human well-being	"Human well-being is an important criterion in store designs."

Table 2 | Distribution of participants by professional background and experience (n=60).

Professional Group	Number of Participants (n)	Percentage (%)	Minimum Professional Experience (Years)
Architects	38	63.3%	5 to 20 Years
Interior Designers	22	36.6%	5 to 20 Years
Total	60	100%	5 to 20 Years

representative. To maintain focus on professional qualifications and ensure participant anonymity, no additional demographic data such as age or gender was collected, allowing the analysis to reflect diversity in expertise rather than broader demographic segments.

3.3 Ethical statement

This research was conducted in accordance with the ethical principles for research involving human participants. At the beginning of the survey, all participants were presented with a comprehensive information sheet and an ethical disclaimer outlining the study's objectives, the voluntary nature of their involvement, and the absolute anonymity of their responses. Informed consent was obtained based on the principle of implied consent; by choosing to proceed and initiate the survey after reviewing the ethical guidelines, participants formally indicated their voluntary agreement to participate in the study.

Since the research relied exclusively on anonymous expert opinions regarding architectural visualizations and did not involve the collection of sensitive personal, medical, or identifiable biometric data, it was classified as a non-invasive, observational expert-based study. Under current academic guidelines, formal ethics committee approval was not required for this type of anonymous professional consultation, as it posed no risk to the participants and focused solely on design-related evaluations. All data were processed anonymously to maintain the highest standards of academic integrity and ensure participant privacy.

3.4 ChatGPT 4.o evaluation

To complement expert evaluations, the study incorporated an AI-based assessment using ChatGPT 4.0. This component aimed to contrast machine-based analytical reasoning with human judgment, particularly in interpreting design concepts for future technology stores. ChatGPT 4.0 was selected for its broad training on architectural principles, retail design trends, and speculative foresight.

Prior to evaluation, the model was primed with contextual data derived from the literature review, including key design principles and future-oriented projections. Using structured prompts aligned with the 14 survey criteria, ChatGPT was instructed to provide ratings on a 1–5 scale mirroring the human survey format.

Multiple iterations were conducted to ensure reliability across outputs. While ChatGPT demonstrated strong alignment with quantifiable criteria such as technology integration, its assessments on subjective elements e.g., human well-being or customer guidance, required critical interpretation.

Rather than replacing human insight, the AI evaluation served as a secondary analytical lens, exposing potential biases and highlighting the tension between algorithmic objectivity and experiential nuance. This dual-assessment approach underscores the study's commitment to exploring human–AI synergy in design evaluation.

3.4 Data analysis techniques

The analysis employed both descriptive and inferential methods to assess expert and AI evaluations. Internal consistency of the 14-item scale was confirmed using Cronbach's alpha. Normality tests (Shapiro-Wilk) indicated non-normal data distribution, prompting the use of non-parametric techniques. Mann-Whitney U tests compared responses between architects and interior designers, while Spearman correlations explored relationships among design criteria. Exploratory Factor Analysis (EFA) was used to reveal underlying dimensions, and K-means clustering identified expert evaluation profiles. To examine agreement between human and AI assessments, a Bland-Altman analysis was conducted. This highlighted systematic differences, particularly AI's tendency toward optimism in quantifiable criteria. Overall, this multi-method strategy enabled a robust examination of both evaluative trends and AI-human discrepancies in future-oriented store design assessments.

Given the non-normal distribution of the Likert-scale data ($p < 0.01$ in Shapiro-Wilk tests), non-parametric methods including Mann-Whitney U and Spearman's Rho were strictly applied to maintain statistical validity. Furthermore, while traditional Intraclass Correlation Coefficient (ICC) is often preferred for continuous data, this study utilized Cronbach's Alpha (0.88) to confirm internal consistency and Bland-Altman analysis to assess the systematic agreement and bias between human and AI evaluators.

4. Findings and analysis

This section presents a comprehensive statistical examination of the expert evaluations regarding AI-generated visualizations of technology stores for the year 2070. A range of methods were employed to ensure the reliability, consistency, and interpretability of the data gathered from 60 professionals, including architects and interior designers. The analyses include reliability testing, distribution assessment, correlation examination, dimensional reduction, clustering, and AI-human evaluation comparison.

4.1 Internal consistency: Cronbach's alpha

To determine the internal consistency of the 14 survey items rated on a five-point Likert scale, Cronbach's alpha was calculated. This statistical technique is widely used to evaluate the reliability of instruments that measure latent variables, especially in design and behavioral research settings (Tavakol & Dennick, 2011). While the overall scale reliability is represented by a single Cronbach's Alpha coefficient, the contribution of each individual item to this consistency is evaluated through item-total correlations.

The resulting Cronbach's Alpha coefficient was *0.88,* indicating a high degree of internal consistency among the evaluation items. Figure 3 visualizes these item-total correlations, illustrating how each specific design criterion aligns with the overall scale construct. This suggests that the criteria selected to assess the AI-generated store visuals were cohesive and measured a unified construct related to futuristic retail design expectations.

When examining the contribution of individual criteria to the overall reliability, certain items stood out:

- "Technology Integration" (q7: evaluating how effectively technological systems were incorporated) exhibited a strong positive item-total correlation with the total scale, suggesting that experts consistently valued technological foresight as central to futuristic store environments.

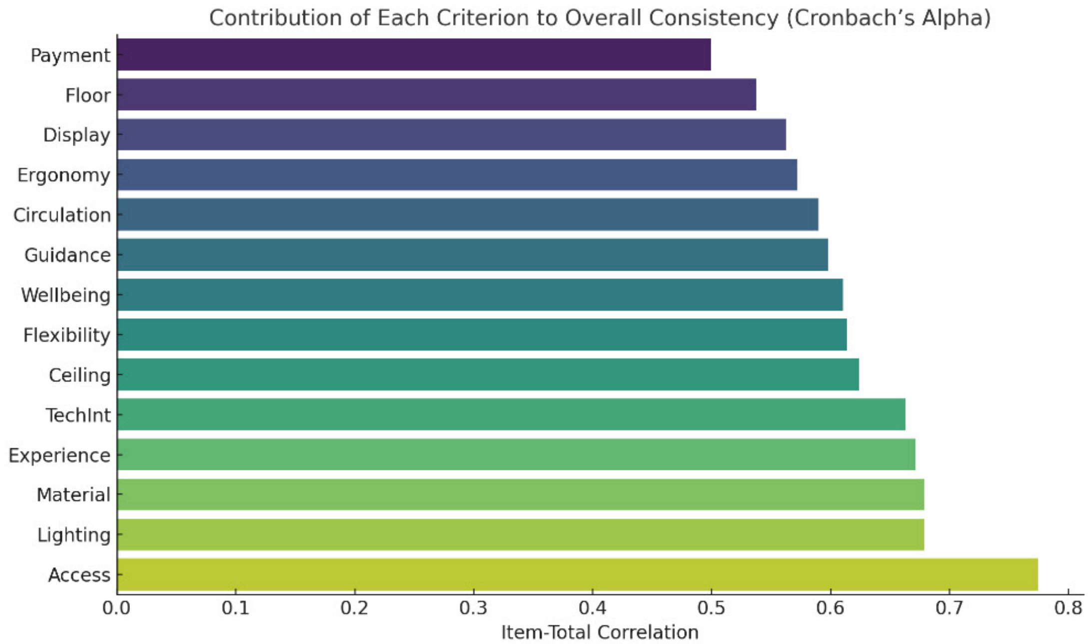

Figure 3 | Item-total correlations for survey criteria representing individual contribution to internal consistency.

- "Accessibility" (q12: assessing user-friendliness for diverse customer groups) and "Human Well-being" (q14: measuring environmental support for comfort and health) also showed high item-total correlations, underscoring the importance of inclusive and health-oriented spatial qualities.

- On the other hand, "Emphasized Lighting" (q4: the strategic use of intense lighting for highlighting focal points) showed a slightly lower item-total correlation, possibly reflecting varied expert expectations regarding lighting intensity in different store typologies.

These findings affirm that the survey was methodologically sound and that the diverse yet interconnected set of evaluation criteria reliably captured expert perceptions regarding the design of future technology stores. The comprehensive reliability and validity metrics, including KMO and Bartlett's test results, are summarized in Table 3.

4.2 Distribution of responses: Shapiro-Wilk normality test

In order to choose appropriate inferential techniques for further analyses, the normality of score distributions were examined for each survey item using the Shapiro-Wilk test. This method is widely recognized for its power and accuracy in detecting non-normality in moderate-sized datasets (Razali & Wah, 2011).

The test revealed that none of the 14 evaluation criteria followed a normal distribution, as all p-values were below 0.01. For instance, the item regarding "Circulation Space Width" where participants assessed whether aisles were wide enough to facilitate comfortable movement had a Shapiro-Wilk statistic of 0.74 ($p < 0.00001$), indicating a significant deviation from normality. Similarly, the item "Customer Guidance Systems," which prompted experts to evaluate whether signage and wayfinding systems supported intuitive navigation, achieved a Shapiro-Wilk statistic of 0.91 ($p = 0.0006$).

Other notable deviations included:

- "Technology Integration," assessing how well new technologies were incorporated into the retail environment ($p < 0.0001$),

- "Product Display Area Usage," evaluating the adequacy and attractiveness of product exhibition spaces ($p < 0.0005$),

- "Flexibility," measuring the adaptability of the store layout for future modifications ($p = 0.0003$).

Given these results, non-parametric methods such as the Spearman correlation and Mann-Whitney U tests are preferred in the subsequent analyses.

Table 3 | Reliability and validity metrics of the evaluation scale.

Statistical Measure	Value / Result	Interpretation
Cronbach's Alpha	0.88	High Internal Consistency
KMO Measure of Sampling Adequacy	Verified	Suitable for Factor Analysis
Bartlett's Test of Sphericity	p < 0.001	Statistically Significant
Factor Extraction Method	Standard Extraction	Non-rotated (Standardized Scores)

4.3 Correlation analysis: interrelationships among design criteria

to explore how various design criteria evaluated by the experts are interrelated, a correlation analysis was conducted using the Spearman rank-order correlation method. Spearman's rho is particularly suitable for ordinal data and non-normally distributed variables, making it ideal for Likert-scale evaluations (Schober et al., 2018). This analysis helps identify which aspects of store design tend to be rated similarly, thus revealing underlying patterns in expert perceptions (Figure 4).

The analysis revealed several statistically significant positive correlations among the evaluated criteria. For instance:

- There was a strong positive correlation ($p = 0.60$) between "Accessibility" (q12: assessing whether shopping spaces are accessible to all users, including those with disabilities) and "Human Well-being" (q14: evaluating if the store environment enhances physical and emotional comfort).
- "Accessibility" also showed strong correlations with "Emphasized Lighting" (q4: the effective use of intense lighting to highlight products) ($p = 0.54$) and "Product Experience Spaces" (q11: evaluating whether designated areas allow customers to interact directly with products) ($p = 0.53$).
- "Technology Integration" (q7: assessing the seamless incorporation of advanced digital systems into the store environment) correlated positively with "Flexibility and Modularity" (q13: evaluating the adaptability of store layouts for future reconfigurations) ($p = 0.50$).
- A moderate correlation was observed between "Material Diversity" (q5: evaluating the richness of material selection to enhance spatial quality) and "Human Well-being" (q14), suggesting that diverse and thoughtful material usage contributes to a healthier and more engaging retail environment.

The strong linkage between accessibility and well-being ($\rho = 0.60$) signals that inclusive design is foundational to experiential quality, not an add-on. Conversely, weaker correlations for lighting intensity (q4) reveal contextual ambiguity-suggesting AI's struggle to interpret situational nuance in spatial narratives.

These interrelationships suggest that experts perceive accessible, experience-rich, and technologically integrated environments as interconnected pillars of effective future retail design. It also highlights how ergonomic circulation, sensory engagement (through lighting and materials), and flexible spatial organization collectively shape a positive customer experience.

4.4 Professional group comparison: Mann-Whitney U Test

To examine potential differences between architects and interior designers regarding their evaluation of AI-generated store designs, the Mann-Whitney U test was employed. This non-parametric test was selected because the data did not meet the normality assumption, as confirmed by the Shapiro-Wilk test (Razali & Wah, 2011). The results indicated that while both professional groups shared a consistent understanding of futuristic designs across most criteria, significant differences emerged in specific areas. As shown in Table 4, architects placed a significantly higher emphasis on Material Diversity ($U = 324.5$, $p = 0.003$) and Circulation Area ($U = 351.0$, $p = 0.007$) compared to interior designers. This highlights a professional divergence where architects prioritize structural and flow-related parameters more intensely, even as they maintain a shared perspective on broader technological themes.

4.5 Dimensionality reduction: Exploratory Factor Analysis (EFA)

To identify potential latent dimensions underlying the 14 survey items, an Exploratory Factor Analysis (EFA) was conducted. EFA is a widely used data reduction technique in social sciences, helping to uncover the underlying structure of a large set of variables and group related items into coherent factors (Fabrigar et al., 1999).

Given the non-normal distribution of the dataset and the ordinal nature of the data, a standard factor extraction method without rotation was applied to the standardized scores. The analysis revealed a three-factor solution that captured the essential relationships among

Figure 4 | Heatmap of strong Spearman correlations between design criteria.

Table 4 | Comparison of evaluations between architects (n=38) and interior designers (n=22).

Criterion	Mann-Whitney U	p-value	Significance / Effect
Material Diversity (q5)	324.5	0.003*	Significant (Architects > ID)
Circulation Area (q8)	351.0	0.007*	Significant (Architects > ID)
Technology Integration (q7)	-	$p > 0.05$	No Significant Difference
Human Well-being (q14)	-	$p > 0.05$	No Significant Difference
Other Criteria (*Average*)	-	$p > 0.05$	Generally Consistent

**Significance level α = 0.05*

the evaluated criteria (Figure 5). The factor analysis results indicated that the identified dimensions accounted for a substantial proportion of the total variance, confirming that the three-factor structure effectively represents the underlying patterns in the expert evaluations.

The following groupings emerged from the factor structure:

Factor 1: Human-Centered and Experiential Design

This factor grouped together criteria such as:

- "Accessibility" (q12: ensuring easy access for all users, including those with disabilities),
- "Human Well-being" (q14: promoting comfort and health within the retail environment),
- "Material Diversity" (q5: using varied materials to enrich spatial quality),
- "Product Experience Spaces" (q11: providing areas for direct customer interaction with products).

These items reflect a shared emphasis on creating engaging, inclusive, and comfortable shopping experiences, central to human-centered design thinking.

Factor 2: Operational Functionality

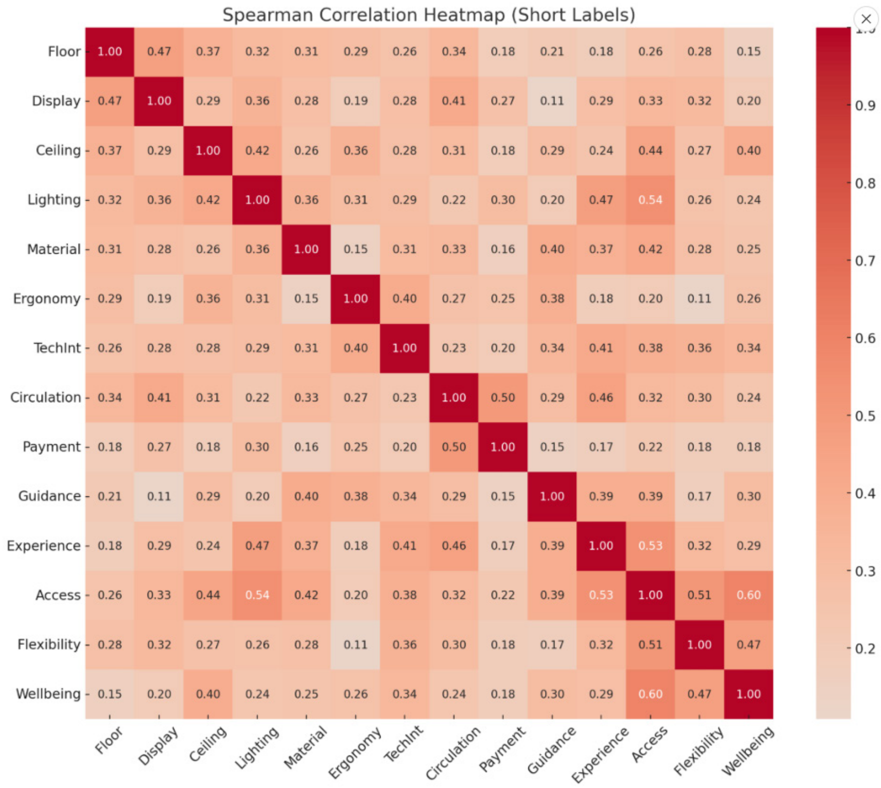

Figure 5 | Factor loadings heatmap of survey items.

This factor showed moderate loadings for:

- "Circulation Space Width" (q8: ensuring wide aisles for fluid movement),
- "Payment Point Organization" (q9: strategically placing checkout points for efficiency),
- "Ergonomics" (q6: considering human physical comfort in spatial arrangements).

Collectively, these criteria highlight the operational and functional aspects necessary for efficient store layouts.

Factor 3: Spatial Adaptability

- The third factor, although weaker, captured variations mainly related to:
- "Product Display Area Usage" (q2: optimizing product exhibition spaces),
- "Flexibility and Modularity" (q13: enabling store layout adaptability for future needs).

This dimension underscores the growing importance of flexible, reconfigurable retail environments capable of adapting to technological and consumer trends.

These results demonstrate that experts perceive futuristic store design along three primary dimensions: human-centered experiential quality, operational efficiency, and flexible spatial adaptability. The specific factor loadings and associated key themes for each design criterion are detailed in Table 5. The extracted factors were selected based on their conceptual relevance and statistical contribution to the total variance, ensuring that the primary dimensions of the design evaluations were effectively captured and represented.

4.6 Cluster analysis: identification of expert evaluation profiles

To further explore whether the professional evaluations could be segmented into distinct patterns of perception, a K-means cluster analysis was performed (Figure 6). Cluster analysis is an unsupervised learning technique that partitions participants into mutually exclusive groups based on their similarity across multiple dimensions (Hair et al., 2010).

Given the nature of the survey data, a two-cluster solution was initially tested to uncover potential expert profile differences.

The analysis revealed two distinct clusters among the 60 participants:

Cluster 1 *(n=45):*

This majority group exhibited generally high evaluations across criteria related to human-centered design, such as:

- “Accessibility” (q12: facilitating inclusive access for all users),
- “Human Well-being” (q14: enhancing customer comfort and emotional well-being),
- “Material Diversity” (q5: promoting sensory richness through varied material use).

Participants in this cluster emphasized the importance of creating emotionally supportive and engaging shopping environments, aligning with trends in experiential retail design.

Cluster 0 *(n=15):*

This smaller group placed relatively greater emphasis on operational efficiency and technological integration, reflected in criteria like:

- “Technology Integration” (q7: embedding advanced technological features into the spatial design),
- “Flexibility and Modularity” (q13: ensuring adaptable and reconfigurable store layouts),
- “Payment Point Organization” (q9: strategically managing customer flow and transaction points).

These participants appeared more focused on practical functionality and technological readiness of store designs for future needs. Cluster 0’s prioritization of operational efficiency (n=15) reflects an industry trend toward automation, yet risks marginalizing human well-being a tension echoing broader ethical debates about AI’s role in dehumanizing spaces. This divergence underscores the need for design protocols that reconcile technical prowess with psychosocial stewardship.

Overall, the cluster analysis suggests that while a broad consensus exists regarding the overall vision for future technology stores, professional perspectives diverge between those prioritizing human experience and those emphasizing operational-technological efficiency. This segmentation may reflect differences in participants’ professional backgrounds (e.g., architecture vs. technology design) or personal design philosophies.

Figure 6 | Cluster analysis of expert evaluation profiles.

Table 5 | Exploratory Factor Analysis (EFA) results and factor loadings.

Factor Label	Associated Criteria (High Loadings)	Key Theme
Factor 1	q5, q11, q12, q14	Human-Centered & Experiential
Factor 2	q6, q8, q9	Operational Functionality
Factor 3	q2, q13	Spatial Adaptability

4.7 Comparison of human and AI evaluations: Bland-Altman analysis

To assess the level of agreement between human expert evaluations and AI-based assessments (specifically ChatGPT 4.0), a Bland-Altman analysis was conducted (Figure 7). This method is widely used to evaluate the consistency and interchangeability of two measurement techniques by plotting the differences against the averages (Bland & Altman, 1986).

Unlike simple correlation, which measures association, Bland-Altman analysis reveals the actual bias and variability between methods, providing a deeper understanding of how AI assessments align or deviate from human judgments.

In this study, the average human expert evaluation success rate across all 14 design criteria was 77.1%, while the corresponding average success rate from ChatGPT was 86%. The Bland-Altman analysis revealed a mean

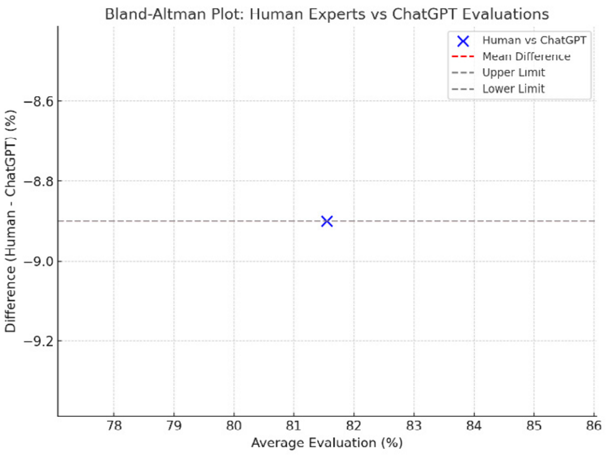

Figure 7 | Bland-Altman plot comparing human expert and ChatGPT evaluations.

difference (bias) of -8.9%, indicating that ChatGPT consistently rated the AI-generated store designs approximately 9 percentage points higher than human experts (Figure 6). This identified systematic bias represents a moderate-to-high effect size in the divergence between algorithmic optimism and human expert conservatism. The detailed metrics of this agreement analysis, including the limits of agreement, are provided in Table 6. ChatGPT's 9% over-optimism isn't random error but systemic bias favoring quantifiable criteria (e.g., technology integration). This exposes AI's blind spot: its training data lacks embodied, sensory knowledge critical for evaluating human-centered domains like well-being (q14) or guidance (q10), where expert conservatism anchors realism.

Despite this systematic bias, the relatively narrow limits of agreement observed suggest a consistent pattern:

- ChatGPT's assessments tend to be more optimistic, especially for criteria emphasizing technology integration (q7) and flexibility (q13).
- Human experts, on the other hand, were more conservative in their evaluations, particularly regarding emotional well-being (q14) and customer guidance systems (q10), which require nuanced, experience-based judgments.

These findings highlight an important distinction: while AI can offer reasonably consistent and scalable evaluations, it may overestimate success in areas demanding subtle human-centered considerations. Therefore, although ChatGPT provides valuable preliminary insights, human oversight remains crucial, particularly in complex domains like architectural design where subjective experience and empathy are vital.

5. Conclusion

This research aimed to examine the potential of AI in shaping the future of technology store design, employing a mixed-methods approach that integrated quantitative expert evaluations with qualitative insights from ChatGPT 4.0. By generating AI-driven visualizations of stores projected in 2070 and evaluating them against established design criteria, this study sought to provide actionable insights for designers and retailers navigating the integration of AI into the retail sector.

The findings reveal a complex interplay between human expertise and AI capabilities. Preliminary analyses confirmed the survey instrument's reliability (Cronbach's alpha = 0.88), indicating strong internal consistency among the evaluation items. However, the non-normal distribution of the data confirmed by Shapiro-Wilk tests necessitated the use of non-parametric tests. Contrary to initial broad assessments, comparative analyses using Mann-Whitney U tests highlighted significant professional divergences in specific criteria. Architects placed a significantly higher emphasis on material diversity ($U = 324.5$, $p = 0.003$) and circulation area ($U = 351.0$, $p = 0.007$) compared to interior designers, underscoring the importance of considering diverse professional perspectives in the AI-driven design process.

Furthermore, Spearman correlation analyses unveiled significant relationships between key design elements. Technology integration was positively correlated with both accessibility ($\rho = 0.54$) and human well-being ($\rho = 0.60$), suggesting that a focus on advanced technologies can enhance both functionality and user satisfaction in future store designs. The correlation between these elements implies that strategies focused on AI technologies like those driving smart mirrors or dynamic displays must emphasize convenience for continued gains for clientele.

The 9% AI-human evaluation gap isn't merely statistical noise but evidence of AI's inherent reductionism. While AI excels in generating modular, tech-forward concepts, it falters in interpreting cultural subtleties and emotional needs realms where human insight remains irreplaceable. To ensure AI can best capture the scope of needs, future avenues for research include: exploring the integration of cultural and regional design elements into AI systems to create more contextually relevant designs; examining the ethical implications of AI in design, particularly regarding bias, transparency, and the potential impact on human creativity and employment; investigating how AI can be used to create more sustainable and energy-efficient store designs; and examining the impact of AI on architectural

Table 6 | Agreement between human experts and ChatGPT 4.0 (Bland-Altman metrics).

Metric	Value	Interpretation
Mean Human Success Rate	77.1%	Conservative/Realistic
Mean ChatGPT Success Rate	86.0%	Optimistic
Mean Difference (Bias)	-8.9% (approx. 9%)	Systematic AI Optimism
Limits of Agreement	Narrow	Consistent Pattern of Bias

education and training, exploring how future architects and designers can be effectively trained to work alongside AI tools and leverage their capabilities.

Future work must also formalize 'ethical calibration' protocols for AI, embedding equity audits and sensory validation into predictive models. For instance, equity audits could involve mandatory simulation of diverse user profiles during AI training to preempt accessibility oversights. This synergy could redefine retail not as transactional arenas but as community-centric habitats.

These findings have several important implications for the future of technology store design. First, they suggest that AI has the potential to be a valuable tool for generating innovative and visually compelling designs, but recognizing AI's limitations and incorporating human expertise, particularly in areas requiring nuanced judgment and contextual awareness, is also crucial. Second, the study highlights the importance of creating store environments that are both technologically advanced and human-centered, emphasizing accessibility, well-being, and positive customer experiences. The findings suggest that creating a futuristic store design that is both high-tech and accessible creates the best user experience and is not easily replaceable.

Nevertheless, it is important to acknowledge the limitations of this research. The sample size of expert evaluations (n=60), while sufficient for preliminary insights, may not capture the full spectrum of professional perspectives, potentially amplifying the observed 9% AI-human evaluation gap. Similarly, reliance on a single AI platform (Playground AI) limits the generalizability of the findings other systems like DALL-E or Midjourney could produce visuals with different biases.

Beyond methodological improvements, the evolving role of AI in architecture highlights the need to reconsider architectural education. Training curricula should focus not only on technical competencies related to AI systems but also on developing critical thinking skills that emphasize ethical awareness, creativity, and human-centered design. Equipping future professionals with these capabilities will ensure that AI-driven innovations continue to enhance rather than replace the human essence of architectural design.

In conclusion, this research contributes to the growing body of literature on technological forecasting in the retail sector and provides actionable insights for designers and retailers seeking to harness the power of AI. While AI offers tremendous potential for innovation and efficiency in store design, human expertise, ethical considerations, and a focus on creating positive customer experiences and human well-being should remain central to the design process.

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