Enhancing Interior Design by Exploring Mindset and Preferences of Twitter (X) Users

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Abstract

Selecting an appropriate interior architectural solution often remains challenging because applicants' underlying design mindsets are not fully captured, while designers' stylistic orientations may unintentionally dominate decision-making. As users' attitudes and preferences toward interior architectural styles evolve over time, ignoring these dynamics can lead to misalignment between applicants and designers, ultimately affecting design outcomes. This research aims to improve interior architecture outcomes by identifying users' evolving design mindsets and systematically relating them to interior designers whose stylistic orientations are most compatible, before assigning an interior designer to an applicant. To this end, large-scale social media data from Twitter (X) are analyzed using an AI-based analytical approach. User-generated content is examined through sentiment analysis to capture expressed attitudes toward interior architectural styles across time, and these attitudes are represented as temporally informed user profiles. Based on these profiles, an optimized clustering strategy is employed to model both designers' relatively stable stylistic orientations and users' evolving design mindsets. By linking users to designers with closely aligned stylistic and cognitive patterns, the proposed approach enables more compatible designer–applicant matching. Overall, the approach supports more informed design decisions and contributes to improved interior architectural outcomes by reducing stylistic mismatch and enhancing alignment between applicants' mindsets and designers' design approaches.

Keywords: *Interior Architecture Style Preference, User Mindset Modeling, Twitter (X) User Data, Sentiment Analysis, and Optimized Clustering approach.*

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1. Introduction

Interior architecture is not merely the arrangement of furniture, finishes, lighting, color, and spatial components; it is a human-centered discipline through which built environments are shaped to support functional performance, emotional comfort, identity, and everyday behavior. The quality of an interior environment depends not only on technical correctness or visual coherence, but also on the extent to which the space corresponds with the psychological expectations, lived experiences, and aesthetic orientations of its users. Design principles such as balance, rhythm, proportion, unity, emphasis, contrast, and harmony provide a formal basis for organizing interiors, yet the success of these principles ultimately depends on how they are perceived and experienced by occupants [1]. Interior architectural elements can influence mood, attention, behavior, interpersonal interaction, and perceived comfort, which makes the relationship between spatial design and human psychology a central concern in design practice [2]. Evidence from virtual-reality studies similarly indicates that different interior configurations may produce distinct responses in psychological well-being and mental health, underscoring the need to consider users' emotional reactions when evaluating design alternatives [3].

Despite this human-centered imperative, the conventional interior design process often remains designer-led. Clients may participate through interviews, mood boards, questionnaires, precedent images, and consultation sessions, but these methods do not always reveal the deeper structure of their preferences. A client may describe a desired space as "modern," "comfortable," or "luxurious," while attaching meanings to these terms that differ substantially from those assumed by the designer. Preferences may also be hybrid, internally inconsistent, or difficult to verbalize. Consequently, a designer's established stylistic vocabulary can unintentionally dominate the process, creating a gap between the client's underlying mindset and the final architectural solution. Evidence-based design has been proposed as a means of making design decisions more transparent and responsive, while circular and iterative design processes can support more informed choices across the project lifecycle [4]. However, a persistent challenge is how to generate reliable evidence about users' preferences before major design decisions are made.

This challenge is becoming more important as interior design is transformed by digital technologies. Digital modeling, visualization, virtual environments, automated documentation, and computational analysis have altered the way interiors are conceived, represented, evaluated, and communicated [5]. Digital information technologies have also expanded the possibilities for designing temporary and permanent exhibitions by enabling more flexible presentation, interaction, simulation, and information management [6]. In parallel, modern technologies and artificial intelligence have increasingly entered the design of interior spaces, providing tools for ideation, decision support, pattern recognition, simulation, and operational improvement [7]. A systematic review of artificial intelligence in interior design shows that AI is now being applied across multiple stages of the design process, although questions remain concerning integration, professional roles, ethics, reliability, and the preservation of human creativity [8].

The architectural and engineering literature demonstrates a broad range of AI applications. Artificial intelligence has been used in conceptual architectural design to explore alternatives, support generative processes, and assist designers in navigating large solution spaces [9]. Deep learning has been integrated into CAD/CAE environments to generate three-dimensional concepts and evaluate their engineering performance, illustrating how generative systems can link design production with technical assessment [10]. AI-assisted CAD methods have also been applied to interior layout generation, where computational models can support the arrangement and evaluation of spatial elements [11]. Related studies have developed AI-based systems for evaluating interior design schemes and establishing structured assessment frameworks for design alternatives [12, 13]. These developments indicate that AI can serve not only as a drafting or visualization tool, but also as an evaluative mechanism capable of comparing design options according to multiple criteria.

Optimization is another major area of AI-enabled design research. Multi-objective algorithms have been used to optimize building interiors and spatial structures by balancing competing requirements and improving the efficiency of design configurations [14]. Data-driven intelligent systems have been proposed to assist the design of interior environments, using computational models to improve decision-making and recommendation processes [15]. Embedded digital imaging and artificial intelligence have further supported interior design visualization, information processing, and practical design development [16]. Virtual-reality-based optimization has enabled designers and users to experience and assess spatial alternatives before construction, thereby improving the evaluation of scale, composition, and environmental quality [17]. Intelligent three-dimensional virtual technologies have similarly been applied to smart-home interiors, where visualization and computational interaction can help coordinate spatial functions and user needs [18].

AI applications have also expanded beyond spatial configuration to include design management, cultural representation, and creativity. Artificial intelligence has been used to improve the management of interior design operations by supporting coordination, scheduling, and process efficiency [19]. In culturally responsive design, traditional elements can be interpreted and incorporated into contemporary interiors through AI-assisted analysis of patterns, colors, forms, and spatial compositions [20]. The concept of "Robotecture" highlights the possible effects of robotics and AI on creative production in interior spaces, suggesting that machine-supported processes may reshape both the designer's role and the nature of originality [21]. More speculative discussions regarding the progression from artificial intelligence toward artificial consciousness further raise questions about agency, interpretation, and the future relationship between human designers and intelligent systems [22]. At the broader engineering level, emerging AI methods have demonstrated the value of machine learning, pattern recognition, and deep learning for solving complex structural and design problems [23], while smart-society applications show how big-data scheduling and intelligent maintenance can improve the management of built environments [24].

Although these studies confirm the growing technical capacity of AI, much of the literature concentrates on automation, optimization, visualization, evaluation, or process efficiency. Comparatively less attention has been given to a prior and fundamentally human question: whose preferences should guide the design, and how can those preferences be inferred accurately? A technically optimized interior may still be unsuccessful when it is inconsistent with the client's emotional orientation, symbolic expectations, or stylistic mindset. Moreover, design preferences are not necessarily stable. They may change with age, cultural exposure, housing conditions, economic circumstances, emerging trends, professional experience, and repeated encounters with images and discussions online. A one-time questionnaire therefore offers only a static representation of a potentially evolving preference structure. The development of more responsive interior design systems requires methods capable of detecting not only what users prefer, but also how their preferences develop over time.

Social media offers a potentially valuable source of such evidence. The global expansion of digital platforms has produced an environment in which billions of individuals encounter, share, evaluate, and discuss visual and cultural content on a routine basis [25, 26]. Twitter, now known as X, is especially relevant because users publicly express short-form reactions, judgments, interests, and emotions through posts, hashtags, replies, and reposts. Unlike formal surveys, these expressions are generated in ordinary communicative settings and may therefore capture spontaneous attitudes that users would not necessarily articulate during a design consultation. Text mining on platforms such as Twitter and Facebook has established the value of social media data for identifying themes, opinions, and behavioral patterns in large volumes of unstructured text [27]. Sentiment-enhanced information discovery can further improve the extraction of socially meaningful signals from online content by incorporating the polarity and intensity of users' evaluations [28].

Sentiment analysis provides the principal computational bridge between user-generated text and interpretable preference information. It seeks to identify whether a text expresses a positive, negative, or neutral orientation and, in more advanced systems, to estimate emotional strength, subjectivity, and contextual meaning. Yet social media language is complex: posts are brief, informal, context-dependent, and frequently contain slang, irony, abbreviations, emojis, negation, and ambiguous word senses. These features make sentiment classification a nontrivial natural-language-processing problem [29]. Surveys of social-media sentiment analysis emphasize the diversity of available techniques and the importance of preprocessing, feature representation, contextual interpretation, and domain adaptation [30]. Lexicon-based methods offer interpretability and low computational cost, whereas machine-learning methods can capture more complex patterns when sufficiently large labeled datasets are available [31]. Contemporary reviews also highlight the growing importance of credibility, conversational structure, and interaction context in the interpretation of online sentiment [32].

Recent advances have improved the analytical sophistication of sentiment systems. Self-supervised attention mechanisms can incorporate lexical sentiment strength to enhance the representation of affective meaning [33]. Hybrid recommendation systems increasingly combine deep learning with lexicon-based sentiment analysis to exploit both contextual pattern learning and interpretable affective signals [34]. Deep learning and lexical investigation have also been jointly applied to large collections of evaluative text, showing the usefulness of combining statistical representation with language-based interpretation when analyzing opinions and experiences [35]. These developments suggest that sentiment analysis can move beyond the classification of isolated statements and contribute to richer user profiles. In the context of interior design, repeated positive or negative expressions toward particular styles, materials, spatial qualities, or cultural motifs can be aggregated to represent a person's evolving orientation across multiple design categories.

However, user profiling alone does not resolve the challenge of matching individuals with appropriate designers. The resulting sentiment profiles must be organized into meaningful groups that reflect similarity, hybridity, and temporal change. Clustering is well suited to this purpose because it does not require predefined class labels and can identify latent structures within multidimensional data. This is important in interior design, where users may simultaneously align with several stylistic tendencies and where fixed labels may obscure mixed or transitional preferences. Metaheuristic methods have become increasingly prominent for clustering because conventional algorithms can be sensitive to initialization, local optima, and irregular data distributions [36]. Hybrid optimization strategies, such as artificial bee colony methods improved through whale optimization, have demonstrated the potential to enhance cluster quality and convergence

[37]. More recent weighted k-means and gray wolf optimization methods likewise seek to improve the balance between exploration and exploitation in clustering problems [38]. Firefly-based optimization has also been employed in cluster-based data aggregation, illustrating the broader usefulness of swarm intelligence for organizing complex networked data [39].

For interior design applications, optimized clustering can perform two complementary functions. First, it can group users according to the similarity of their sentiment-based profiles, revealing dominant, mixed, stable, and changing stylistic mindsets. Second, it can model the stylistic orientations of interior designers and establish representative reference points for designer–applicant matching. Designers often develop relatively coherent approaches through education, professional practice, portfolio development, and repeated engagement with particular forms, materials, and spatial principles. Users, by contrast, may display more variable and evolving attitudes. Treating designer profiles as relatively stable anchors and comparing users with these anchors can therefore support a more interpretable matching process. Such a model shifts AI from the role of autonomous designer to that of mediator: the system does not replace professional judgment, but helps identify designers whose stylistic orientations are more compatible with a user's expressed mindset.

This approach also addresses a practical limitation in conventional recommendation systems. Many recommendation models infer preference from clicks, purchases, ratings, or previously selected items; however, interior architecture projects are infrequent, expensive, and highly individualized, so direct behavioral histories are often unavailable. Social-media discourse provides an alternative source of preference evidence that can be analyzed before a client has commissioned a project. By integrating multi-year sentiment profiles with optimized clustering, it becomes possible to capture both the direction and evolution of users' attitudes. Such temporal modeling is especially relevant because online design discourse is continuously reshaped by new trends, technologies, cultural exchanges, and changing living conditions. A longitudinal framework can distinguish transient enthusiasm from persistent orientation and can identify users whose preferences move toward emerging or hybrid styles.

Accordingly, a significant research gap exists at the intersection of interior architecture, social-media analytics, sentiment modeling, and metaheuristic clustering. Existing AI-based interior design studies provide important tools for generation, evaluation, optimization, visualization, and management, but they rarely integrate longitudinal social-media evidence with designer–user alignment. Similarly, sentiment-analysis research has developed increasingly capable methods for interpreting online opinions, yet interior architectural preferences remain an underexplored application domain. Bringing these areas together can contribute to a more human-centered design process in which computational analysis supports early-stage understanding, reduces stylistic mismatch, and improves the basis for collaboration between clients and designers.

Therefore, the aim of this study is to develop an AI-based approach that analyzes multi-year Twitter (X) sentiment data, models users' evolving preferences across interior architectural style categories, and applies optimized clustering to align applicants with interior designers whose stylistic mindsets are most compatible.

2. Methodology

2.1. Assumptions

This study is based on several practical assumptions. First, Twitter (X) users who actively post content containing interior design–related hashtags are considered representative of individuals expressing their stylistic interests and attitudes toward interior architectural design. Users without such content are excluded from the analysis.

Second, users expressed opinions and sentiments on Twitter are assumed to reflect their underlying mindset toward interior design styles and can be meaningfully compared across time. To capture this evolution, data collected between 2020 and 2024 are analyzed as consecutive yearly snapshots.

Third, interior designers are assumed to maintain relatively stable stylistic orientations over time compared to general users. Accordingly, designers are treated as fixed reference profiles across all datasets, enabling consistent comparison and alignment. Finally, each user is represented through a compact sentiment-based profile consisting of eight style-related components, corresponding to the most common interior design style categories identified through hashtag analysis.

2.2. Overview

The proposed method aims to enhance interior design outcomes by identifying and modeling the evolving mindsets of users over time and aligning them with interior designers whose stylistic orientations are cognitively compatible. Unlike conventional approaches that rely on static questionnaires or one-time consultations, this study adopts a data-driven and temporally informed approach based on social media evidence.

First, publicly available Twitter (X) data related to interior architectural styles are collected over a five-year period (2020–2024). After preprocessing and noise removal, sentiment analysis is applied to extract users' attitudes toward different interior design styles. These sentiment signals are then aggregated at the user level to construct longitudinal representations of user preferences.

Next, optimized clustering techniques are employed to group users according to similarities in their evolving mindset patterns rather than isolated preferences. This temporal clustering enables the identification of stable, shifting, or hybrid stylistic tendencies across time. In parallel, interior designers are characterized based on their dominant stylistic approaches and design philosophies.

Finally, a matching mechanism is introduced to align users with designers whose stylistic profiles exhibit the highest cognitive and attitudinal compatibility. By integrating temporal mindset modeling with designer–user alignment, the proposed method supports more personalized and psychologically coherent interior design outcomes. Figure 1 presents a conceptual overview of the proposed approach, where an AI mediator leverages social data from Twitter (X) to enable mindset-based alignment between interior design applicants and compatible designers.

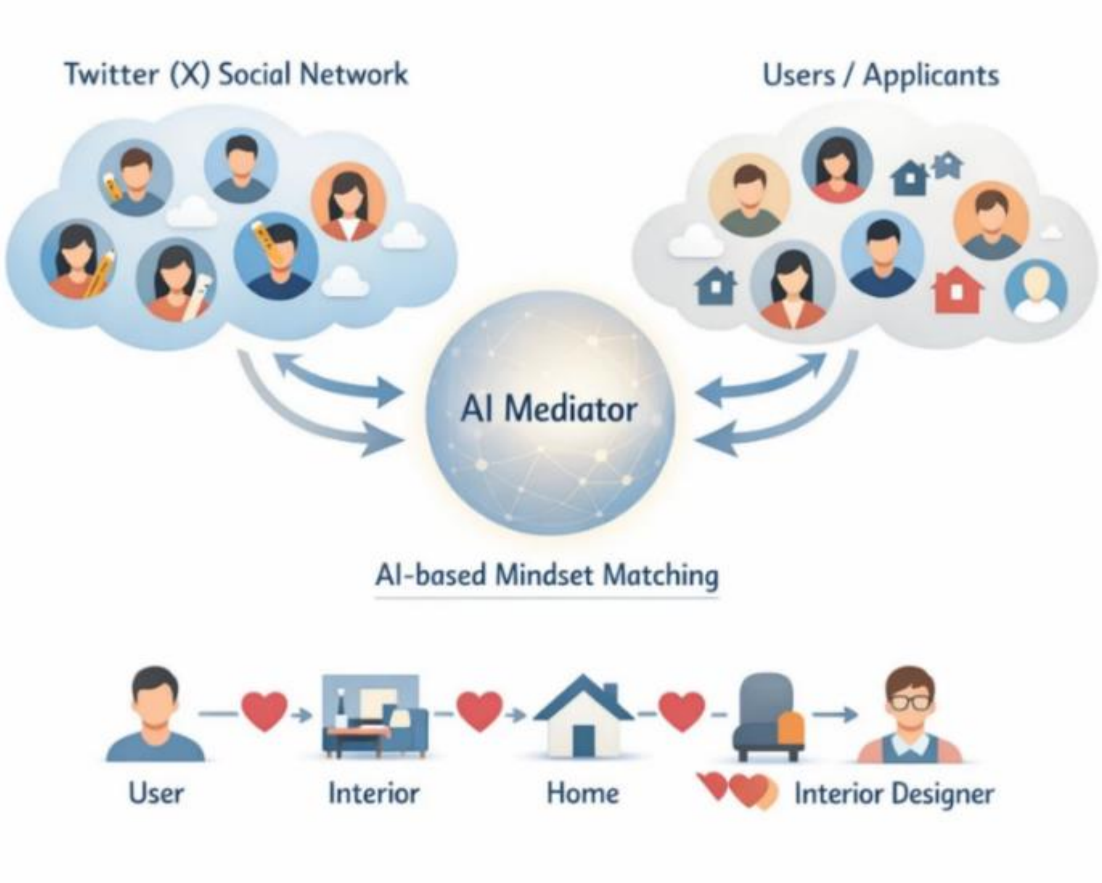


Figure 1. Conceptual illustration of the proposed AI based mindset matching approach

Twitter (X) is considered a social environment containing interior designers and users whose expressed attitudes reflect their evolving mindsets toward interior design styles. An AI mediator analyzes these social signals and facilitates alignment between users (applicants) and interior designers with compatible stylistic mindsets, aiming to enhance interior design outcomes.

2.3. Details of AI Mediator

2.3.1. Determining Hashtags to collect Data from Twitter

In the first step, extracting primary data from the Twitter social network requires identifying hashtags relevant to the research topic. This research monitors users' interests in interior architecture design styles. Accordingly, popular interior architecture styles among users worldwide were first examined.

Due to the diversity of interior architecture design styles and the changing interests of users over time, this research focuses on five years from 2020 to 2024, based on yearly trend styles. Prior studies indicate that applicants' preferences are generally concentrated on a limited number of predominant styles. Although these styles differ in elements and characteristics, they also share common features. Since the main objective is to identify users with similar viewpoints and sentiments toward interior design styles, styles with common elements such as light, symmetry, structure, color, and design were grouped, resulting in eight interior architecture style categories:

1. Rustic-Native: simplicity and nature-related elements.
2. Villa-Cottage: simplicity, comfort, and harmony in color and design.
3. Luxurious / Classic / Old-Fashioned: formal styles emphasizing symmetry and large decorative elements.
4. NewArts: revival of artistic styles with natural and rhythmic decorations.
5. Modern: contemporary styles adapted to geographical contexts.
6. Minimal: simplicity and avoidance of decorative balance and harmony.
7. Industrial: dominant use of industrial elements such as iron and wood.
8. Today's styles: a combination of past styles with new design technologies.

Based on these categories, relevant hashtags were identified to extract tweets and assign users' opinions to their corresponding style groups. Hashtags were selected according to trending styles from 2020 to 2024 and categorized as follows:(1) Bohemian/Boho chic, gypsy, farmhouse, rustic, shabby chic; (2) Mediterranean, country house; (3) Mid-century, classic, classicism, French, traditional; (4) Art Deco, French; (5) marine, nautical, modern, modernism, Japanese, Scandinavian, hygge, Nordic; (6) minimalism, minimal, Bauhaus; (7) industrial, loft; (8) modern classic, neoclassical. The categorized hashtags used in this research are presented in Table 2.

Table 1. The 8 categorized hashtags related to interior design styles used in this research

Head Styles	Rustic-Native styles	Villa-cottage styles	Luxurious, Classic, and Old-Fashioned	New Art styles	Modern styles	Minimal styles	Industrial styles	Today's styles
Related Hashtags	# Bohemian, #Boho chic #gypsy style, # Farm or farmhouse #rustic #shabby chic	# Mediterranean, #Country house	#Mid-century style #Classicism, #classic style #French, #Traditional	#Art Deco, #French	#Marin #Nautical #Modern Modernism, #Japanese, #Scandinavian, #hygge # Nordic	# Minimalism #minimal style #Bauhaus style	# Industrial, #loft style	# Modern classic #Neoclassic style #Neoclassical style

Therefore, by extracting tweets related to the selected hashtags and assigning each tweet to its relevant group, the primary dataset of this research is obtained from the Twitter social network. The data collection process consists of three main steps: 1. Tweets are randomly retrieved for each hashtag keyword used in this research. 2. Based on the selected hashtags, tweets together with user IDs and occupation information are extracted. Each user may have multiple tweets per hashtag or none for others, while users without any of the specified hashtags are excluded. Tweets related to users whose profession is interior architecture design are stored separately. 3. Finally, tweets are categorized into 8 groups according to the associated hashtags, forming the initial dataset.

2.4. Constructing the Dataset

2.4.1. Pre-processing

After data extraction, the data must be prepared for information retrieval methods, including sentiment analysis and clustering. This process involves data cleaning, separation, and required pre-processing steps. Due to character limitations on Twitter, tweets are often short and include emoticons and abbreviations, while each tweet represents positive, negative, or neutral feelings. Therefore, analyzing all related tweets is necessary to determine an individual's overall sentiment toward a specific topic.

Tweets are extracted using relevant hashtags categorized into eight groups, as defined in the previous section. Data cleaning includes removing mentioned entities, eliminating hashtag symbols (#) while retaining hashtag names, deleting irrelevant events, extraneous characters (except capital letters and numbers), and URL addresses. In addition, repetitive and meaningless words (stop words) are removed. After completing these steps, the dataset is ready for sentiment analysis and for calculating each user's final emotional score related to interior architecture design styles.

2.4.2. Sentiment Analysis Method

Sentiment analysis methods include lexicon-based, machine-learning, and hybrid approaches, each suitable for different tasks. Lexicon-based methods are efficient for short texts such as tweets, provide fast results, and do not require a training phase, whereas machine-learning methods generally achieve higher accuracy but need large labeled datasets and extensive training time, limiting their applicability. Considering the rapid growth of Twitter data, processing speed is prioritized over maximum accuracy in this research. Accordingly, a lexicon-based sentiment analysis method using the SentiWordNet dictionary is adopted, with accuracy enhancement techniques applied.

Sentiment analysis can be conducted at the text, sentence, or entity levels. Due to tweet brevity, this research focuses on entity-level sentiment analysis, where each tweet is treated as an entity. The analysis identifies sentiment polarity (positive, negative, or neutral), intensity of emotions, objectivity, and expert opinions related to architectural styles.

The SentiWordNet 3 dictionary, an extended version of WordNet ontology, is used in this research. Words are organized into synonym sets (synsets) with Part-of-Speech information and emotional scores. Emotional values range from $[-1, +1]$, where −1 indicates completely negative, 0 neutral, and +1 completely positive meaning. Pre-processing includes tokenization, lemmatization, and Part-of-Speech tagging, followed by Word Sense Disambiguation (WSD) and negation handling to improve accuracy.

Finally, the sentiment score of each tweet is calculated as the average emotional score of its words, and user-level sentiment vectors are formed to support clustering and information retrieval.

2.4.3. Forming the Feature Vectors:

After computing the sentimental score of each word using the proposed sentiment analysis pipeline, sentiment values are aggregated hierarchically from the word level to the user level. Each tweet is first decomposed into sentences, and the emotional score of each sentence is calculated as the average sentiment of its constituent words. The sentimental score of a tweet is then obtained by averaging the scores of all its sentences.

Since a user ID may post multiple tweets under the same hashtag, the overall sentiment of a user toward that hashtag is computed by averaging the sentiment scores of all tweets posted by that user under the corresponding hashtag. This process results in a single sentiment score per user ID per hashtag.

To model user preferences in interior architecture, hashtags are grouped into eight interior design style categories. For each user ID, the sentimental scores of all hashtags belonging to the same style group are aggregated to produce a single emotional score per style. This ensures that every user is consistently evaluated across all defined interior architecture styles.

Consequently, each user ID is represented by an eight-dimensional sentiment feature vector, where each component corresponds to the user's emotional orientation toward one interior architectural style group. All feature values lie within the range $[-1, +1]$. Each Twitter user ID is represented by an eight-dimensional features vector:

$$\mathrm{X}_i = (X_1, X_2, \dots, X_8) \tag{1}$$

At this stage, the sentiment-based feature vectors form a user-level dataset that captures emotional orientations toward interior architecture design styles. For uncovering latent user groups, we apply KCGWO clustering, which has been previously demonstrated in related studies to achieve a low Exploitation/Exploration Rate (EER) (is an important measure for evaluating metaheuristic clustering methods) on large-scale, high-dimensional data and to produce more stable clustering structures, making it well-suited for the characteristics of the proposed dataset.

2.5. Clustering

2.5.1. Similarity Measure and Fitness Formulation

Clustering aims to group data samples such that the similarity among members of the same cluster is maximized, while the dissimilarity between different clusters is preserved. In this research, similarity between data samples is quantified using the Euclidean distance, which is well-suited for numerical feature spaces and sentiment-based vector representations.

Given two data vectors o_i and o_j in a d-dimensional space, their Euclidean distance is defined as:

$$D(o_i, o_j) = \|o_i - o_j\| = \sqrt{\sum_{m=1}^{d} (o_{im}, o_{jm})^2} \qquad (2)$$

Let the dataset be represented as

$$X = \{x_1, x_2, \dots, x_n\},$$

where each $x_i \in \mathbb{R}^d$. In this research, $n$denotes the number of Twitter user IDs and $d = 8$corresponds to the number of interior architectural style groups derived from the sentiment analysis stage. Each user is therefore represented by an 8-dimensional sentiment feature vector.

Clustering is performed by identifying a set of cluster centers

$$M = \{m_1, m_2, \dots, m_k\}, m_j \in \mathbb{R}^d,$$

such that each data vector is assigned to its nearest center. Based on the Euclidean distance, clustering quality is evaluated using the within-cluster distance (WCD), defined as:

$$Minimize\ WCD = \sum_{i=1}^{n} \min_{1 \le j \le k} d(x_i, m_j) \qquad (3)$$

Minimizing this objective leads to compact clusters by reducing intra-cluster distances, thereby reflecting stronger similarity among users with respect to their sentiment-derived interior architectural preferences. This formulation establishes the similarity metric and the fundamental objective used for clustering.

2.5.2. Fitness Function

To guide the clustering process, a distance-based fitness function is employed. The objective is to ensure that users grouped within the same cluster exhibit high sentimental similarity toward interior architectural design styles, while maintaining clear separation between different clusters. In this research, the number of clusters is fixed at eight, corresponding to the predefined architectural style categories.

Given $k$clusters, the fitness function is defined as the cumulative intra-cluster distance between data points and their associated cluster centers:

$$Fitness\ Function = \sum_{i=1}^{C} \sum_{j=1}^{C_i} \left\| X_i^j - C_j \right\|^2 \qquad (4)$$

where X_i^jdenotes the j-th data vector in the i-th cluster, C_i represents the center of the i-th cluster, and $\left\| X_i^j - C_j \right\|^2$indicates the squared Euclidean distance. Minimizing this fitness value reduces intra-cluster dispersion and promotes the formation of compact and coherent clusters.

In addition to the primary fitness formulation, two complementary error-based measures are used to assess data distribution within clusters: Mean Absolute Error (MAE) and Mean Squared Error (MSE). MAE captures the average absolute deviation of data points from their assigned cluster centers, while MSE emphasizes larger deviations due to its squared error structure. These measures provide supplementary insight into cluster compactness and overlap without altering the main clustering objective.

The defined fitness function serves as the evaluation criterion guiding the clustering procedure. Based on this formulation, the clustering process adopts the K-means Clustering-based Gray Wolf Optimizer (KCGWO) to iteratively refine cluster centers and produce stable, interpretable groupings grounded in sentiment-based representations. The details of the adopted clustering algorithm are presented in the following subsection.

2.5.3. K-means Clustering Gray Wolf Optimization Method

Based on the defined similarity measure and fitness formulation, this research adopts the K-means Clustering-based Gray Wolf Optimizer (KCGWO) as the clustering engine within the proposed method. This method combines the global search capability of Gray Wolf Optimization (GWO) with the local partitioning mechanism of K-means to iteratively refine cluster centers under a fixed number of clusters.

Gray Wolf Optimization models the social hierarchy and hunting behavior of gray wolves, where solutions are ranked as α, β, δ, and **ω** according to their fitness values. During the iterative process, the leading wolves guide the position updates of other solutions. The encircling and position-updating mechanisms are governed by the following equations:

$$\vec{D} = \left| \vec{C}.\overrightarrow{X_p}(t) - \vec{X}(t) \right| \qquad (5)$$

$$\vec{X}(t+1) = \overrightarrow{X_p}(t) - \vec{A}.\vec{D} \qquad (6)$$

where $t$denotes the current iteration, $\vec{X}_p$ represents the prey position, and $\vec{X}$ denotes the current position of a wolf. The coefficient vectors $\vec{A}$ and $\vec{C}$are defined as:

$$\vec{A} = 2a.\overrightarrow{r_1} - \vec{a} \qquad (7)$$

$$\vec{C} = 2.\overrightarrow{r_2} \qquad (8)$$

where $\vec{r}_1$ and $\vec{r}_2$ are random vectors in the range $[0,1]$, and the control parameter a decreases linearly from 2 to 0 over successive iterations. This mechanism enables a gradual transition from exploration to exploitation during the search process.

The positions of the α, β, and δ wolves are used to estimate the prey location, and the distance vectors are calculated as:

$$\overrightarrow{D_\alpha} = \left|\overrightarrow{C_1}.\overrightarrow{X_\alpha} - \vec{X}\right| , \overrightarrow{D_\beta} = \left|\overrightarrow{C_2}.\overrightarrow{X_\beta} - \vec{X}\right| , \overrightarrow{D_\delta} = \left|\overrightarrow{C_3}.\overrightarrow{X_\delta} - \vec{X}\right| \quad (9)$$

Accordingly, three candidate position updates are computed:

$$\overrightarrow{X_1} = \overrightarrow{X_\alpha} - \overrightarrow{A_1}.\left(\overrightarrow{D_\alpha}\right)$$

$$\overrightarrow{X_2} = \overrightarrow{X_\beta} - \overrightarrow{A_2}.\left(\overrightarrow{D_\beta}\right) \quad (10)$$

$$\overrightarrow{X_3} = \overrightarrow{X_\delta} - \overrightarrow{A_3}.\left(\overrightarrow{D_\delta}\right)$$

The final position update is obtained by averaging these estimates:

$$\vec{X}(t+1) = \frac{\overrightarrow{X_1}+\overrightarrow{X_2}+\overrightarrow{X_3}}{3} \quad (11)$$

Within KCGWO, the K-means mechanism is incorporated to structure the population and refine cluster assignments. K-means iteratively assigns data points to the nearest cluster centers using the Euclidean distance and updates the centers to minimize the within-cluster sum of squared distances:

$$\sum_{i=1}^{C} \sum_{j=1}^{C_i} \left\| X_i^j - C_j \right\|^2 \quad (12)$$

In KCGWO, gray wolf populations may be grouped using K-means during the search process, and fitness values are evaluated at the cluster level or the population level, depending on the iteration conditions. This hybrid mechanism allows cluster centers to be updated in a guided yet flexible manner. A weighted position update is applied as:

$$\vec{X}(t+1) = \frac{3\overrightarrow{X_1}+2\overrightarrow{X_2}+\overrightarrow{X_3}}{6} \quad (13)$$

where hierarchical weighting improves stability in convergence. The algorithm iteratively updates position vectors and returns the final set of cluster centers corresponding to the minimum fitness value.

2.5.4. Two-Step Application of KCGWO (TSKCGWO)

To enhance stability and interpretability in large-scale, sentiment-based data, KCGWO is applied in a two-step execution method (TSKCGWO). In this approach, each gray wolf represents a candidate solution encoding cluster centers in a vector of dimension $d \times k$, where d denotes the number of sentiment features and k represents the predefined number of clusters.

At each iteration, the fitness of each solution is evaluated using the intra-cluster distance objective defined in Section 3.4.2. The best-performing solutions guide subsequent position updates, ensuring progressive refinement of cluster centers. For each cluster C_j, the cluster center is computed as:

$$y_j = \frac{1}{n_j} \sum_{\forall X_p \in C_j} X_p \quad (14)$$

and the distance between a data point and its corresponding center is given by:

$$Distance\left(X_p - y_j\right) = \sqrt{\sum_{i=1}^{a} (X_p - y_j)^2} \quad (15)$$

where X_p denotes the p-th data point, y_j is the center of the j-th cluster, a is the number of features, and n_j is the number of elements in the cluster C_j. By applying KCGWO in two sequential steps, cluster centers are progressively stabilized, reducing sensitivity to initialization and improving coherence in sentiment-based user groupings. This execution method ensures that clustering outcomes remain consistent with the predefined architectural style categories while maintaining scalability for large datasets.

We apply KCGWO in a two-phase execution method. In the first phase, clustering is conducted on the designer dataset to obtain representative cluster centers. In the second phase, these centers are transferred and used as reference initializations for clustering the full user dataset. The overall workflow of the proposed AI Mediator is illustrated in Figure 2.

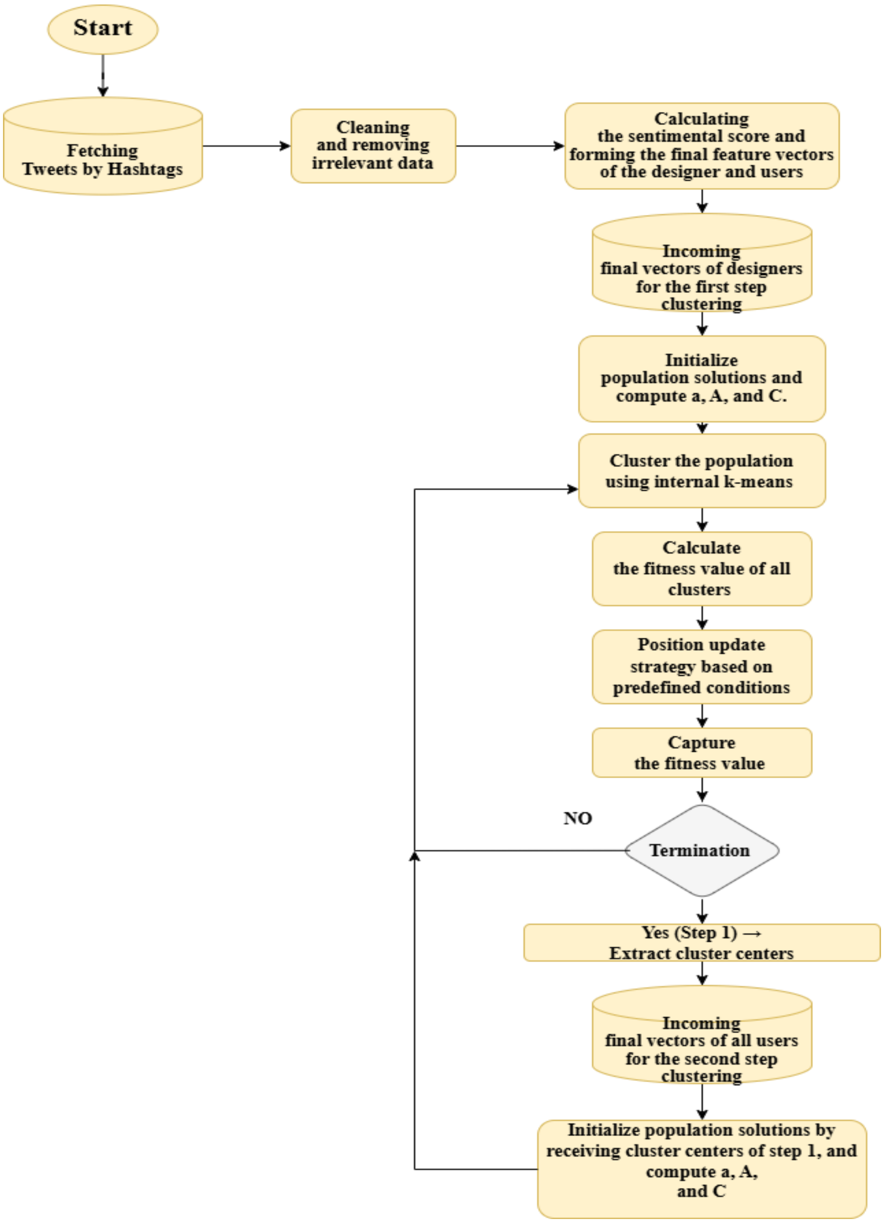


Figure 2. Workflow of the proposed AI Mediator

3. Findings and Results

This research investigates people's attitudes and emotional orientations toward interior architecture design with the aim of supporting more informed and human-centered design decisions. Twitter was selected as a data source because it provides an open environment in which users freely express opinions and engage in discussions related to contemporary design styles.

Following the methodology described in the previous sections, users' tweets were collected and preprocessed, and sentiment analysis was applied to extract emotional scores for predefined interior architectural style categories. These scores were subsequently aggregated into 8-component feature vectors representing individual users' and designers' stylistic orientations. The extracted vectors were then analyzed through the adopted two-stage sentiment–clustering method.

The dataset spans May 2020 to May 2024, covering five years selected to reflect recent and actively discussed interior design styles. Analyzing multiple years of data makes it possible to capture both stable preferences and gradual shifts in stylistic attitudes over time. All selected interior architecture styles remained relevant during this period, justifying the temporal scope of the research.

Due to the inherently subjective and diverse nature of emotional expressions, data normalization was not applied. Instead, the original sentiment values were preserved to maintain interpretability. To increase numerical resolution for clustering, sentiment scores in the range $[-1,1]$were linearly scaled to $[-10,10]$. Each clustering execution was repeated 800 iterations to ensure convergence toward a steady state, where the values of the global cost and global best indicators no longer exhibited significant fluctuations.

A key motivation for adopting a two-stage execution method lies in the differing temporal stability of participants. Interior architecture designers are assumed to exhibit relatively consistent stylistic orientations over time, whereas general users may display higher variability in activity and sentiment. Accordingly, designers were analyzed first to establish reliable and semantically meaningful reference cluster centers, which were subsequently used to initialize the clustering of the broader user population. This approach reduces sensitivity to random initialization and supports more coherent alignment between users and designers based on shared stylistic viewpoints.

It is important to emphasize that this research does not aim at prediction. Classification techniques are typically used for predictive purposes, whereas clustering is more suitable for analyzing existing structures and relationships within data. The following considerations motivated the use of clustering over classification:

1. Many users are unwilling to disclose personal or demographic information.
2. The objective is not to predict future behavior, but to organize applicants and users into groups reflecting similar levels of satisfaction and stylistic alignment.
3. Perspectives and stylistic affiliations of both users and designers evolve over time, making static labels unsuitable for meaningful analysis.

Consequently, the operational method of this research is guided by three principles:

(1) data are continuously updated,

(2) user participation varies over time, and

(3) individuals are evaluated longitudinally without predefined labels.

After applying the adopted KCGWO-based two-stage clustering method to the extracted feature vectors, coherent clusters were formed for both designers and users. Each individual is associated with clusters based on relative proximity, reflecting positive or negative alignment with specific stylistic groups. The total population consisted of 240 individuals, and each experiment was independently repeated 30 times under identical conditions to ensure stability. All experiments were conducted on a Lenovo laptop equipped with an Intel® 11th Gen Core™ i7-1165G7 processor and 24 GB RAM.

The visual results illustrate that the proposed method produces well-structured and interpretable clusters, particularly when architect-derived cluster centers are used as references for clustering users. This design-centered initialization, illustrated in Figure 3, supports logical associations between designers and applicants and helps maintain cluster consistency across iterations. Accordingly, the subsequent discussion focuses on the clustering outcomes produced by the adopted two-stage KCGWO execution method and their relevance to interior architecture design analysis, as presented in Figure 4.

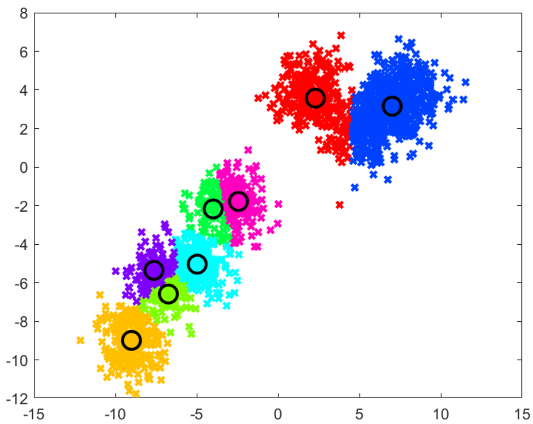


Figure 3. Cluster formation obtained from interior architecture designers using the adopted two-stage execution

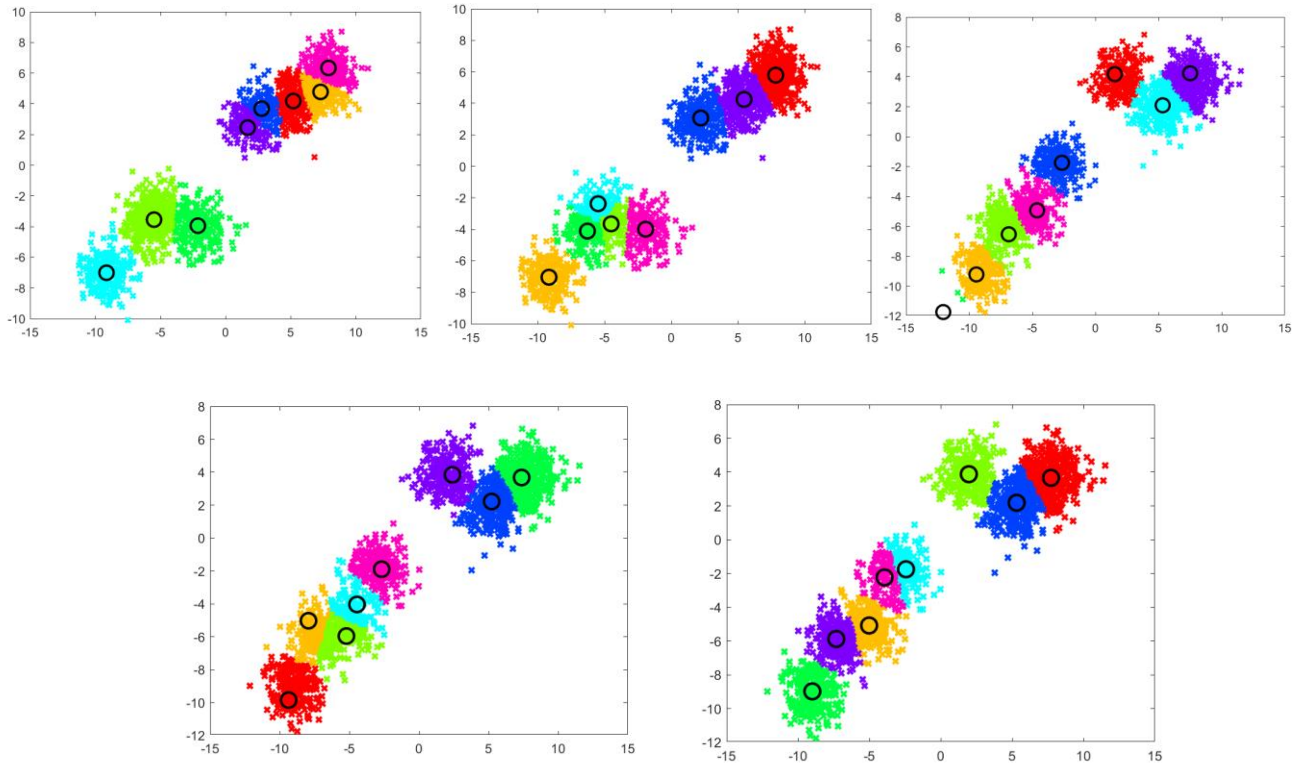


Figure 4. The result of final user clustering over multiple years, 2020 to 2024, from top left to bottom right, respectively.

Figures 4 presents visualization of user cluster assignments initialized by designer-derived reference centers during 2020-2024. To examine whether the adopted sentiment–clustering method produces stylistic representations that remain meaningful in real design settings, a design-oriented validation is conducted using representative interior architecture cases.

To evaluate the practical effectiveness of the proposed sentiment–clustering method in real design scenarios, the resulting clusters were empirically validated using representative interior design case data. The evaluation focuses on the ability of the adopted hybrid sentiment and clustering mechanism to produce stable, well-separated cluster centers that support more accurate alignment between designers' stylistic orientations and users' expressed preferences.

Representative samples were selected from three widely adopted stylistic categories Modern, Minimalist, and Rustic. For each category, semantic centroid vectors were extracted under two different analysis settings:

(i) a designer-anchored, stepwise clustering method, in which designers' sentiment profiles were first stabilized and subsequently used to guide user clustering, and

(ii) a single-stage clustering baseline, where designers and users were analyzed jointly without distinction.

To quantify stylistic alignment, the similarity between designer-derived and user-derived centroids was measured across eight style dimensions using Cosine Similarity, defined as:

$$\mathrm{Sim}(A,B) = \frac{A \cdot B}{\|A\| \, \|B\|} \tag{16}$$

where A and B represent centroid vectors corresponding to designers and users, respectively.

The stepwise sentiment–clustering method yielded consistently higher centroid alignment values, with a mean similarity of 0.82 ± 0.09, indicating strong perceptual coherence between designer intentions and user sentiment patterns. In contrast, the single-stage clustering baseline exhibited markedly lower and less stable alignment across all examined styles.

Beyond numerical alignment, the proposed method produced more compact and better-separated clusters, reducing centroid drift and overlap between stylistic groups. This improved separability enables clearer interpretation of stylistic mindsets and supports more precise matching between applicants and interior design styles.

Overall, the results demonstrate that combining sentiment analysis with a structured clustering method enhances the formation of stable, discriminative stylistic representations. This, in turn, facilitates more reliable designer–user alignment without relying on supervised labels or explicit preference elicitation, reinforcing the method's suitability for human-centered, preference-driven interior design applications.

Table 2. Comparison of stylistic alignment and clustering quality under different analysis strategies

Analysis method	Mean Cosine Similarity (Designer–User)	Std. Dev.	Cluster Compactness ↓	Cluster Separability ↑
Single-stage clustering (joint data)	0.65 ± 0.14	0.14	Lower (0.48)	Moderate (0.31)
Designer-anchored stepwise method	0.82 ± 0.09	0.09	Higher (0.32)	Clearer (0.47)

The reported standard deviation reflects the variability of cosine similarity values across different interior design styles, indicating the stability of designer–user stylistic alignment. The observed improvements in cluster compactness and separability indicate that the adopted method facilitates clearer stylistic distinctions, enabling more reliable interpretation and alignment in human-centered interior design decision-making.

As described earlier, interior architecture styles were categorized into eight groups, each associated with representative hashtags. Based on this categorization, individuals are expected to exhibit either a dominant or mixed intellectual orientation toward these style groups. To establish reliable reference patterns, a sample of 240 interior architecture designers was first selected from Twitter and analyzed using the proposed sentiment–clustering method.

During the initial clustering stage, designers' feature vectors were treated as the primary dataset. Cluster centers were first approximated using k-means clustering to reflect general stylistic tendencies. Although partial overlap among styles was observed, the resulting centers provided a reasonable representation of dominant intellectual patterns. These centers were then adopted as the initial population for the KCGWO-based clustering process, allowing the analysis to proceed without reliance on random initialization.

The resulting clusters reveal clearer distinctions among interior architecture styles from both intellectual and architectural perspectives. The stable thinking patterns exhibited by professional designers make them suitable references for guiding the subsequent analysis of the broader user population. Since designers typically maintain consistent stylistic orientations over time and align their professional output with their core interests, the clusters derived from this group serve as representative models for identifying corresponding patterns among general users.

Using these designer-derived cluster centers, the complete Twitter user dataset was re-clustered. Users were grouped based on their proximity to predefined stylistic centers, enabling differentiation between intellectual orientations toward interior architecture styles. In this process, designers act as fixed reference points, while users' positions reflect varying degrees of alignment with these dominant styles.

To capture temporal dynamics, five independent datasets corresponding to the years 2020 to 2024 were analyzed. While clustering was conducted separately for each year, the cluster centers remained fixed according to the patterns established by designers. This approach enabled consistent interpretation of stylistic changes while preserving temporal comparability across years.

As shown in Figure 5, the analysis highlights that user preferences toward interior architecture styles are not static. Instead, they evolve gradually in response to emerging design trends, increased discussion of contemporary aesthetics, and growing exposure to innovative styles. In particular, new stylistic clusters emerge over time, reflecting changing collective interests. For example, a previously underrepresented design orientation becomes noticeable from 2022 onward and continues to gain attention in subsequent years. Additionally, even when users cluster around designers associated with the same style group, variations in interpretation and preference lead to observable diversity within user clusters.

This longitudinal clustering method provides a practical basis for examining individuals over time, particularly for applicants seeking interior architecture services. By aligning users with designers whose intellectual orientations most closely match their preferences, the method offers a structured way to support designer–client matching based on shared stylistic perspectives. Any Twitter user actively engaged in discussions related to interior architecture can be treated as a test case, and designers with compatible thinking styles can be identified accordingly.

Although eight style categories were used in this research, this parameter remains flexible and can be expanded as new styles emerge. To analyze trends from 2020 to 2024, the distribution of users across clusters was examined by counting the number of data points assigned to each cluster for every year. Cluster identifiers were used to compute average cluster sizes, enabling analysis of relative interest levels among different styles. Variations in cluster size and balance reflect shifts in user attention and the concentration or dispersion of stylistic preferences over time.

By examining yearly changes in cluster proportions, the research illustrates how interest in interior architecture styles evolves across the five years. Percentage-based trend visualizations further clarify these dynamics, revealing both emerging preferences and declining interest in specific styles. Collectively, these findings demonstrate that sentiment-driven clustering provides meaningful insights into evolving user mindsets and supports a deeper understanding of interior architecture style preferences in real-world social media environments.

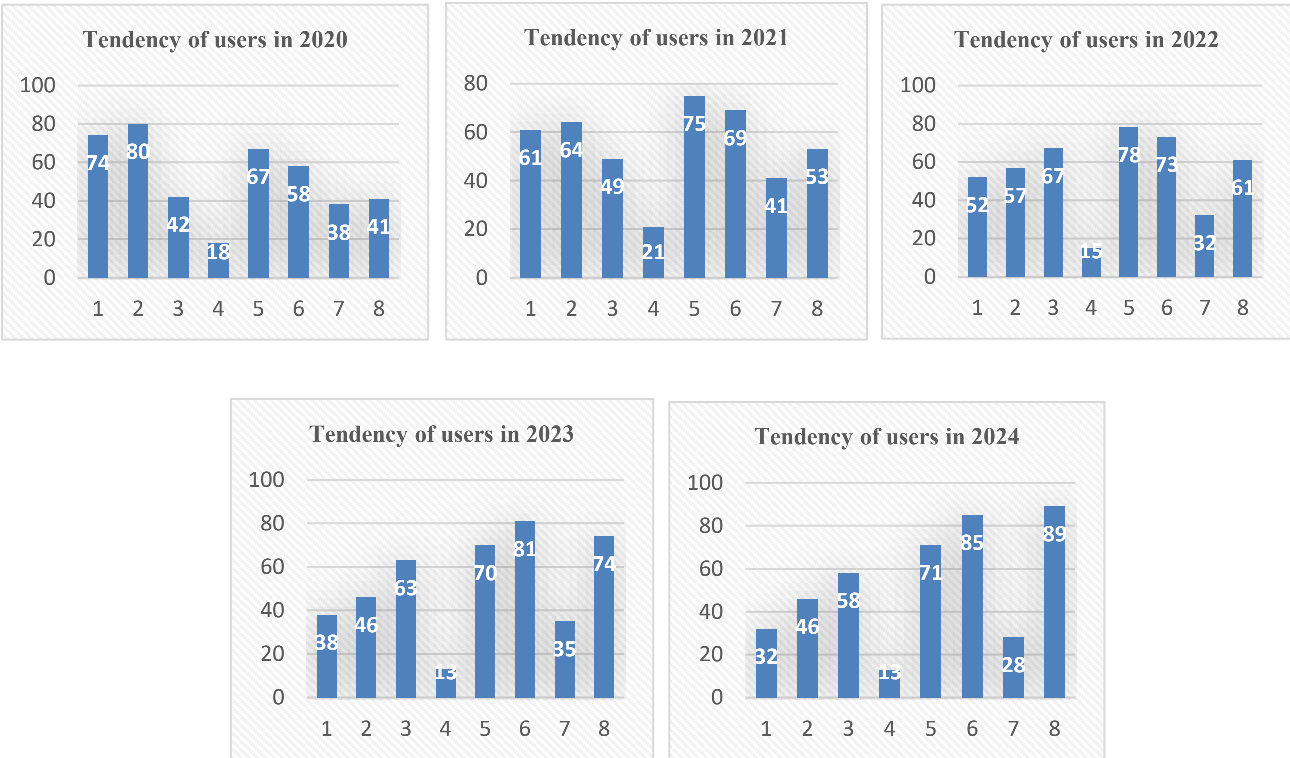


Figure 5. Tendency of users on the 8 style categories during 2020 to 2024, the numbers on cherts are based on percent.

Changes in people's attitudes and opinions toward the eight interior architecture style categories defined in Section 3.2.1, were observed across the analyzed time period. These categories include: (1) Rustic–Native, (2) Villa–Cottage, (3) Luxurious, Classic, and Old-Fashioned, (4) New Arts, (5) Modern, (6) Minimal, (7) Industrial, and (8) Today's Hybrid styles.

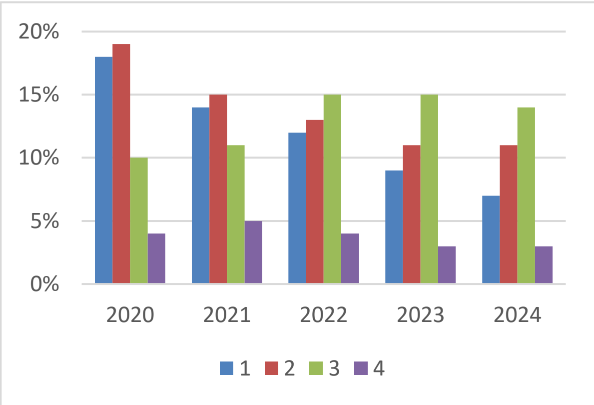
Analyzing trends associated with these categories provides meaningful insight into evolving user mindsets and helps interior architects and designers better understand the moods, expectations, and preferences of their potential clients. By observing how stylistic interests change over time, designers can adapt their approaches more effectively, leading to improved alignment with user demands and higher levels of satisfaction in interior design projects.

Because interior architecture styles differ in terms of spatial requirements, materials, and visual complexity, the trend analysis considers two relative groups separately. Styles 1 to 4 were analyzed in relation to each other, and styles 5 to 8 were analyzed in a separate comparative group. This distinction reflects fundamental differences in design characteristics and application contexts. Figures 6 illustrate the temporal changes in user attitudes toward these two groups of styles from 2020 to 2024.

Styles 1 to 4 are generally characterized by heavier architectural elements and layouts that require larger physical spaces for implementation. The results indicate a gradual decline in user interest toward these styles over recent years. In contrast, styles 5 to 8 emphasize lighter, more flexible, and visually refined design elements that can be implemented in smaller or more adaptable spaces. User interest in these styles shows a consistent increase throughout the studied period, reflecting broader shifts in lifestyle, spatial constraints, and contemporary aesthetic preferences.

From a practical perspective, understanding these shifts offers tangible benefits for both designers and applicants. By identifying designers whose intellectual orientations align with emerging user preferences, applicants can reduce both time and financial costs traditionally associated with searching for suitable design professionals. Rather than navigating prolonged trial-and-error processes, users can be guided toward architects whose stylistic thinking resonates with their expectations from the outset.

Ultimately, individuals tend to experience higher satisfaction when the final design outcome corresponds closely with their initial vision. This research contributes to enhancing interior architecture practices by fostering stronger alignment between designers' intellectual styles and users' evolving preferences. Such alignment supports more efficient design processes, improves service quality, and increases overall satisfaction in interior architecture projects.



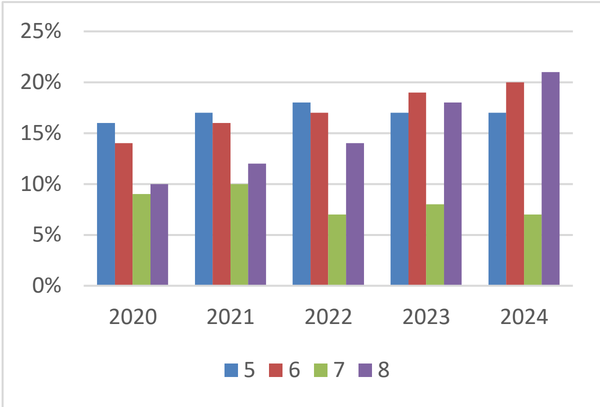


Figure 6. Changing user attitudes towards styles during 2020 to 2024, left: categories 1 to 4 and right: categories 5 to 8

4. Discussion and Conclusion

The present study investigated whether users' evolving attitudes toward interior architectural styles could be extracted from Twitter (X) data and employed to improve alignment between applicants and interior designers. The findings supported the effectiveness of the proposed designer-anchored, two-step K-means Clustering–Gray Wolf Optimizer approach. Sentiment-derived feature vectors enabled both designers and general users to be represented across eight interior architectural style dimensions, while the use of designers' profiles as initial reference centers produced coherent and interpretable user clusters. In the practical validation, the designer-anchored stepwise method achieved a mean designer–user cosine similarity of 0.82 ± 0.09, compared with 0.65 ± 0.14 for the single-stage approach. The proposed method also produced greater cluster compactness, reflected in the lower value of 0.32 compared with 0.48, and clearer cluster separability, reflected in the higher value of 0.47 compared with 0.31. Moreover, the longitudinal analysis demonstrated that users' stylistic orientations changed between 2020 and 2024. Interest in the first four categories—Rustic–Native, Villa–Cottage, Luxurious/Classic/Old-Fashioned, and New Arts—generally declined, whereas preferences for Modern, Minimal, Industrial, and contemporary hybrid styles increased. A previously less visible stylistic orientation also became more apparent from 2022 onward, showing that the method was able to detect emerging patterns rather than merely reproduce fixed stylistic classifications.

The higher cosine similarity obtained through designer-anchored clustering indicates that separating the modeling of professional designers from that of general users improved the semantic alignment of the resulting clusters. In the single-stage method, designers and users were clustered jointly despite differences in the stability, consistency, and professional formation of their stylistic orientations. This likely increased centroid drift and caused partially incompatible profiles to influence the same cluster centers. By contrast, the two-step method first extracted relatively stable reference patterns from interior designers and then used those patterns to organize users. The lower standard deviation obtained by the designer-anchored method further indicates that alignment was not limited to one style category but remained relatively consistent across the examined styles. This finding supports the broader proposition that AI systems can assist interior design when they operate as decision-support mechanisms rather than as replacements for designers' professional judgment [8]. It is also consistent with evidence that data-driven intelligent systems can make interior-environment recommendations more structured and responsive by converting complex design information into usable decision variables [15].

The improvement in cluster compactness and separability can also be explained by the hybrid optimization structure of the proposed approach. Conventional k-means clustering is efficient but remains sensitive to random initialization and may converge toward locally optimal cluster centers. The use of Gray Wolf Optimization expands the search process and permits a more effective balance between global exploration and local refinement. Previous methodological research has shown that metaheuristic clustering methods can improve the search for cluster centers in complex and multidimensional datasets [36]. Hybrid swarm-based approaches have similarly been developed to reduce premature convergence and improve the quality of data partitions [37]. The findings are especially compatible with research on weighted k-means and Gray Wolf Optimization, in which enhanced initialization and adaptive search mechanisms improved clustering performance [38]. Firefly-based optimization has likewise demonstrated that swarm-intelligence mechanisms can strengthen clustering and aggregation in large networked datasets [39]. Therefore, the improved separation observed in the present study appears to result not only from the selected features but also from the capacity of the hybrid algorithm to establish more stable reference centers.

The results further demonstrate the suitability of sentiment analysis for translating unstructured social-media expressions into meaningful design-preference profiles. Twitter posts are brief, informal, and often emotionally charged, making them potentially informative but computationally difficult to interpret. Sentiment analysis research has shown that social-media language contains ambiguity, abbreviations, irony, contextual shifts, and complex linguistic structures that complicate straightforward polarity detection [29, 30]. Nevertheless, lexicon-based methods remain useful for processing high-volume short texts because they do not require extensive labeled training sets and can produce interpretable sentiment scores [31]. The integration of word-sense disambiguation and negation handling in the current study likely strengthened the validity of the user-level feature vectors by reducing errors caused by ambiguous terms or reversed polarity.

The usefulness of aggregating repeated posts into longitudinal user profiles also aligns with developments in text and sentiment analytics. Social-media text mining can uncover patterns that are difficult to identify through direct observation or conventional surveys [27]. Sentiment-enhanced social-information discovery can facilitate the identification of shared attitudes and emerging communities in large collections of online content [28]. More advanced sentiment systems have shown that incorporating lexical strength and attention mechanisms can improve the representation of emotional intensity and contextual meaning [33]. Recent hybrid models similarly integrate deep learning and lexicon-based sentiment information to produce more comprehensive recommendation profiles [34]. The integration of lexical and deep-learning approaches in the analysis of evaluative textual data also suggests that large collections of naturally produced comments can serve as reliable sources for understanding users' experiences and orientations [35]. Although the present study adopted a lexicon-based approach, its findings support the central assumption underlying these studies: meaningful user characteristics can be inferred through the systematic aggregation of dispersed textual evaluations.

Another important result was the ability of the method to represent hybrid preferences. Users were not necessarily positioned as pure representatives of a single architectural style; instead, their eight-dimensional vectors reflected varying degrees of positive, neutral, or negative orientation toward multiple categories. This is an important advantage because real interior-design preferences rarely correspond exactly to rigid labels. A person may prefer minimalist spatial organization while also favoring traditional materials, industrial details, or classical decorative elements. Fundamental design principles such as harmony, rhythm, contrast, proportion, and unity may be realized differently across styles, allowing individuals to value features that extend beyond one conventional category [1]. The observed diversity within clusters is therefore not necessarily evidence of classification error. Rather, it may reflect the multidimensional nature of aesthetic judgment and the coexistence of several design orientations within one person.

The emergence and reorganization of clusters between 2020 and 2024 further confirm that interior architectural preferences should not be treated as static attributes. The growth of digital platforms has increased exposure to international design images, trends, cultural references, and professional discussions [25, 26]. Digital technology has also changed how interiors are visualized, communicated, and experienced, allowing users to compare design alternatives before physical implementation [5]. Virtual-reality systems and intelligent three-dimensional environments have expanded users' opportunities to encounter and evaluate spatial configurations, thereby increasing familiarity with contemporary design solutions [17, 18]. Consequently, user preferences may be continuously reconstructed through online exposure rather than formed solely through direct experience with physical interiors.

The decreasing interest in the first four style groups and the increasing attraction to Modern, Minimal, Industrial, and contemporary hybrid styles may reflect changes in living conditions and aesthetic expectations. The earlier categories generally involve heavier ornamentation, larger visual elements, greater material complexity, or spatial arrangements that may require more extensive physical environments. By contrast, modern and minimal styles often prioritize flexibility, reduced ornamentation, functional organization, and adaptability to smaller spaces. Multi-objective optimization research has emphasized the importance of balancing spatial structure, functionality, and competing design requirements in interior environments [14]. AI-assisted layout design similarly supports the efficient organization of spatial components within CAD environments [11]. The growing preference for lighter and more adaptable styles may therefore correspond to broader demands for efficient spatial use, although this interpretation should be viewed as an explanation of the observed pattern rather than direct evidence of causation.

At the same time, the increased visibility of contemporary hybrid styles suggests that technological modernization does not necessarily eliminate cultural or historical references. AI-based design methods can support the reinterpretation of traditional cultural elements in modern interiors by recombining patterns, forms, colors, and spatial motifs [20]. Embedded digital imaging and computational visualization can similarly facilitate experimentation with multiple stylistic components before implementation [16]. The movement toward hybrid styles may therefore represent a shift from strict adherence to traditional classifications toward selective integration of historical, regional, technological, and contemporary elements. This interpretation is consistent with the development of generative CAD/CAE systems that permit rapid production and evaluation of multiple conceptual alternatives [10], as well as AI-supported evaluation systems that compare interior schemes through structured criteria [12, 13].

The findings also reinforce the value of AI as a mediator in the interior-design process. Existing applications have mainly focused on conceptual generation, technical evaluation, optimization, visualization, or operations management [9, 19]. Modern technologies can improve efficiency and expand creative opportunities in interior spaces [7], while robotics and AI may alter how designers explore and develop creative concepts [21]. Discussions of artificial consciousness have even raised broader questions about future relationships among computational systems, designers, and users [22]. However, the present findings indicate that an equally important application is the preliminary identification of designer–applicant compatibility. Rather than automatically producing a final design, the system can recommend professionals whose established stylistic orientations are close to the client's evolving preferences.

Such alignment has meaningful psychological and practical implications. Interior environments influence emotional states, behavior, comfort, and interpersonal experience [2]. Research using interiors presented through virtual reality has further demonstrated that spatial characteristics can affect psychological well-being and mental-health-related responses [3]. A design process that begins with a substantial mismatch between designer and client may produce repeated revisions, dissatisfaction, increased costs, and an interior that does not support the user's emotional expectations. The stronger designer–user similarity found in the present study suggests that sentiment-informed matching could reduce this initial mismatch. It may also strengthen communication because designers and applicants who share closer stylistic orientations are more likely to interpret descriptive terms, reference images, and aesthetic priorities in comparable ways.

Overall, the study extends previous AI-based interior-design research by combining longitudinal preference modeling, sentiment analysis, optimized clustering, and designer–applicant matching within a unified framework. Its primary contribution is not simply the identification of popular styles, but the creation of a temporally sensitive mechanism for organizing individuals according to their expressed orientations and relating them to professional reference profiles. The results indicate that designer-anchored clustering produces more compact, separable, and semantically aligned groups than joint clustering. They also show that social-media data can reveal both stable preferences and emerging stylistic shifts. Accordingly, the proposed AI mediator provides a potentially valuable foundation for recommender systems intended to support more personalized, efficient, and human-centered interior architectural decision-making.

The study has several limitations. Twitter users who post design-related content may not represent the wider population of interior-design applicants, and users who rarely post or use different terminology were excluded. Public posts may reflect temporary reactions, self-presentation, promotional activity, or engagement with trends rather than genuine preferences. The lexicon-based sentiment method may also misinterpret sarcasm, visual references, multilingual expressions, specialized design terminology, and posts whose meaning depends on accompanying images. The eight style categories simplify a highly diverse field and may conceal distinctions within each category. In addition, the assumption that designers maintain stable stylistic orientations may not apply to multidisciplinary professionals or designers whose approaches change across projects. Finally, the validation was based primarily on computational indicators rather than completed projects, direct client satisfaction, or expert evaluation of real designer–applicant pairings.

Future studies should collect data from multiple social-media platforms and compare textual findings with images, videos, saved collections, engagement patterns, and portfolio content. Multilingual and multimodal models could improve the interpretation of culturally specific styles and visually communicated preferences. Researchers should also compare lexicon-based sentiment analysis with transformer-based and hybrid models and examine whether dynamic or automatically generated style categories provide better representations than eight predefined groups. Longitudinal studies could follow the same individuals across longer periods and investigate the factors associated with preference change. Most importantly, the proposed matching system should be evaluated through controlled design projects in which recommended and conventionally selected designer–client pairs are compared in terms of satisfaction, communication quality, revision frequency, project duration, cost, and perceived correspondence between the final environment and the client's original expectations.

Interior-design firms and digital platforms can use the proposed approach as an early-stage decision-support tool rather than as a substitute for consultation and professional judgment. Applicants could authorize the analysis of relevant public content or complete a comparable sentiment-based preference task, after which several compatible designers could be recommended with an explanation of the matching criteria. Designers should review these profiles collaboratively with clients, verify ambiguous preferences, and use the results to guide mood boards, preliminary concepts, and discussions of conflicting stylistic priorities. The system should provide privacy controls, informed consent, data-minimization procedures, and an option to correct or delete inferred profiles. Regular updating is also necessary so that recommendations reflect changing user interests, emerging styles, and the continuing development of designers' professional portfolios.

Authors' Contributions

Authors equally contributed to this article.

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Declaration of Interest

The authors report no conflict of interest.

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Ethical Considerations

All procedures performed in this study were under the ethical standards.

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