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Leveraging Artificial Intelligence to Translate Computational Simulation Results of Natural Ventilation in Tall Office Buildings into Human-Centered Insights

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ABSTRACT

Tall office buildings are increasingly designed with sustainability and occupant comfort in mind, and natural ventilation plays a critical role in achieving these goals. However, their height and exposure to complex, variable wind conditions introduce significant challenges, often producing uneven airflow patterns that limit effective air movement and directly affect human experience and behavior. Computational simulations are widely used to analyze the natural ventilation potential in buildings, as they provide comprehensive information on airflow behavior. Velocity contour visualizations quantify airflow distribution, yet their direct translation into human experiential and behavioral understanding remains limited, despite their interpretive insights. This study presents a visualization method using Artificial Intelligence (AI) to translate computational simulation results into design-oriented visualizations, including atmospheric diagrams and collages, that communicate relative experiential and behavioral tendencies rather than precise predictions of human behavior. AI serves as the primary tool, generating interpretable visualizations from prompts composed of keywords representing airflow behavior and insights derived from selected published simulation results on natural ventilation in tall office buildings. The proposed framework bridges quantitative technical data and experiential interpretation through a structured, two-stage embedding process, allowing airflow distributions and associated emotional and behavioral responses to be represented visually. The resulting images emphasize perceptual legibility and comparative interpretation to support design reasoning and pedagogy. Limited to simplified airflow conditions and experiential indicators, the framework provides an early-stage method that supports design exploration, architectural education, and communication by integrating quantitative analysis, qualitative experience, and architectural representation into a coherent visual reasoning process.

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1. Introduction

1.1. Challenges of Natural Ventilation in Tall Buildings

Natural ventilation has been applied to many types of office buildings in various ways to improve energy performance and support healthy indoor environments, primarily when climatic conditions are suitable for effective airflow. Numerous studies have examined the advantages of natural ventilation, and many naturally ventilated or hybrid office buildings have been built worldwide. However, most natural ventilation strategies have been developed for low- and mid-rise office buildings (i.e., below 200 meters), where thermal and wind conditions are more stable and predictable. These strategies are often not appropriate for tall office buildings, which experience more variable and extreme environmental conditions due to their height. Natural ventilation in tall office buildings faces major challenges, including high wind pressures at upper floors that can cause excessive air velocities, high concentrations of incoming air, and occupant discomfort, particularly on the windward side [1], as well as amplified stack effects that generate strong, variable airflow difficult to control [2, 3]. Deep lease spans, typical in high-rise buildings [4], further limit airflow penetration, reducing the effectiveness of typical passive ventilation strategies.

Many design strategies have been developed for tall office buildings to address these challenges. Among them, double-skin facades (DSFs) have been widely explored because they help moderate high wind pressures and can harness the pressures to support natural ventilation. The outer layer functions as a protective buffer and reduces wind effects, allowing occupants to open the inner windows for natural ventilation [5]. As a result, DSFs can create indoor environments that not only enhance building performance but also positively influence human experience by providing access to fresh air, improving perceived comfort, and fostering a sense of connection to the outdoors, all of which shape human behavior and support overall well-being.

1.2. Computational Fluid Dynamics (CFD)

Computational Fluid Dynamics (CFD) provides a flexible and interactive environment for visualizing fluid flow and supporting design decisions in architecture [6]. CFD enables comprehensive analysis of airflow, including velocity, temperature, pressure, and particle concentration, under various design options and operating conditions [7]. Its predictive capability has been validated against experimental data such as wind tunnel tests, demonstrating good agreement and reliability [8, 9]. Research highlights the use of CFD across a wide range of topics in DSFs, including ventilation types and design parameters [1, 10].

CFD thus serves as a robust tool to integrate technical airflow data into architectural design processes. However, architectural students at the early design stages often face challenges in the interpretation of wind environments in tall buildings, particularly in relation to how different façade design strategies produce distinct environmental effects when prior experience is limited. Although CFD velocity contours and vector plots contain detailed information, their numerical complexity often limits accessibility for students. This gap highlights the need for an interpretive visual language that can translate technical simulation outputs into forms that align more closely with architectural ways of perception and reasoning. While CFD contours provide some interpretive guidance, they do not effectively convey how airflow conditions may be perceived or experienced. To address this gap, this study introduces an AI-based visualization approach that reinterprets simulation results as communicative images, including atmospheric diagrams and collages.

1.3. AI-Based Visualization

Rather than relying on numerical values, AI visualization operates as a visual aid that explains potential wind conditions under different design strategies through intuitive, image-based representations. As a result, it provides a means to support students in incorporating wind environment considerations into the design of high-rise buildings at earlier and more exploratory stages of the design process. Airflow in naturally ventilated tall buildings needs to be understood not only in relation to ventilation potential but also with respect to its psychological and experiential impacts. Existing research shows that wind and wind-induced motion shape how occupants perceive comfort, safety, and habitability. These studies clarify why airflow is a determinant of both physical and psychological experience in high-rise environments. Wind affects both body and mind, and tall buildings become environments where sensory perception and emotional interpretation closely interact with physical airflow behavior.

Specifically, prior research demonstrates that wind-induced motion in tall buildings significantly influences occupant comfort and perception, even at relatively low acceleration levels. Surveys and field measurements show that upper-floor occupants often experience discomfort triggered by perceptible lateral motion, with sensory cues such as creaking sounds, swaying fixtures, and bodily sensations leading to dizziness, queasiness, or motion-sickness-like symptoms. Occupants distinguish between merely perceiving motion and finding it objectionable, with acceptability strongly influenced by the frequency of wind events and prior experience [11]. Once building motion enters the perceptible range, it can also produce psychological effects such as fear, reduced concentration, heightened stress, and behavioral responses, including productivity loss or avoidance of certain floors during extreme conditions. These findings highlight acceleration-based thresholds as central to evaluating habitability and underscore the importance of integrating perceptual and psychological responses along with structural performance in design decisions [12].

Building motion significantly affects occupant perception at the structural scale. In contrast, this study focuses on indoor airflow within interior spaces, which is influenced primarily by ventilation strategies and environmental design rather than lateral building movement. Indoor airflow similarly affects occupant comfort, cognition, and well-being. Increased outdoor air ventilation in office buildings has been shown to reduce Sick Building Syndrome symptoms, improve cognitive performance, and lower short-term absenteeism. Economic analyses indicate that the productivity gains from higher ventilation outweigh potential energy savings from reduced airflow, highlighting indoor air quality as a critical determinant of health and workplace performance [13].

Although all these findings address the impact of wind on occupants through human-centered outcomes, it remains challenging to directly connect them to airflow simulations. Emerging AI-based visualization methods provide an approach to bridge this gap, translating simulation data into intuitive representations that can reflect potential human experience. Machine learning models can translate complex aerodynamic data into intuitive visual representations that incorporate human comfort metrics. Neural networks trained on simulation data can predict zones of likely discomfort, while AI tools can produce layered visuals connecting wind speed, building motion, and anticipated emotional responses. Recent studies [14,15] demonstrate that AI-driven models, particularly deep learning surrogate models trained on CFD simulation output, can now generate rapid predictions of wind comfort in urban or built environments, offering a viable tool for early-stage design and wind comfort assessment. However, the present work does not aim to advance predictive accuracy or develop new surrogate models. Instead, it focuses on the semantic–experiential interpretation and visual representation of airflow data, reframing simulation outputs as narratives that can be interpreted and discussed during the design process. AI-generated airflow narratives can help students interpret airflow behaviors under specific velocity conditions or identify floor levels where occupants may feel psychological discomfort. AI visualization thus represents a bridge between wind engineering and environmental psychology and allows the experiential dimension of tall-building wind environments to be incorporated into design decisions.

Recent research in architectural education has increasingly emphasized the role of visualization and performance-based tools in helping students engage with abstract environmental data and translating quantitative metrics into design-relevant understanding. A study demonstrates that integrating building performance simulation into architectural pedagogy enhances students' spatial data sensemaking, enabling them to interpret quantitative environmental data through visual audits and reflective engagement rather than purely numerical evaluation [16]. The study further suggests that such visualization-based pedagogical frameworks help bridge the gap between abstract performance metrics and design reasoning, allowing students to internalize environmental concepts as experiential and spatial qualities within the design process. However, much of the current work on AI-assisted visualization in architecture focuses primarily on data aggregation, statistical representation, or high-fidelity rendering. While these approaches produce accurate visually compelling outputs, they do not fully support interpretive understanding or experiential reading. Moreover, AI has remained largely underexplored as a pedagogical and interpretive tool to connect environmental simulation results to human experience in early-stage design.

Recent research also demonstrates that AI and digital twin technologies are increasingly applied in building studies to enhance energy efficiency, environmental performance, and climate-responsive design. Reviews indicate that AI and big data have been widely used to predict energy consumption, optimize building systems, and evaluate indoor comfort, with a focus on performance optimization, control strategies, and lifecycle efficiency rather than experiential communication or representational clarity [17]. AI-enabled digital twins for bioclimatic building design support adaptive, feedback-driven processes and provide real-time monitoring, simulation, and optimization aligned with local climate conditions [18]. Advances in digital twin infrastructures address challenges of data integrity, security, and system reliability through lightweight authentication and blockchain frameworks, ensuring trustworthy synchronization within sensor-driven environments. These contributions primarily address computational efficiency and system robustness [19]. Collectively, these studies highlight a shift toward data-intensive intelligent building systems while emphasizing the need for approaches that connect technical performance data with perceptual and semantic representations.

Collectively, the literature demonstrates that wind and airflow affect occupants on sensory, emotional, and behavioral levels, and human perception often becomes the most restrictive comfort criterion, exceeding structural or mechanical limits. Prior studies highlight both building-scale wind-induced motion and interior airflow as important determinants of comfort, cognition, and well-being. Since methods for translating technical aerodynamic results into experiential and interpretable insights are still underdeveloped, this study focuses specifically on indoor airflow behavior in naturally ventilated tall office buildings and develops an AI-based visualization approach to convert simulation results into intuitive, communicative images.

2. AI-Based Framework for Experiential Airflow Visualization

2.1. Translational Workflow: Data to Experience

The proposed methodology utilizes AI as a mediator and ultimately develops a framework that transforms numerical airflow behavior information, such as air velocity and airflow distribution, into atmospheric and possibly informative imagery grounded in human perception. Thus, the methodology builds a bridge between quantitative technical data and experiential interpretation through a three-layer process consisting of a Data Layer, a Semantic Layer, and an Image Layer, which functions strictly as a translational workflow rather than a model of human experience.

This approach is motivated by environmental psychology and comfort research demonstrating that humans are highly sensitive to subtle air movements: minimum detectable velocities often fall between 0.15 and 0.2 m/s [20, 21], while discomfort from drafts typically emerges above 0.3 m/s depending on turbulence intensity and body location [22]. Wind engineering research additionally shows that gustiness, directional variability, and vortex-induced oscillations have strong psychological effects, shaping feelings of stability, vulnerability, or alertness within tall buildings [23]. The methodology begins with CFD simulation results, including air velocities that impact human experience, as a source of information on spatial airflow behavior and extends toward an interpretive, perceptually informed visualization of airflow behavior.

2.2. Semantic Mapping of Airflow and Human Response

Despite the abundance of existing literature and empirical datasets on wind environments, architectural students often have limited means to translate these findings into concrete design insights or actionable responses to conditions such as air velocity and airflow distribution. Scholarly discussions and numerical results are typically presented in disciplinary formats that prioritize technical rigor over interpretive accessibility. As a result, further work is needed to better bridge the gap between research knowledge and design decision-making. In response to this gap, the first step of the proposed methodology focuses on extracting semantically meaningful keywords from representative studies on wind environments, human perception, and behavioral response.

Keyword extraction employed AI-assisted natural language processing (NLP), which identified candidate terms related to airflow conditions, sensory perception, psychological response, and behavioral adaptation. These outputs were then manually reviewed to remove redundancies, resolve ambiguity, and ensure relevance to architectural interpretation, while maintaining computational consistency. Using AI-assisted NLP techniques, these keywords are systematically classified and organized into a Self-Organizing Map (SOM), allowing semantic patterns and latent relationships within the literature to emerge visually. Rather than treating wind solely as a physical phenomenon, this semantic mapping translates airflow-related discourse and psychological response data into an interpretable structure that supports clustering analysis and embedding exploration across design, architectural research, and AI modeling workflows. The SOM was implemented with a two-dimensional grid (8 × 8 nodes), trained over 250 epochs with an initial learning rate of 0.5 that decayed linearly over training iterations. These parameters were selected to balance semantic resolution and map stability and to ensure reproducibility of the clustering behavior. The SOM enables semantically related concepts to self-organize based on similarity, revealing conceptual groupings that are difficult to detect through linear reading alone.

To demonstrate this process, five influential studies [12, 23-26] were selected and subjected to AI-based semantic analysis. The review of SOM-generated results examined the spatial distribution of keywords and evaluated the coherence of emerging clusters. The most representative terms reflected the study's pedagogical and interpretive goals. Based on this validation and refinement process, the resulting mapping organizes the extracted concepts into four primary clusters: Sensory, Psychological, Behavioral, and Spatial–Atmospheric clusters (Fig. **1**). Presented in a diagrammatic form, this logic highlights causal and associative pathways that are often implicit in existing studies. The dashed connections between keywords indicate semantic relationships identified by the AI model and reveal links across clusters that may not be immediately apparent in existing studies [27, 28]. A central component of the methodology lies in understanding the macro-structure that links the four experiential clusters into a continuous feedback loop. This framework conceptualizes airflow, perception, and spatial experience as interconnected, where each layer informs and transforms the next, rather than as independent variables.

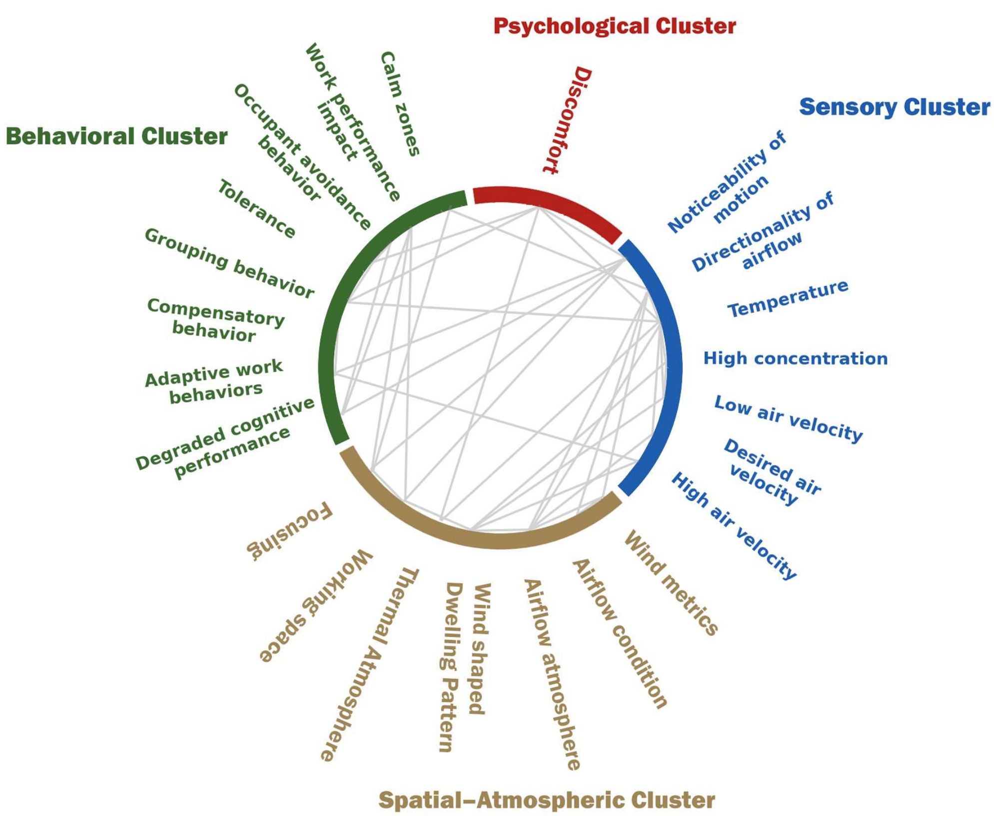


Figure 1: Semantic mapping of velocity and human reactions.

2.3. Sensory, Psychological, Behavioral, and Spatial Loop

The loop begins with the Sensory cluster, where sudden temperature gradients, gusts, or pressure fluctuations are first registered by the body. Although these terms are drawn from the two studies mentioned earlier, the current study focuses specifically on airflow distribution, which is most relevant to the reference simulation results used to validate the AI-assisted framework developed here. These micro-events constitute the primary data of atmospheric awareness and form the “raw perceptual input” that activates cognitive and emotional responses. As these sensations accumulate or intensify, they transition into the psychological cluster, as discomfort, producing feelings of anxiety, vulnerability, and loss of control. This shift is essential because it marks the point where airflow moves beyond the purely physical to become experiential, shaping a person’s sense of safety, comfort, and orientation within tall building environments. These psychological responses, in turn, have a tangible impact on behavior. Within the Behavioral cluster, users may avoid façade zones, relocate to sheltered interior regions, close windows, adjust posture, or shorten outdoor exposure. These actions are not random but follow recognizable patterns related to perceived environmental stability. Over time, these collective behaviors create recognizable spatial atmospheres, understood not merely as physical conditions but as shared, perceived ways of being in space. Feeding into the Spatial–Atmospheric cluster, such atmospheres are often described using familiar phrases, including focusing atmosphere, working atmosphere, and restful atmosphere, which students can easily understand. These expressions do not label measurable microclimates alone and indicate how patterns of occupation and avoidance subtly shape the mood, orientation, and focus within interior spaces. These spatial conditions cycle back into the Sensory cluster as form, porosity, façade geometry, and ventilation strategies alter the qualities of airflow itself (e.g., airflow distribution), modifying pressure sensations and draft detectability.

This closed loop (i.e., sensation, psychology, behavior, and spatiality) provides a conceptual foundation for AI-assisted visualization. Fig. (**2**) visualizes directional pathways through which velocity-driven airflow behavior are translated from sensory perception to psychological response, behavioral adaptation, and spatial–atmospheric reconfiguration, highlighting both causal and feedback relationships across clusters. By embedding each cluster into a semantic structure, AI models can translate CFD simulation results into experiential imagery and generate visual mappings of anxiety intensity, refuge zones, expected movement flows, or perceptual thresholds. The semantic relationships give the model an interpretative grammar that bridges quantitative simulation and qualitative experience. For design strategy, the loop identifies leverage points, such as modifying geometry to interrupt turbulent pathways, reorganizing programs around calm zones, shaping openings to moderate sensory shock, or embedding micro-climatic buffers where behavioral avoidance is predicted. Thus, the macro-structure not only guides visualization but also provides a strategic framework for using airflow simulations to inform design decisions.

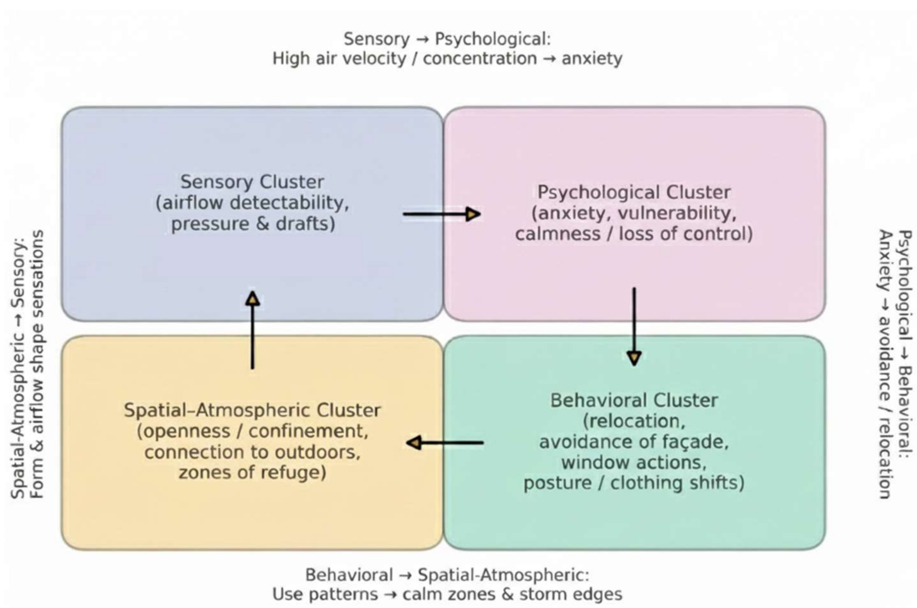


Figure 2: The relational logic between sensory, psychological, behavioral, and spatial–atmospheric clusters.

The SOM functions not only as a visualization of existing knowledge but also as a heuristic device for guiding subsequent research and design exploration. By identifying areas of semantic density, the mapping highlights well-established relationships that can be directly operationalized in design strategies, such as mitigating perceptual discomfort at velocity thresholds associated with anxiety or avoidance behaviors. Conversely, sparsely populated regions of the map point to underexplored connections between airflow characteristics and experiential outcomes, suggesting directions for future empirical study or simulation-based inquiry. In this sense, the SOM serves as an intermediary research tool that informs the next stages of embedding development, AI-based visualization, and design experimentation, enabling students to engage wind as a perceptual factor rather than a purely technical constraint.

3. AI-Assisted Translation from Airflow Simulation to Experiential Visualization

3.1. CFD Simulation Input and Parameter Selection

Based on semantic analysis of velocity and human reactions, AI was employed as the primary tool in this study to generate communicative images from keyword-based prompts that concisely capture airflow behavior and the corresponding human experience and behavioral responses derived from selected published CFD simulation results on natural ventilation in tall office buildings [1, 29]. The methodology focuses exclusively on air velocity and airflow distribution, reflecting a deliberate limitation imposed by the reference CFD simulations, which are conducted under isothermal conditions and for which velocity is the primary outcome used in performance assessment. According to the reference study, as shown in Fig. (**3**), a two-story office block was selected as the CFD model to reduce geometric and computational complexity. Depending on the applied inlet wind speed, the block represents higher (55-56F), middle (30-31F), and lower (5-6F) floors of a 60-story office building. The model incorporated a 4 ft (1.2 m) cavity depth, a staggered opening configuration, and one outer skin opening for every two floors. An open-plan office layout was used, with a 130 ft (39.6 m) wall-to-wall distance, a 35 ft (10.7 m) lease span, a 13 ft (4 m) floor-to-floor height, and a 9 ft (2.7 m) ceiling height. Among the four DSF typologies, this study focused on the multi-story DSF described in [5].

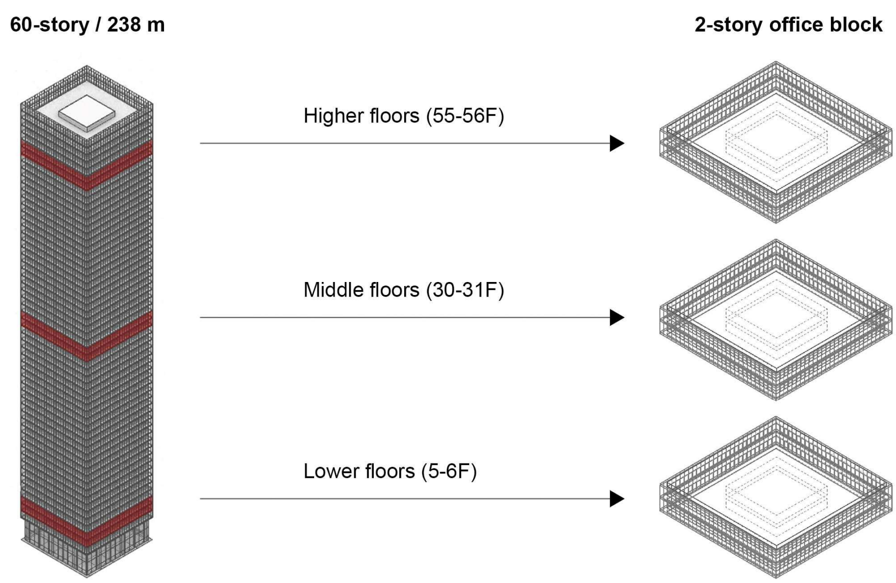


Figure 3: Geometry of the simulation model and location of the 2-story office block.

The selected published simulation results capture variations across facade type (single-skin vs. double-skin), outer skin opening size, opening arrangement (aligned vs. staggered), and floor location (higher, middle, and lower floors) (Fig. **4**). In these simulations, the opening sizes (i.e., 8 cm and 27 cm) indicate the degree to which the openings (e.g., air inlet louvers) on the outer skin and the windows on the inner skin are open, not the absolute dimensions of the openings and windows. Although the reference studies [1, 29] investigate multiple design parameters and variables, the simulation results indicate that façade type, opening size, opening arrangement, and floor location affect airflow behavior and produce markedly different outcomes across configurations. Therefore, a set of representative parameters was selected to demonstrate and validate the developed AI framework and its potential to translate technical data into experiential representations. Analysis proceeded in two steps: (1) descriptive interpretation of plotted velocity contours to examine airflow patterns and wind-driven responses, and (2) radar-chart comparisons based on average indoor air velocities on windward, leeward, and side zones for each configuration.

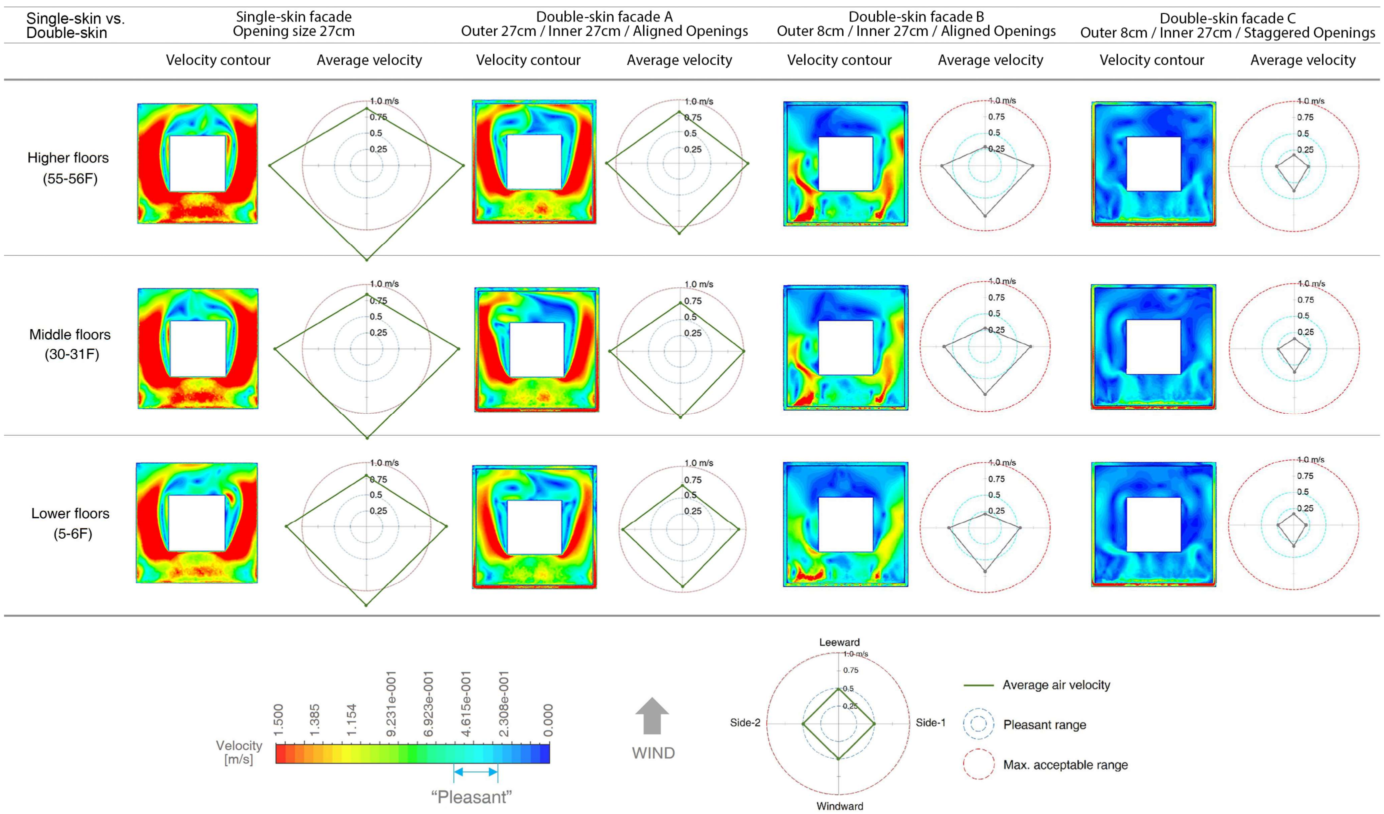


Figure 4: Indoor air velocities for different outer opening size configurations.

Drawing on the simulation results, the AI-assisted visualization strategy incorporates these core dimensions of experience: sensory, psychological, and behavioral responses. These dimensions are treated as interrelated indicators through which airflow behavior in tall buildings contributes to differentiated environmental atmospheres. Although human experience is not examined directly, the study integrates established relationships among air velocity, perceptual thresholds, emotional responses, and behavioral tendencies into a representational framework. This framework provides the conceptual basis for the subsequent translation model, in which physical airflow data is progressively mapped onto experiential and visual representations to support design-oriented exploration.

3.2. Two-Stage Translation Model

The translation model operates through a two-stage learning architecture that systematically links physical airflow data, human experiential responses, and generative visual outputs (Fig. **5**), following established principles of representation learning in which intermediate embedding spaces mediate between raw physical descriptors and higher-level experiential interpretation [30]. In the first stage, a supervised multi-layer perceptron (MLP) is trained to predict experiential embeddings from physical embeddings derived exclusively from previously published simulation results [31]. As an initial pedagogical and experimental implementation, physical embedding is intentionally reduced to a velocity-based representation to simplify the learning task and demonstrate the feasibility of the translation framework. This approach focuses on airflow characteristics as the dominant perceptual driver under controlled conditions. Velocity data are extracted from the published contour plots and radar charts, normalized, and encoded into compact physical embedding vectors representing characteristic airflow behavior across different floor levels and opening configurations.

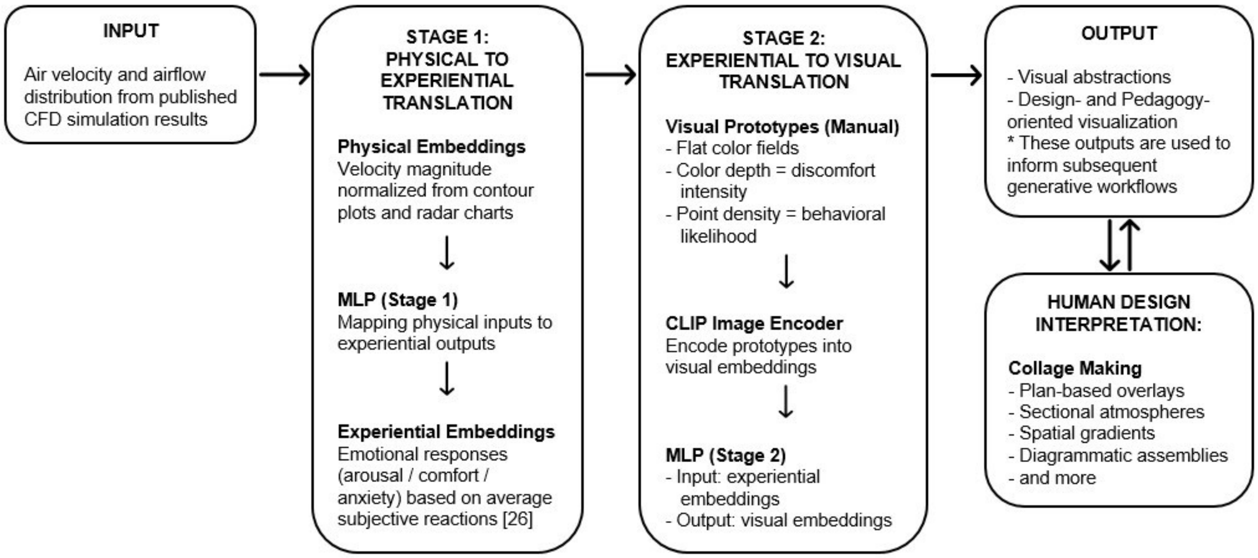


Figure 5: Two-stage AI-assisted translation of airflow simulations into experiential and architectural representations.

By restricting the physical input to air velocity under isothermal conditions, the model focuses exclusively on wind-induced perceptual effects while excluding thermal influences, thereby clarifying the relationship between physical airflow patterns and experiential responses. Correspondingly, the experiential embedding is simplified to a low-dimensional representation centered on emotional response. Building on established environmental perception research, this abstraction maps airflow velocity to subjective response using the average experiential reactions to different air movement intensities reported in [32] and shown in Table **1**. Emotional response dimensions are defined based on established comfort-related thresholds and perceptual categorizations reported in the literature, allowing the published velocity data to be associated with graded levels of arousal, comfort, and anxiety. These experiential variables are not treated as empirically measured psychological states but as an interpretive embedding layer that mediates between physical airflow data and generative visual expression (Table **2**).

Table 1: Average subjective reactions to various velocities. Adapted from [32].

Air Velocity	Average Reactions
<0.25 m/s	Unnoticed
0.25-0.5 m/s	Pleasant
0.5-1.0 m/s	Awareness of air movement
1.0-1.5 m/s	Drafty
>1.5 m/s	Annoyingly drafty

The MLP takes velocity-based physical embeddings as input features and learns a continuous proxy mapping toward corresponding experiential response representations, mediating between documented airflow behavior and its visualized experiential interpretation. Training is conducted in Google Colab using PyTorch [33], with mean squared error (MSE) as the loss function and the Adam optimizer [34] to ensure stable convergence. Early stopping is applied to prevent overfitting. This implementation functions as a minimal yet extensible prototype for AI-assisted translation from physical simulation data to experiential and visual representation, emphasizing airflow-driven perceptual effects rather than predicting or modeling actual psychological responses. Using only the mapping rules defined in Fig. (**4**) (e.g., velocity contour, pleasant range, and maximum acceptable threshold) together with the five-level visual encoding scheme, a reproducible, rule-derived training set and a two-stage MLP workflow were conducted to translate the velocity fields into a discomfort-oriented visualization. Each published CFD result (e.g., facade configuration and floor level) was converted into multiple samples by spatially tiling the velocity contour into small patches. For each patch, a compact physical feature vector was computed consisting of mean velocity, which drives the dot-size pattern level, and a small set of heterogeneity descriptors that are perceptually salient yet computationally minimal. These include the hotspot ratio above the maximum pleasant threshold, the average velocity gradient magnitude, and a simple bias index capturing windward–leeward asymmetry, which together drive the five-level intensity. Velocity conditions falling below perceptual salience thresholds were treated as non-contributory to discomfort.

Table 2: Mapping between airflow parameters, experiential interpretation, and visual attributes.

Airflow Parameter: CFD Simulation	Experiential Attribute	Visual Attribute: Sensory / Psychological / Behavioral
Very low velocity	Neutral or imperceptible airflow	Minimal point density / white / light pink points
Low to moderate	Mild awareness and pleasant	Low point density / pale pink / light pink points
Moderate velocity	Noticeable airflow	Neutral point density / mid-pink / moderately saturated pink points
High velocity	Discomfort associated with air movement	High point density / deep pink / saturated pink points
Strong velocity	Instability and pronounced discomfort	Very high point density / dark pink / dark, highly saturated pink points

This process produced 250 normalized physical-to-experiential proxy pairs. Although the dataset is modest in size, the low dimensionality of the engineered descriptors constrains the hypothesis space, enabling stable convergence for this pedagogical prototype. To mitigate overfitting and avoid patch-level leakage, we employed grouped 5-fold cross-validation with folds split by CFD condition, and report performance averaged across folds. Standard ReLU activations were adopted as a stable and widely used mechanism to introduce nonlinearity, supporting the model's role as an interpretive proxy. The model adopts a lightweight two-stage MLP (fully connected layers of 64, 32, and 16 neurons with ReLU activations), chosen to match the compact input representation. Stage 1 predicts a five-level velocity code derived from the rule-based encoding, and Stage 2 maps the intermediate representation to a scalar discomfort score. This staged design follows the sequence from velocity encoding to discomfort aggregation, improving traceability to the rule set while retaining the flexibility of a trained neural approximation.

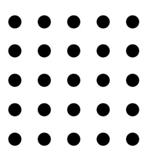
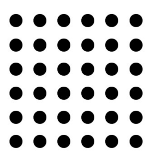
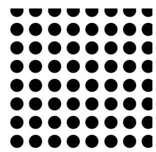
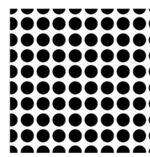
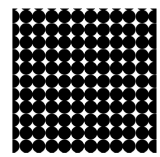
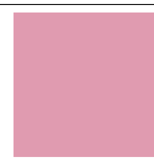
In the second stage, experiential embeddings are translated into visual embeddings compatible with generative AI systems. Given the exploratory and pedagogical nature of this stage, visual attributes are intentionally reduced to a minimal visual language consisting primarily of color variation and point density. Rather than constructing complex visual grammar, this simplified approach is adopted to explicitly test the feasibility of translating experiential states into abstract visual expressions.

3.3. Visual Encoding of Experiential States

At this stage, the multi-dimensional experiential responses identified in the first stage are further abstracted into a single emotional response dimension, representing degrees of discomfort as a dominant negative affective state associated with airflow perception. This single-axis discomfort dimension consolidates correlated experiential responses into a single, legible scalar suitable for visual translation. Research has consistently shown that feelings of anxiety or heightened alertness in high-rise environments arise from various factors beyond airflow, including perceived height, enclosure and openness, visual exposure, and issues of accessibility and egress, which cannot be isolated from CFD-derived data [35, 36]. Accordingly, this study does not model comprehensive psychological states but interprets responses only where they overlap with velocity-induced discomfort. The study restricts the experiential dimension to discomfort and maintains analytical focus on airflow effects while keeping other spatial or environmental stressors separate.

This emotional response is visually encoded through the depth of color saturation within planar color fields, where darker tones correspond to higher levels of perceived discomfort, and lighter tones indicate more neutral or tolerable conditions (Table **3**). Internal consistency is maintained by enforcing a monotonic correspondence between increasing experiential discomfort and increasing visual contrast across all visual mappings. The mapping of discomfort conditions is intentionally reductive and does not aim to represent the full spectrum of human emotion but instead establishes a clear and legible correspondence between experiential intensity and visual contrast. This reduction is justified by the study's focus on comparative design reasoning rather than affective completeness. Human behavior is represented as a generalized physical reaction mapped onto spatial fields as colored point distributions. Point locations indicate likely areas of behavioral response, while density conveys the probability of occurrence, allowing patterns to be visualized spatially without specifying discrete actions or deterministic models.

Table 3: Semantic clusters and keyword set for embedding-based translation of wind-related experience.

Clusters	Visualized Language for Embedding					Keywords (From Text)
Indoor Airflow Behavior (Sensory Cluster)						velocity and airflow distribution
Emotional Response (Psychological Cluster)						discomfort
Physical Reaction (Behavioral Cluster)						adjust posture, orientation, and position, rest, taking breaks, relocation, self-managing discomfort, closing windows

All visual prototypes are manually constructed as abstract, non-representational graphical samples. These prototypes consist of controlled combinations of flat color fields, gradients, and point-based textures, in which visual attributes such as color depth, tonal contrast, point density, and spatial dispersion are systematically varied to correspond to different levels of emotional discomfort and behavioral tendency. Each manually constructed prototype is encoded into high-dimensional visual embedding using a Contrastive Language Image Pretraining (CLIP)-based image encoder, establishing a latent visual space in which systematic variations in minimal visual attributes are numerically represented. A second MLP is then trained to learn a deterministic mapping from experiential embeddings to these visual embeddings, using MSE loss and Adam optimization to ensure consistency between experiential states and visual expression. Once trained, the two-stage system enables a complete computational pipeline in which physical airflow data are embedded, translated into experiential states, converted into visual embedding vectors, and subsequently used to condition or modulate generative workflows in later design stages.

4. Results

4.1. Visualizing Airflow

The resulting images do not function as literal simulations of airflow, nor as predictions of human behavior. Instead, they operate as semantically grounded visual abstractions that externalize airflow-related discomfort and spatially distributed behavioral tendencies (Fig. **6**-**8**). By deliberately restricting the visual language to minimal attributes such as color depth and point density, this stage clarifies the translation logic between experiential meaning and visual expression, providing a controlled foundation for future expansion into richer visual grammars and more differentiated behavioral representations. A simplified visual language plays an important pedagogical and design-oriented role in communicating the experiential impact of airflow within architectural space. Building on this conceptual framework, the following visualizations demonstrate how these abstractions represent both physical airflow and experiential responses.

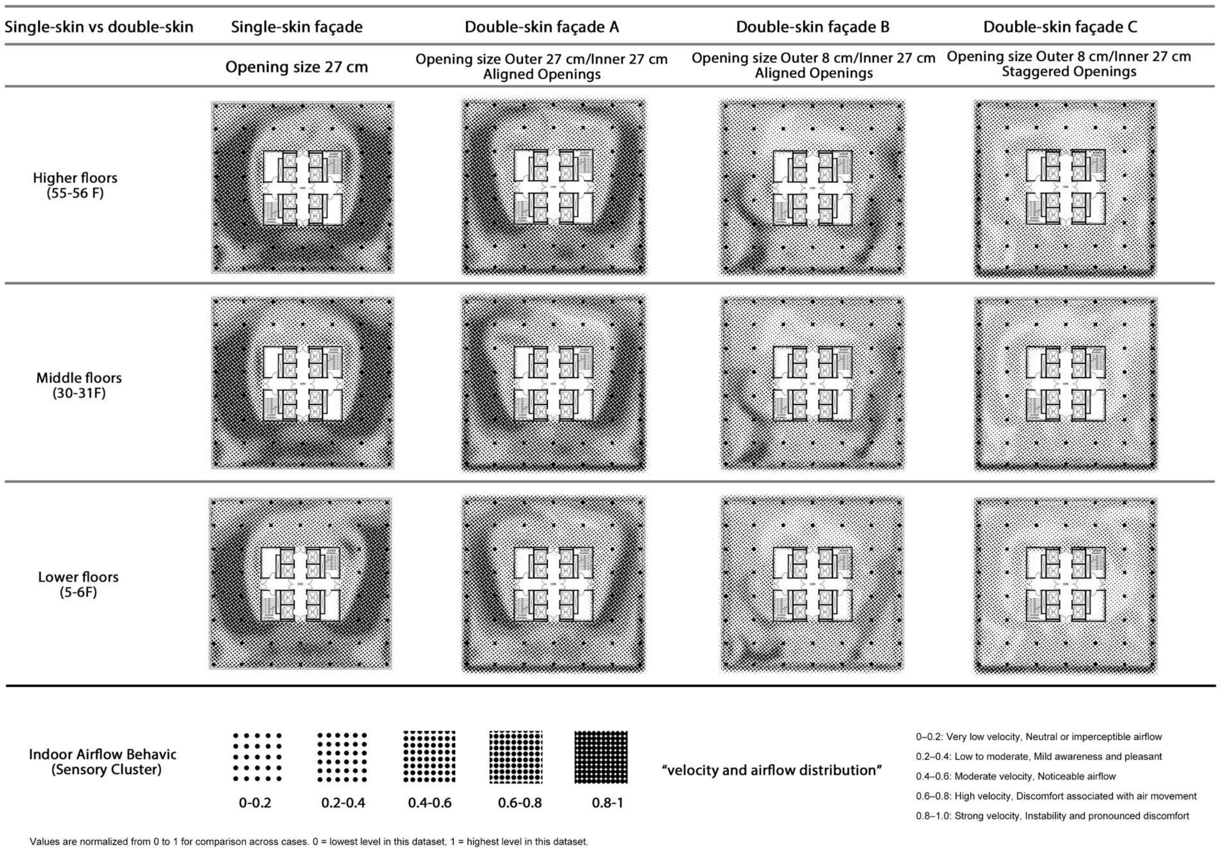


Figure 6: Sensory cluster visualization for velocity and airflow distribution.

This simplification offers clear advantages over traditional CFD visualizations in pedagogical contexts. Conventional CFD displays use multicolored bands to encode a wide range of values, forcing viewers to translate between legends, color intervals, and spatial patterns. Students without CFD experience may focus on reading the scale rather than understanding airflow effects. A single-color family with gradual variations lets students perceive relative intensity directly, without interpreting discrete thresholds or legends. Continuous color changes reflect how students experience airflow and spatial atmosphere, as gradual rather than abrupt shifts. Lower visual complexity reduces the cognitive barrier and allows students to attend to patterns, gradients, and spatial tendencies rather than numerical precision. The visualizations thus serve less as technical outputs and more as interpretive diagrams that link airflow behavior with experiential understanding in architectural space.

The black point density (Fig. **6**) serves as a direct encoding of airflow velocity, where higher concentrations indicate regions of intensified wind speed derived from the underlying simulation data. This point-based representation preserves a legible connection to the physical layer of airflow behavior. Superimposed upon this physical layer, the pink tonal fields (Fig. **7**) represent the predicted emergence of spatial discomfort under the corresponding airflow conditions. These pink regions do not indicate absolute thresholds of comfort or discomfort and instead function as relative experiential indicators, highlighting zones where airflow intensity and fluctuation are more likely to be perceived as intrusive, unsettling, or difficult to accommodate. As shown in Fig. (**8**), the pink tonal points indicate behavioral responses to airflow conditions. Although the specific behaviors represented by each point are not explicitly defined in the resulting images, each pink tonal point conveys the degree to which occupants are likely to take action in response to the magnitude of air velocity and the concentration of high air velocities. For instance, more intense physical reactions are observed in high-velocity zones. When compared across different design configurations and floor locations, Fig. (**6**-**8**) further reveal how the design parameters and variables systematically reshape the experiential consequences based on various airflow behaviors. The single-skin facade (SSF) configuration tends to produce more pronounced velocity concentrations and higher average air velocities throughout the space than DSF configurations, typically more intense on the windward and both sides, which translate into broader or more continuous discomfort fields. Within the DSF configurations, comparisons between DSF "A" and "B" configurations show that smaller outer-skin openings generate more localized and diffuse patterns, in which airflow intensity and associated discomfort are confined to smaller areas and dissipate more gradually. Although lower floors generally exhibit slightly fewer discomfort zones than middle and higher floors, experiential outcomes are influenced more strongly by design configuration than by floor location alone. The DSF "C" configuration further demonstrates that staggered opening arrangements can significantly reduce discomfort zones across all floor levels.

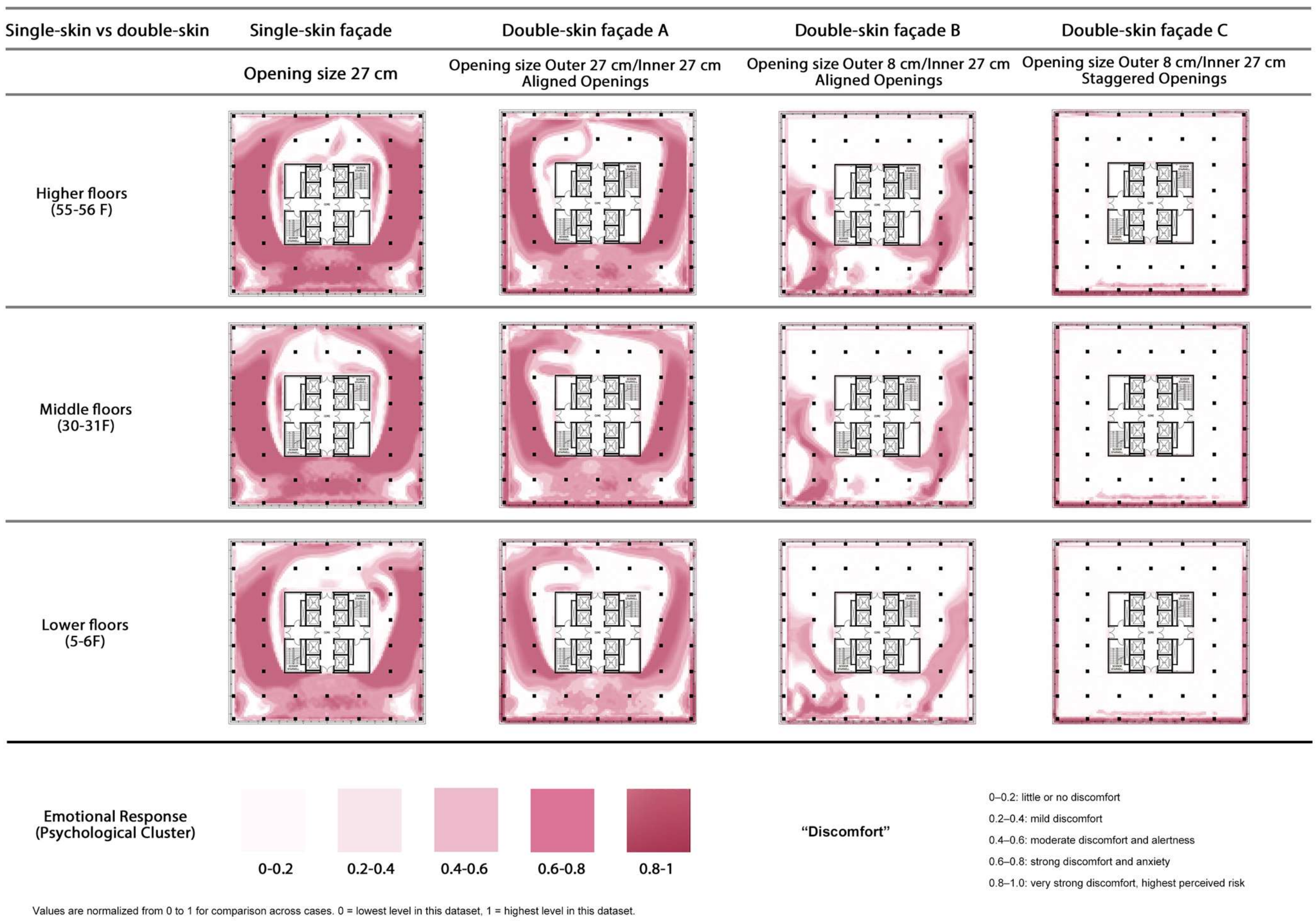


Figure 7: Psychological cluster visualization of predicted spatial discomfort zones.

4.2. Behavioral Responses and Spatial Patterns

Behavioral responses closely mirror these airflow and discomfort behaviors. In areas with higher velocity concentrations, occupants are more likely to engage in pronounced adaptive actions, such as relocating to sheltered zones, adjusting posture to reduce exposure, or limiting time spent near facades. Conversely, in regions characterized by lower or more diffuse airflow, behavioral responses tend to be subtler and more dispersed, reflecting greater environmental tolerance. This alignment between airflow behavior, experiential discomfort, and behavioral adaptation emphasizes the value of the proposed visual framework in linking physical simulation data to patterns of human response.

Based on the average subjective reactions listed in Table **1**, the "unnoticed" air velocities are particularly observed on the DSF "C" configuration with a smaller opening size and a staggered opening type, occurring more prominently on the suction sides except for the windward side. These velocities are represented as less intense experiential responses, although their interpretation can be subjective depending on specific project goals when using the developed framework. For example, students may choose to treat the "unnoticed" air velocities as areas to avoid for their project objectives and visualize or highlight them differently to represent the corresponding behavioral responses.

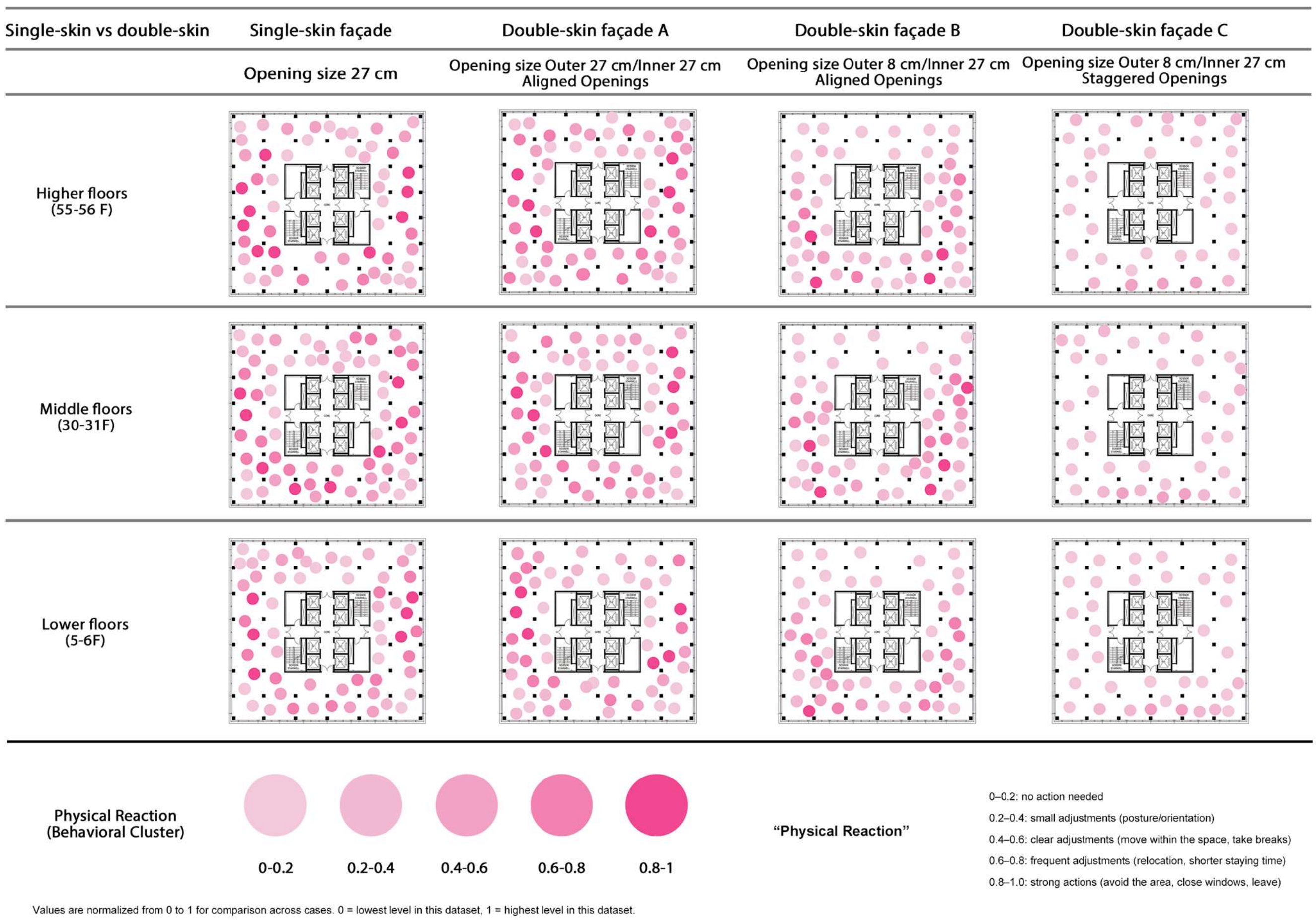


Figure 8: Behavioral cluster visualization of physical reactions.

Overall, these comparative readings reinforce the value of the abstract visual language because the diagrams maintain a consistent encoding scheme across scenarios and enable rapid cross-comparison of environmental atmospheres. This abstraction allows students to intuitively grasp how changing wind conditions shape emotional atmospheres, from calmness and tolerance to tension and unease, by providing a design-oriented perspective that complements detailed aerodynamic analysis.

4.3. Integrative Collage

Through this process, quantitative airflow data expressed in numerical and analytical form are translated into a visual language that prioritizes perceptual legibility over technical precision. Once encoded as abstract visual fields of color and density, these representations can be further reinterpreted through collage techniques into architectural languages that are already familiar to students, such as plan-based overlays, architectural atmospheres, spatial gradients, or diagrammatic assemblies. In Fig. (**9**), the sensory, psychological, and behavioral cluster visualizations are overlapped within a single collage example, as the result of spatial atmospheric cluster, providing a more comprehensive view of how airflow behavior shapes human experience and associated behavioral responses, while incorporating additional project-related images and drawings. The circulation pathway is also integrated into the collage, linking spatial patterns of movement with zones of discomfort, calm, or adaptation. By overlapping these clusters, the collage allows students to simultaneously perceive the interrelationships between physical airflow, experiential discomfort, and behavioral tendencies, and reveals patterns that may not be evident when examining each cluster in isolation. This approach enhances the interpretability of complex environmental data, supports design-oriented reasoning, and enables a more holistic understanding of airflow impacts within architectural space, while maintaining a legible and intuitive visual grammar. The collage is an illustrative design translation rather than a direct analytical result and thus serves primarily to communicate interpretive insights derived from the data. It also represents one of many possible visualizations the developed framework can generate, and the framework can be adapted in various ways depending on specific project goals. Collage functions here as a mediating representational practice, allowing visual embeddings derived from data to be re-situated within architectural conventions of drawing, composition, and spatial reasoning. This collage as a visualization does not aim to produce a single, optimized solution. Instead, it creates conditions for interpretation, reflection, and productive uncertainty in the design process. By emphasizing ambiguity and relational reading over definitive solutions, the collage invites students to treat data as a prompt for inquiry, where unexpected visual alignments or tensions generate new questions about spatial performance and experience.

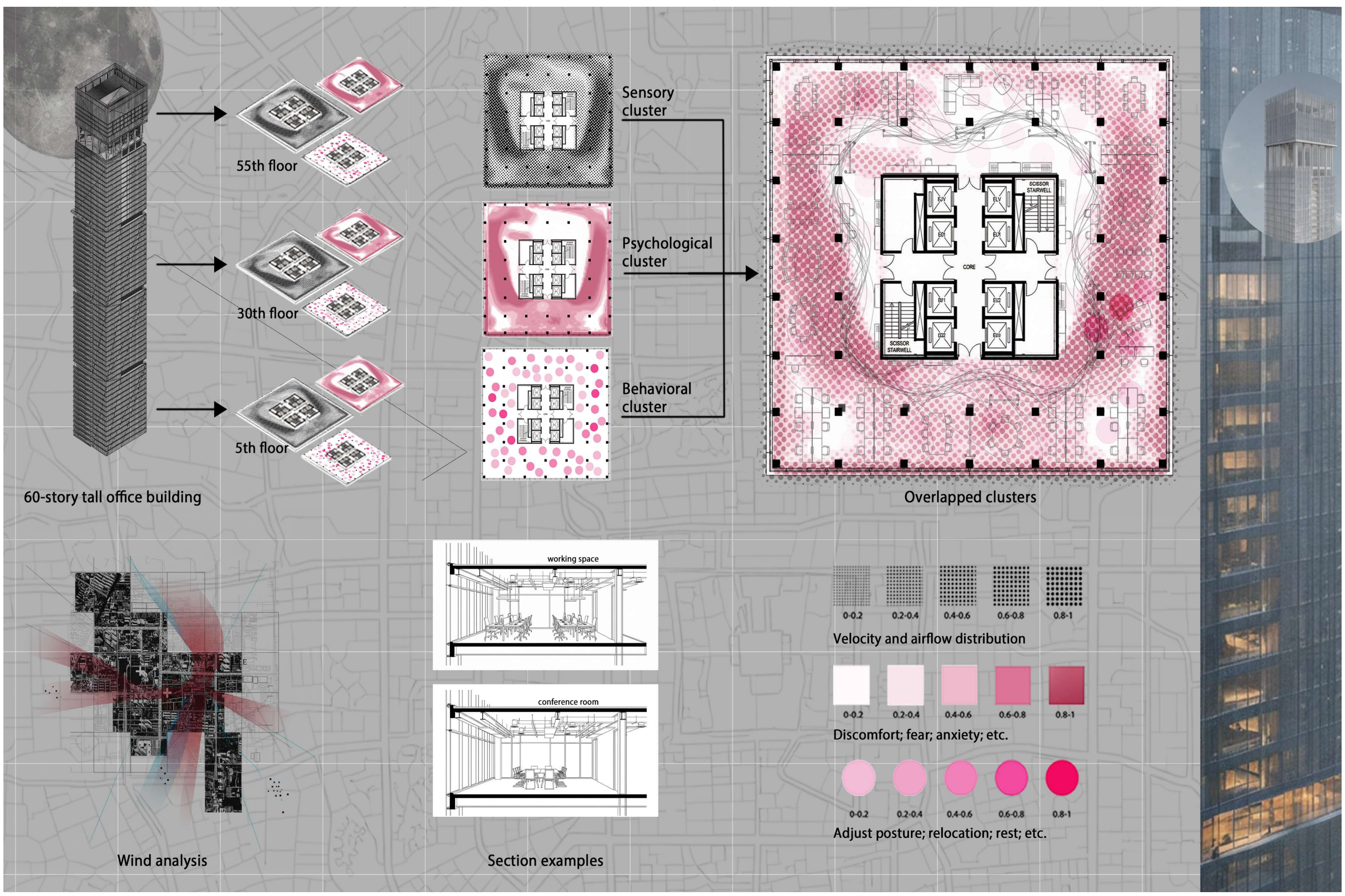


Figure 9: Illustrative collage translating airflow data into architectural representations.

By operating across these representational layers, airflow behavior becomes instrumental beyond its conventional role in simulation-based evaluation, enabling students to engage airflow as a spatial and atmospheric condition rather than as isolated technical output. Integrated into familiar design conventions, these abstractions support discussion, comparison, and speculative exploration in early design stages, where rapid interpretation and qualitative assessment are essential, and help cultivate sensitivity to how environmental forces shape emotional atmosphere and spatial experience. This multi-step translation positions visualization not as a final explanatory image, but as an active design instrument, bridging numerical simulation data with architectural thinking and allowing students to integrate experiential wind conditions into their conceptual and representational practices.

5. Conclusion and Discussion

This study represents an early step toward establishing a systematic method and framework for translating technical airflow data into experiential visualizations, and it therefore provides potential for several future research directions. It also serves as a teaching approach that supports students' learning by helping them connect technical performance data with human experience through visual interpretation. Although the current work relied on a limited set of general keywords derived from selected simulation results and published references, future studies can focus on developing a more adaptable framework that can generate project-specific outcomes. Such a framework could incorporate keywords tailored to the specific goals of each project, enabling more practical representations of the experiential and behavioral implications of airflow or other performance metrics across diverse architectural contexts. By refining the framework and applying it across diverse case studies, the method can evolve into a practical tool that enhances the visualization of human experience and behavior, increases its applicability, and ultimately supports the design process, analysis, and communication.

An additional limitation of this study is that the AI-generated images were derived from simulation results focusing solely on wind effects under isothermal conditions. Future research should address a broader set of environmental factors, such as temperature and thermal gradients that impact airflow behavior as well, to refine the framework and produce more comprehensive representations of airflow-induced human experiences. Similarly, while the study demonstrates the framework using naturally ventilated tall office buildings, the translation logic is not inherently limited to this building type or ventilation strategy. With appropriate simulation or experimental data, the framework could be extended to other building typologies and ventilation approaches, including mechanical and hybrid systems. Finally, while direct validation through user studies, surveys, or case-study comparisons was not conducted, future research could pursue such validation to further support the visualizations in human experience and assess their effectiveness in educational contexts.

The use of abstract visualizations plays an important role in design education by making complex environmental information accessible and interpretable. The framework provides intuitive cues of comfort, discomfort, and potential behavioral tendencies, and helps students understand how airflow and wind conditions influence emotional atmosphere and spatial experience. This approach allows learners to engage conceptually with environmental effects and integrate them into the design process in studios or design-oriented courses. It also supports reflection and discussion within familiar architectural representational formats, encouraging students to consider environmental conditions as integral to design decisions from the early stages.

When integrated into architectural drawing and collage exercises, these abstractions become active learning instruments rather than static outputs. Students move beyond passively receiving data and instead explore how environmental conditions shape spatial organization, circulation, façade design, interior–exterior transitions, and more. The framework considers airflow-related comfort and discomfort as a relative, scenario-based design parameter, informed by consistent mapping rules rather than predictive evaluations, supporting iterative reasoning and enabling learners to assess the usefulness of visualizations by their coherence across design alternatives and alignment with airflow behaviors.

Moreover, the framework contributes to ongoing discussions on the role of AI in architectural design by framing AI not as an autonomous generator of form, but as a mediator of meaning between data and design intent. The proposed translation process demonstrates how computational models can support architectural thinking by revealing latent experiential dimensions embedded within environmental data. While the current study adopts a deliberately simplified visual and experiential scope, the methodology establishes a scalable foundation for future research incorporating richer physical parameters, more differentiated experiential dimensions, and expanded visual grammars. Ultimately, this approach underscores the value of integrating environmental performance, human experience, and architectural representation within a unified design-oriented workflow, fostering more responsive architectural outcomes.

Conflict of Interest

The authors declare that they have no conflict of interest.

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