

Article

LLM-Assisted Semantic Mining of Passenger Perception in Humanistic Airport Waiting Areas: A Framework for Cultural Heritage Dissemination

Ran Zhang^{1,*}
¹ Shenyang Aerospace University, Shenyang, China

* Correspondence: Ran Zhang, Shenyang Aerospace University, Shenyang, China

Abstract: Airport waiting areas increasingly function as transport, cultural-communication, and informal public-learning spaces, yet spontaneous passenger perceptions are difficult to capture through preset questionnaires. This study develops a large language model (LLM)-assisted semantic mining framework that translates multi-source passenger text into traceable evidence for humanistic airport design. Reviews, social-media posts, service messages, and field interviews are cleaned and coded into five fields: spatial area, perceptual object, perceptual word, sentiment polarity, and design implication. The extracted semantics are organized into five dimensions: spatial scale, physical environment, humanistic atmosphere, functional facilities, and psychological emotion. Perception intensity, negative concentration, and a comprehensive shortcoming index support zone-specific diagnosis. Illustrative expressions such as "oppressive," "cold," "weak regional identity," "insufficient seating," and "waiting anxiety" are linked to circulation, environmental comfort, cultural integration, facilities, and emotional support. By connecting passenger language with spatial diagnosis and culturally responsive design strategies, the framework provides a concise methodological route for improving waiting-space experience and supporting cultural heritage dissemination.

Keywords: Large Language Models; Airport Waiting Area; Passenger Perception; Semantic Mining; Humanistic Airport; Cultural Heritage Dissemination

1. Introduction

Airport terminals are not only transport infrastructure but also urban gateways where mobility, public service, and cultural communication intersect. Waiting areas create sustained contact with local imagery, materials, displays, and service environments, giving them potential to support place recognition and informal cultural learning. At the same time, long dwell periods expose passengers to fatigue, uncertainty, boredom, and anxiety. Under China's humanistic airport agenda, waiting-space evaluation should therefore extend beyond capacity and processing efficiency to comfort, care, cultural identity, and place memory [1-2].

Conventional evaluations rely on questionnaires, expert scoring, observation, and interviews, but preset indicators may overlook implicit perceptions embedded in spontaneous language. Expressions such as "too cold," "hard to navigate," "like a shopping mall," and "too few seats" simultaneously reveal a spatial object, an evaluative judgment, an emotional tendency, and a possible design problem. Airport service-quality research likewise indicates that density, environmental conditions, accessibility, service organization, and anxiety jointly shape passenger experience [3-10].

LLMs can interpret large volumes of unstructured text, identify evaluated objects, group semantically similar expressions, infer sentiment, and retain contextual meaning. Building on aspect-based sentiment analysis and LLM-assisted qualitative research [11-19], this study develops the pathway "Passenger Text - Perception Dimensions - Spatial

Received: 20 August 2026

Revised: 26 September 2026

Accepted: 09 October 2026

Published: 12 October 2026



Copyright: © 2026 by the authors. Submitted for possible open access publication under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

Problems - Design Translation." The aim is to turn everyday passenger language into traceable evidence for spatial diagnosis while preserving the cultural and emotional meanings that conventional satisfaction scores may underrepresent.

2. Theoretical Basis and Research Logic

2.1. Waiting-Area Experience and Humanistic Airports

Service-scenario research shows that physical settings influence perceived quality and emotion [3]. In airport waiting areas, layout, lighting, noise, temperature, furniture, wayfinding, commerce, and cultural symbols jointly affect judgment. From a humanistic perspective, regional culture should not be reduced to decorative motifs; it should be integrated into circulation, waiting, rest, information, and display experiences. The waiting area can therefore function as an informal public-learning environment in which passengers encounter local heritage through spatial experience rather than formal instruction.

2.2. Applicability of LLM-Assisted Semantic Mining

Aspect-based sentiment analysis decomposes comments into object-evaluation-sentiment relationships [11-13], while LLMs can recognize non-standard expressions, group related meanings, and generate interpretable labels [14-19]. For spatial research, this supports a four-stage logic: extract perceptual semantics, aggregate them into explainable dimensions, associate those dimensions with concrete waiting zones, and translate recurrent negative perceptions into design responses. Manual verification remains necessary so that ambiguous expressions and culturally specific meanings remain traceable to their source text.

3. Research Design

3.1. Research Subjects and Data Sources

The proposed framework is designed for airport waiting-space analysis across check-in areas, post-security waiting areas, commercial mezzanines, corridors, boarding gates, and lounges. For case application, four complementary source types are considered: tourism-platform reviews, social-media posts, airport complaints or public service messages, and open-ended field interviews. Before analysis, advertisements, reposts, duplicates, meaningless short phrases, privacy-sensitive content, and text unrelated to spatial experience are removed (As shown in Table 1).

Table 1. Passenger-text Data Sources and Analytical Value

Data source	Main content	Analytical value / control
Tourism-platform reviews	Overall waiting, commerce, rest, hygiene, access	Large samples reveal recurrent issues; remove ads, duplicates, and very short text.
Social-media posts	Visual-textual experiences, check-ins, complaints, cultural perception	Captures emotional expression; separate spatial experience from general travel emotion.
Complaints / service messages	Facilities, wayfinding, service inconvenience, environment	Concentrates negative weak points; protect privacy and limit direct quotation.
Field interviews	Open spatial perception, circulation experience, design suggestions	Adds context and supports verification; standardize interview and transcription rules.

Together, platform reviews support frequency analysis, social media captures emotionally salient experience, complaints reveal operational weak points, and interviews provide contextual verification. Combining these sources reduces dependence on a single platform and helps preserve both service-related and culture-related perceptions.

3.2. Technical Procedure and Annotation Rules

The procedure comprises text collection, cleaning, LLM semantic extraction, dimension clustering, sentiment quantification, and design translation. Each valid text is decomposed into five fields: "Spatial Area - Perceptual Object - Perceptual Word - Sentiment Polarity - Design Implication." For example, a statement such as "The post-security waiting hall is large, but there are too few seats, making the wait tiring" can be coded by location, evaluated object, perception words, sentiment, and a tentative response such as distributed seating and short-stay support. Model outputs are manually checked before aggregation (As shown in Table 2).

Table 2. LLM Annotation Fields and Spatial Interpretation

Field	Meaning	Typical output
Spatial area	Locates where the perception occurs	Check-in area; post-security waiting area; commercial mezzanine; corridor; boarding gate
Perceptual object	Identifies the evaluated space, facility, or environmental element	Seating; lighting; ceiling height; circulation; commerce; cultural display
Perceptual word	Retains the passenger's original evaluative semantics	Oppressive; spacious; cold; cluttered; distinctive local character
Sentiment polarity	Classifies the evaluation tendency	Positive; negative; neutral; mixed
Design implication	Translates semantics into an optimization direction	Optimize lighting; increase seating; improve wayfinding; strengthen regional culture

The schema keeps model output traceable by preserving the passenger's original perceptual wording while separately recording location, object, polarity, and design implication. Synonyms are merged only after contextual checking, and ambiguous expressions such as "too empty," "cold," or "hard to find" remain available for manual review. In this framework, the LLM functions as an assisted coder and semantic organizer rather than a substitute for spatial interpretation.

3.3. Humanistic Perception Framework and Diagnostic Indicators

Five perception dimensions are retained from waiting-space characteristics and passenger semantics. Together they link spatial-material conditions with emotional and cultural responses, providing a shared structure for service analysis, humanistic evaluation, and design translation (As shown in Table 3).

Table 3. Humanistic Perception Dimensions and Design Correspondence

Dimension	Key indicators	Typical perception words	Design correspondence
Spatial scale	Spaciousness, enclosure, crowding, permeability	Open, oppressive, empty, crowded	Ceiling height, interface enclosure, circulation, density
Physical environment	Lighting, noise, temperature, cleanliness, texture	Bright, dim, noisy, cold, clean	Lighting, acoustics, HVAC, maintenance, materials
Humanistic atmosphere	Regional culture, place identity, distinctiveness, warmth	Cultural, sterile, mall-like, unremarkable	Cultural integration, thematic display, local symbols

Functional facilities	Rest, charging, commerce, accessibility, wayfinding	Few seats, difficult charging, unclear signage	Furniture, convenience facilities, commercial boundaries, wayfinding
Psychological emotion	Anxiety, fatigue, boredom, security, relaxation	Tired, annoyed, secure, bored, relaxed	Waiting rhythm, rest nodes, comfort, experiential activity

To support spatial comparison, this study defines three diagnostic indicators. Perception intensity is $H(r,k)=n(r,k)/N(r)$, where $n(r,k)$ is the number of texts mentioning dimension k in area r and $N(r)$ is the number of valid texts in that area. Negative concentration is $P-(r,k)=n-(r,k)/n(r,k)$. A comprehensive shortcoming index can be expressed as $I(r,k)=\alpha H(r,k)+\beta P-(r,k)+\gamma M(r,k)$, where $M(r,k)$ is an importance weight confirmed through manual verification. Zones with both high mention intensity and high negative concentration should receive priority in subsequent spatial diagnosis.

The five dimensions should be interpreted as an interconnected system. "Cold," for example, may involve material texture, lighting, thermal conditions, and a weak sense of place, while "crowded" may reflect both density and circulation conflict. Cross-dimensional interpretation prevents a single keyword from being converted into an overly simple design response.

3.4. Spatial Problem Diagnosis and Design Translation

Semantic mining becomes useful for design when recurrent perceptions are translated into spatial decisions rather than left as word-frequency results. Table 4 illustrates how typical semantic shortcomings can be connected to plausible spatial causes and actionable responses.

Table 4. Illustrative Semantic Shortcomings and Design Responses

Illustrative semantic shortcoming	Design response
"Oppressive, crowded, detour"	Open enclosed interfaces where possible; separate crossing flows; strengthen continuous sightlines and visual guidance nodes.
"Cold, noisy, dark, uncomfortable"	Improve daylight and layered lighting; strengthen acoustic control; stabilize thermal comfort; introduce warmer material interfaces.
"No character, like a mall, cold"	Integrate local cultural themes and public art into circulation and stay nodes; control commercial interfaces so they do not dominate place identity.
"Few seats, difficult charging, limited rest"	Add distributed seating, charging tables, quiet rest areas, and flexible furniture near boarding and waiting nodes.
"Anxious, tired, annoyed, bored"	Create a clearer waiting rhythm with static rest, cultural display, parent-child interaction, and information-prompt nodes.

The translation logic is zone-sensitive. In post-security waiting areas, repeated references to insufficient seating, charging difficulty, and fatigue would indicate weak stay-support capacity; in commercial mezzanines, descriptions such as "chaotic," "confusing," or "like a shopping mall" would instead point to commercial-boundary control, clearer wayfinding, and stronger cultural integration.

At the dimension level, spatial-scale complaints can guide inspection of enclosure, pedestrian-flow intersections, and sightlines, while physical-environment complaints can direct attention to daylight, acoustics, thermal comfort, maintenance, and material texture.

Humanistic, facility, and psychological perceptions require integrated responses. Weak regional identity, uneven seating and charging, or anxiety and boredom may call

for cultural themes, public art, distributed rest facilities, clearer information, and experiential nodes rather than isolated decorative interventions.

Zone-oriented diagnosis thus converts generalized passenger feedback into a location-sensitive basis for environmental and cultural-experience design.

4. Discussion and Research Value

The framework contributes in three ways: it treats waiting space as a humanistic environment carrying emotional, cultural, and place meanings; it combines LLM-assisted semantic extraction with dimension clustering, sentiment assessment, and manual verification; and it links perceptual expressions to concrete zones, problem types, and culturally responsive design strategies.

Its value lies in making qualitative perception operational while keeping interpretation traceable to source text. Because the present study is methodological rather than a completed airport case validation, future work should test the framework with real terminal datasets and cross-check LLM coding against site evidence, passenger-flow observations, behavior trajectories, and manual coding across different airports and passenger groups.

5. Conclusion

This paper proposes an LLM-assisted semantic mining framework that connects passenger language with spatial diagnosis and cultural-experience design in airport waiting areas. Multi-source text is organized into five annotation fields, aggregated into five perception dimensions, and interpreted through three diagnostic indicators. The framework provides a traceable route from everyday perception to location-sensitive responses while foregrounding comfort, place identity, and cultural heritage dissemination.

References

1. Civil Aviation Administration of China, "Interpreting the 'Guidelines for Humanistic Airport Construction'," [EB/OL], Nov. 3, 2020.
2. Civil Aviation Administration of China, "Interpreting the 'Action Plan for Building Four Types of Airports in Chinese Civil Aviation (2020–2035)'," [EB/OL], Jan. 9, 2020.
3. D. Fodness and B. Murray, "Passengers' expectations of airport service quality," *Journal of Services Marketing*, vol. 21, no. 7, pp. 492–506, 2007.
4. A. R. Correia, S. C. Wirasinghe, and A. G. de Barros, "Overall level of service measures for airport passenger terminals," *Transportation Research Part A*, vol. 42, no. 2, pp. 330–346, 2008.
5. V. Bogicevic, W. Yang, A. Bilgihan, and M. Bujisic, "Airport service quality drivers of passenger satisfaction," *Tourism Review*, vol. 68, no. 4, pp. 3–18, 2013.
6. V. Bogicevic, W. Yang, C. Cobanoglu, et al., "Traveler anxiety and enjoyment: The effect of airport environment on travelers' emotions," *Journal of Air Transport Management*, vol. 57, pp. 122–129, 2016.
7. G. C. L. Bezerra and C. F. Gomes, "The effects of service quality dimensions and passenger characteristics on passengers' overall satisfaction with an airport," *Journal of Air Transport Management*, vols. 44–45, pp. 77–81, 2015.
8. G. C. L. Bezerra and C. F. Gomes, "Measuring airport service quality: A multidimensional approach," *Journal of Air Transport Management*, vol. 53, pp. 85–93, 2016.
9. G. Ma, J. Zhang, Y. Ding, et al., "The impact of airport physical environment on perceived safety and satisfaction," *Sustainability*, vol. 14, no. 9, p. 5628, 2022.
10. Transportation Research Board, *ACRP Report 55: Passenger Level of Service and Spatial Planning for Airport Terminals*. Washington, DC: National Academies Press, 2011.
11. S. Ruder, P. Ghaffari, and J. G. Breslin, "A hierarchical model of reviews for aspect-based sentiment analysis," in *Proc. EMNLP Workshop*, 2016.
12. M. S. M. Alaydaa, J. Li, and K. Jenkins, "Aspect based sentimental analysis for travellers reviews," [EB/OL], arXiv:2308.02548, 2023.
13. M. S. M. Alanazi, M. S. M. Alaydaa, J. Li, and K. Jenkins, "Multiclass sentiment prediction of airport service online reviews using aspect-based sentimental analysis and machine learning," *Mathematics*, vol. 12, no. 5, p. 781, 2024.
14. A. Vaswani, N. Shazeer, N. Parmar, et al., "Attention is all you need," in *Advances in Neural Information Processing Systems*, 2017.

15. J. Devlin, M. W. Chang, K. Lee, and K. Toutanova, "BERT: Pre-training of deep bidirectional transformers for language understanding," in *Proc. NAACL-HLT*, 2019.
16. T. B. Brown, B. Mann, N. Ryder, et al., "Language models are few-shot learners," in *Advances in Neural Information Processing Systems*, 2020.
17. C. Ziems, W. Held, O. Shaikh, et al., "Can large language models transform computational social science," *Computational Linguistics*, vol. 50, no. 1, pp. 237–291, 2024.
18. C. F. Barros, B. B. Azevedo, V. V. Graciano Neto, et al., "Large language model for qualitative research: A systematic mapping study," [EB/OL], arXiv:2411.14473, 2024.
19. J. Drápal, H. Westermann, and J. Savelka, "Using large language models to support thematic analysis in empirical legal studies," [EB/OL], arXiv:2310.18729, 2023.

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of Publisher and/or the editor(s). Publisher and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.