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Enhancing public health-oriented travel services: an integrated framework combining FAHP, Kano model, and UTAUT2

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Public transportation plays a vital role in urban mobility, yet many systems lack adequate hygiene and safety measures, especially during pandemics. To address this gap, this study evaluates passenger-centric design attributes for health-oriented travel services and identifies key factors influencing user acceptance using a mixed-methods approach. The Kano Model is employed to categorize hygiene and safety requirements based on passenger preferences, while the Fuzzy Analytic Hierarchy Process (FAHP) is applied to quantify the priority weights of these requirements. The UTAUT2 model is extended to assess user acceptance of the optimized solutions, incorporating pandemic-specific factors like perceived risk and price sensitivity. Key findings reveal that timely sanitation is the most critical requirement, and enhancements such as rapid temperature screening, integrated health/QR code systems, and proactive epidemic prevention measures significantly improve user satisfaction. The UTAUT2 analysis highlights social influence, price sensitivity, and perceived risk as dominant factors affecting user acceptance. These results provide actionable insights for policymakers and urban planners to enhance public transport systems during health crises. By prioritizing mandatory hygiene protocols and addressing user perception gaps, safety outcomes and service adoption rates can be improved. This study offers a scalable framework for balancing operational feasibility and passenger-centric design in future public health emergencies.

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Introduction

The COVID-19 pandemic triggered unprecedented disruptions to global public transportation systems (Sun et al. 2024). Nations adopted multiple containment strategies—from standardized crisis management protocols for rail transit in China (China Association of Metros 2024) to mask mandates integrated with contactless payment systems in England (Chen et al. 2024; Jefferson et al. 2023). Similarly, high-density Asian cities implemented dynamic occupancy controls based on real-time passenger flow predictions, reducing transit capacity to 50% during peak infection periods (Palur et al. 2025). Conversely, the United States prioritized sanitization over mobility restrictions, maintaining full public transport operations while deploying thermal imaging and antimicrobial coatings at major hubs (Rocchetti and De Rosa 2025).

Despite these efforts, the COVID-19 pandemic has fundamentally altered public transportation dynamics worldwide, exposing critical gaps in hygiene infrastructure and safety protocols (Zhao and Gao 2022). Existing research has largely focused on either the technical aspects of service design optimization or user acceptance in isolation, neglecting their interdependence during public health crises. Furthermore, while the pandemic has had a global impact, most studies have concentrated on Western contexts, with limited attention to high-density Asian urban environments where public transport is the dominant mode (Tirachini and Cats 2020). This gap is particularly concerning given the unique challenges faced by these regions, such as higher passenger densities and different cultural attitudes towards public health measures.

To address these gaps, this study aims to systematically design and evaluate public health-oriented travel services that maximize both operational effectiveness and user acceptance during pandemics. Specifically, we address three significant research gaps: the integration gap between service design optimization and user acceptance (Figliozzi and Unnikrishnan 2021), the methodological gap in combining qualitative and quantitative approaches (Creswell and Plano Clark 2023), and the contextual gap in focusing on high-density Asian urban environments. Our research question is: How can public health-oriented travel services be systematically designed and evaluated to maximize both operational effectiveness and user acceptance during pandemics?

To address this question, we develop an integrated FAHP-Kano-UTAUT2 framework for health-oriented service design, identify context-specific hygiene and safety priorities for urban transit systems, and extend UTAUT2 with pandemic-specific constructs such as perceived risk and price sensitivity. The novelty of this study lies in its integrated approach and focus on high-density urban environments. By combining the Kano model, Fuzzy Analytic Hierarchy Process (FAHP), and Unified Theory of Acceptance and Use of Technology 2 (UTAUT2), we provide a comprehensive framework that links passenger-centric design attributes with behavioral adoption factors. This integrated FAHP-Kano-UTAUT2 framework not only fills the identified gaps but also offers practical insights for transit agencies navigating the tension between mandatory health measures and passenger experience during public health emergencies.

The subsequent sections of the paper outline the foundational theories of the research and introduce the proposed research model. Next, a mixed-methods approach is employed, including questionnaire distribution, service attribute classification using the Kano quality attribute model, fuzzy analytic hierarchy process (FAHP) method and service system optimization accompanied by hypothesis formulation. Following this, the UTAUT2 framework is adapted to assess user acceptance regarding the enhanced public transportation system, which is subsequently followed by analysis of the collected data. The concluding segment offers

insights and summarizes the conclusions drawn from the research findings.

Literature review

Previous studies on public transportation and epidemics. Investigations into the interplay between public transportation systems and pandemics have predominantly focused on three domains: transmission mechanisms, travel behavior adaptation, and governance strategies.

Research on pathogen transmission within public transit systems has leveraged epidemiological models to quantify risks. Liu and Xiao (2020) adapted the Wells-Riley equation to bus environments, identifying passenger density, exposure duration, and ventilation rates as critical determinants of COVID-19 spread. Extending this approach, Perez-Zabaleta et al. (2025) integrated aircraft wastewater surveillance with ventilation metrics to establish a multi-scale transmission risk framework, demonstrating that viral load heterogeneity in high-occupancy vehicles correlates strongly with airflow patterns ($r = 0.60$). For rail networks, Wang and Wang (2025) refined the Susceptible-Infected-Recovered (SIR) model by incorporating panic-driven mobility behavior, proving that passenger volume accelerates outbreaks only when interaction duration exceeds threshold levels in confined stations. Recent studies have further integrated real-time mobility data to predict transmission hotspots, as evidenced by Zhang et al. (2023) using cell signaling trajectories of 5.4 million Shanghai residents to quantify Omicron BA.2 dispersion dynamics through subway hubs. Yet these models often neglect passenger perceptions of risk, which may independently influence ridership—particularly the mediating role of protective efficacy beliefs in moderating avoidance behavior, as demonstrated in cross-national surveys of transit users during endemic phases (Chen and Park 2025).

The COVID-19 pandemic precipitated unprecedented declines in public transit usage, with scholars attributing this to safety concerns and alternative work arrangements. Recent research by Wang and Liu (2024) confirmed that safety perception remains the strongest predictor of transit satisfaction, with pandemic-induced health risks amplifying this effect by 37%. Empirical data from Denver RTD's 2025 passenger behavior report revealed that only 12% of individuals would continue using public transit when perceiving high infection risks—a statistic further validated by cross-cultural studies on safety perception in transit environments (Martingano et al. 2025; Guangzhou Transport Bureau 2023). Post-2020 studies, such as Gupta et al. (2022), introduced health safety metrics (e.g., mask compliance, crowding thresholds) into behavioral models, revealing that fear of infection reduced transit reliance by 40–60% in urban centers. However, these analyses predominantly adopt system-level perspectives, overlooking granular passenger demands for hygiene infrastructure or contactless services.

Policy responses to pandemic risks in transit systems have emphasized containment and resilience. Wang et al. (2023) proposed a dynamic line planning and timetabling optimization model for urban rail systems, integrating real-time passenger flow data with queuing theory to balance temporary capacity limits and demand-responsive service frequency adjustments. Complementary work by China Association of Metros (2024) evaluated the institutionalization of crisis management through standardized classification frameworks for rail transit, advocating for integrated “smart mobility” systems that unify operational protocols across ten transit modalities to ensure health safeguards. While such strategies highlight institutional adaptability, they rarely incorporate real-time passenger mobility patterns into

design processes, limiting their alignment with user priorities—as evidenced by the omission of shared-bike usage dynamics near subway hubs in predictive models despite their critical role in first/last-mile connectivity (Chen et al. 2022). This gap is particularly evident in high-density Asian urban environments, where public transport is the dominant mode and passenger demands may differ significantly from those in Western contexts due to unique cultural attitudes toward contactless services and crowding tolerance.

To address these gaps, this study integrates qualitative passenger needs assessment using the Kano model with quantitative prioritization through the Fuzzy Analytic Hierarchy Process (FAHP) and user acceptance modeling using the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2). This integrated approach allows for a more comprehensive understanding of passenger demands and service design priorities during public health crises. Specifically, we extend the UTAUT2 framework by incorporating pandemic-specific constructs such as perceived risk and price sensitivity, which have been identified as critical factors influencing user acceptance in recent studies.

Theoretical background. The Fuzzy Analytic Hierarchy Process (FAHP) employs principles of fuzzy set theory to tackle uncertainties in multi-criteria decision-making (MCDM) contexts. By implementing fuzzy membership functions for pairwise assessments, FAHP quantifies subjective judgments and reduces uncertainty in complex decision environments, as demonstrated in its recent application to optimize roadside unit deployment in vehicular networks through integrated road-traffic analysis (Jain et al. 2024). In transportation research, FAHP has been extended to evaluate system resilience, prioritize infrastructure investments under budget constraints, and design demand-responsive services, particularly in scenarios requiring the integration of real-time data with qualitative criteria (Huang 2024; Palur et al. 2025).

FAHP has been utilized to evaluate public transit service quality by hierarchically structuring criteria such as affordability, accessibility, and reliability (Chen et al. 2023). For instance, a 2024 study applied FAHP-TOPSIS integration to assess non-motorized transportation services, identifying real-time crowding control and ventilation efficiency as critical determinants of passenger satisfaction in high-density urban environments (Wang and Liu 2024). A study by Zhou and Wang (2020) integrated FAHP with failure mode and effects analysis (FMEA) to assess railway operational risks, highlighting human error and equipment failure as dominant hazards. However, existing studies often overlook dynamic risk factors, such as emerging public health threats, which became particularly evident during the COVID-19 pandemic.

However, existing studies often overlook dynamic risk factors, such as emerging public health threats, which became particularly evident during the COVID-19 pandemic.

The Kano model classifies customer preferences into distinct categories based on their impact on satisfaction (Kano et al. 1984). This model is extensively utilized in service development to identify critical elements that enhance user experience while ensuring efficient resource distribution. In transportation research, the Kano model helps identify critical service elements that influence passenger loyalty and perceived value, such as real-time crowding control in high-density environments (Mao et al. 2024) and hierarchical hygiene needs at bus stops (Qu et al. 2022). The COVID-19 pandemic fundamentally altered passenger priorities, elevating health safety to a basic need. Zhang et al. (2021) redesigned Kano surveys for post-pandemic transit systems, identifying mask enforcement and ventilation efficiency as non-negotiable requirements. However, such studies often fail

to quantify the relative importance of these attributes or integrate them into hierarchical decision-making frameworks. Therefore, recent efforts have combined the Kano model with techniques like the Analytic Hierarchy Process (AHP) to resolve its inherent limitation in weighting criteria. For example, Wang et al. (2022) merged Kano-classified attributes with AHP to prioritize airport service improvements, yet their approach lacked mechanisms to handle fuzzy or uncertain passenger feedback—a gap addressed by Fuzzy AHP (FAHP).

The Unified Theory of Acceptance and Use of Technology 2 (UTAUT2), introduced by Venkatesh et al. (2012), extends the original UTAUT framework by incorporating three additional constructs: hedonic motivation, price value, and habit. UTAUT2 has been widely applied to evaluate passenger engagement with technology-driven transit solutions. For example, Ho and his team (2020) identified performance expectancy (e.g., perceived savings in time and cost-effectiveness) as essential factors influencing urban commuters' acceptance of Mobility-as-a-Service (MaaS). In a similar vein, research conducted by Zhang and Li (2021) indicated that established behaviors (e.g., consistent application engagement) and pleasure-driven motivation (e.g., the enjoyment derived from the interface) played a significant role in the prolonged utilization of real-time bus tracking systems. The UTAUT2 framework has been utilized to evaluate how users accept the integration of autonomous shuttles and electric vehicles (EV). Park et al. (2023) found that effort expectancy (e.g., factors such as the convenience of making reservations and the impact of community insights (e.g., recommendations from peers) played a crucial role in the adoption of EV-sharing in Seoul.

Methods

To address the research question of optimizing public health-oriented travel services during pandemics, we employed a mixed-methods approach integrating the Kano model, Fuzzy Analytic Hierarchy Process (FAHP), and Unified Theory of Acceptance and Use of Technology 2 (UTAUT2). This approach was selected for its ability to combine qualitative insights with quantitative rigor, providing a comprehensive framework for evaluating service design and user acceptance. Compared to purely quantitative methods, which offer scalability and statistical validation but lack depth in understanding user needs, our mixed-methods approach captures both broad trends and nuanced user preferences. Unlike purely qualitative methods that provide rich insights but may lack generalizability, our framework ensures structured prioritization and measurable outcomes. Traditional AHP, while robust, assumes precise judgments and may not handle uncertainties well, making FAHP a better fit for our context. Other user acceptance models like TAM are less comprehensive than UTAUT2, which we extended to include pandemic-specific constructs such as perceived risk and price sensitivity. This integrated approach provides a balanced, context-specific methodology that aligns with the complex demands of designing resilient public transport systems during health crises.

Kano model analysis. Compared to water and air transportation, urban road and rail transportation systems are characterized by high passenger capacity, multi-stage travel processes, enclosed environments, and convenient field investigation feasibility. These attributes make them the primary focus of this study on public safety in urban mobility. The research employed a questionnaire survey targeting various age groups using public transportation to identify passenger demands and service design elements. The survey was divided into three parts, with the initial part focused on identifying crucial travel services based on observations made

Table 1 Participant demographics for the Kano questionnaire.

Variable	Category	Frequency	Percentage
Gender	Male	69	41.8%
	Female	96	58.2%
Age	<18 years	9	5.5%
	18-26 years	54	32.7%
	27-36 years	38	23.0%
	36-44 years	30	18.2%
	46-60 years	22	13.3%
Usage frequency	>60 years	12	7.3%
	Daily	51	30.9%
	2-3 times/week	45	27.3%

in the field. The second part is the core part using paired positive and negative sub-questions for service element classification, and the third part is demographic information collection including age, gender, and occupation.

Data collection was facilitated through online platforms and paper-based questionnaires sent to elderly respondents unfamiliar with digital devices. The sample consisted of public transport users across multiple tier-1 and tier-2 Chinese cities (Shanghai, Chongqing, Nanjing, Suzhou, Hangzhou) from April 30 to May 10, 2024. Out of 213 distributed questionnaires, 165 valid responses were returned after eliminating incomplete submissions (completion time <60 s), infrequent users (<weekly usage), and duplicate entries, yielding a 77.5% valid response rate.

The valid survey responses comprised 41.8% male and 58.2% female participants (see Table 1). Age distribution revealed: 5.5% under 18 years, 32.7% aged 18–26, 23.0% aged 27–36, 18.2% aged 36–44, 13.3% aged 46–60, and 7.3% over 60 years. Frequency analysis indicated 30.91% of respondents used public transportation daily, 27.27% 2–3 times weekly, and 41.82% 3–4 times monthly. This demographic profile is consistent with target sample requirements, ensuring the data’s validity for supporting research conclusions.

The first section of the questionnaire revealed five critical safety service function demands prioritized through participant selections: (1) ensuring hygienic in-vehicle environments, (2) providing safety facilities, (3) conducting station entry checks, (4) delivering safety technology solutions, and (5) maintaining safe passenger spacing.

The second section of the questionnaire specifies functional requirements indicators (see Table 2), where respondents selected answers from a five-point response scale - “I like it that way,” “It must be that way,” “I am neutral,” “I can live with it that way,” and “I dislike it that way” - for each functional and dysfunctional of questions under these design elements (Gérson 2007). These responses were categorized into distinct quality attributes using the standardized Kano evaluation table (see Table 3).

Following the original model’s classification methodology, the predominant attribute determines the requirement classification (see Table 4). For instance, SA₈ demonstrated a predominant indifferent attribute (59.4%), indicating it represents an indifferent quality. However, the online survey format may introduce response bias due to participants’ casual engagement, potentially inflating indifferent attribute proportion for multiple service elements. This phenomenon does not negate the service’s importance but necessitates comparative analysis of secondary attribute distributions. Notably, SA₁₀ and SA₁₂ exhibited minimal disparity between attractive and indifferent attribute proportions.

Table 2 Functional requirements indicators.

Indicator code	Indicator
SA ₁	Disinfection status display
SA ₂	Rapid temperature screening at entry
SA ₃	Health code verification for boarding
SA ₄	Contactless entry (e.g., QR code, facial recognition)
SA ₅	Timely sanitation of stations/carriages
SA ₆	Disinfectant dispensers in stations/carriages
SA ₇	Mask detection alert systems
SA ₈	Public health broadcast announcements
SA ₉	On-site PPE vending machines
SA ₁₀	Temporary medical assistance stations
SA ₁₁	Advanced air filtration systems (e.g., fresh air, negative pressure)
SA ₁₂	Station/carriage safety personnel deployment
SA ₁₃	Emergency rescue equipment installation
SA ₁₄	Compartment partition barriers
SA ₁₅	Designated isolation compartments
SA ₁₆	Passenger capacity control

Table 3 Kano evaluation table.

Functional requirement of the question	Functional form	Dysfunctional form of the question				
		Like	Must-be	Neutral	Live with	Dislike
Functional form of the question	Like	Q	A	A	A	O
	Must-be	R	I	I	I	M
	Neutral	R	I	I	I	M
	Live with	R	I	I	I	M
	Dislike	R	R	R	R	Q

A Attractive, O One-dimensional, M Must-be, I Indifferent, R Reverse, Q Questionable.

Table 4 Attribute statistics of traditional KANO model.

Indicator code	M	O	A	I	R	Other	Total	Classification
SA ₁	17	25	43	80	0	0	165	I
SA ₂	23	28	76	36	0	2	165	A
SA ₃	7	20	76	60	2	0	165	A
SA ₄	3	28	89	43	2	0	165	A
SA ₅	19	124	20	2	0	0	165	O
SA ₆	2	14	97	52	0	0	165	A
SA ₇	4	26	56	73	6	0	165	I
SA ₈	5	8	52	98	2	0	165	I
SA ₉	8	22	85	50	0	0	165	A
SA ₁₀	2	19	73	65	4	2	165	A
SA ₁₁	12	47	79	25	0	2	165	A
SA ₁₂	13	23	61	65	2	1	165	I
SA ₁₃	29	55	48	31	2	0	165	O
SA ₁₄	1	14	49	82	19	0	165	I
SA ₁₅	4	13	64	79	3	2	165	I
SA ₁₆	5	37	53	70	0	0	165	I

To enhance the classification accuracy of service design requirements, the Better-Worse coefficients are implemented for prioritization. This analytical framework calculates two indices: Satisfaction Index (SI) and Dissatisfaction Index (DSI). SI is a positive value (0 < SI ≤ 1) quantifying satisfaction enhancement when a service requirement is implemented, where values approaching 1 indicate stronger positive impacts. DSI is a negative value (-1 ≤ DSI < 0) measuring satisfaction

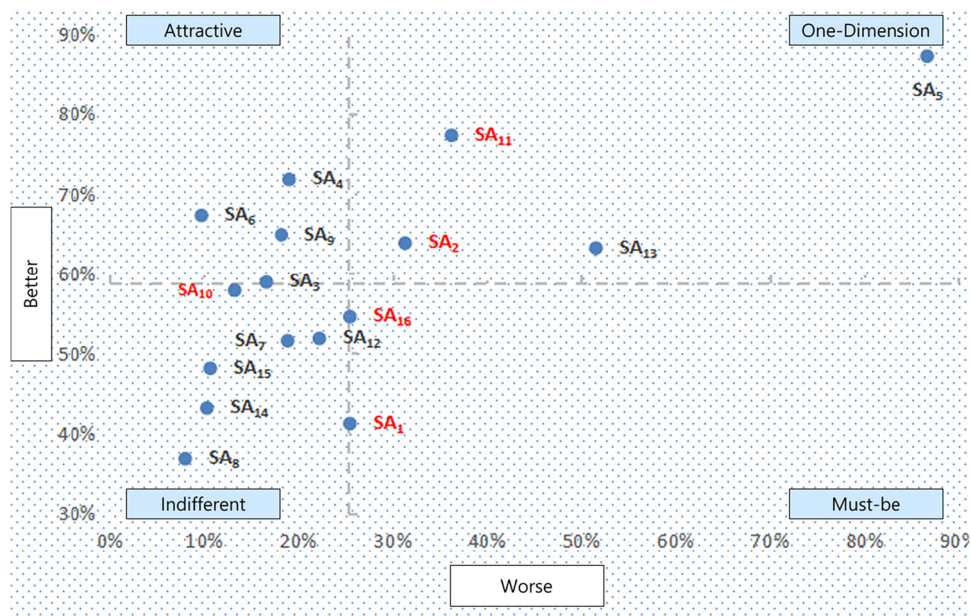


Fig. 1 Quadrant diagram of Better-Worse coefficients.

deterioration when a service feature is omitted, with values approaching -1 denoting greater negative effects.

The quadrant diagram visualizes these coefficients through absolute DSI values plotted against SI values. Service requirements positioned in higher absolute value quadrants (excluding indifferent qualities) warrant prioritized implementation. The computational formulas are as follows:

$$\text{Better(SI)} = \frac{A + O}{A + O + M + I}$$

$$\text{Worse(DSI)} = \left(\frac{M + O}{A + O + M + I} \right) (-1)$$

The analysis integrating Kano model classification and Better-Worse coefficient evaluation (see Fig. 1) identified distinct service quality categories: SA₃, SA₄, SA₆, and SA₉ were classified as Attractive qualities, SA₅ and SA₁ as One-dimensional qualities, while SA₇, SA₈, SA₁₂, SA₁₄, and SA₁₅ exhibited consistent Indifferent quality characteristics. Classification discrepancies emerged in five service elements (SA₁, SA₂, SA₁₀, SA₁₁, SA₁₆). SA₁ and SA₁₆ were classified from the previous Indifferent qualities to Must-be qualities, SA₂ and SA₁₁ were classified from the previous Attractive qualities to One-dimensional qualities, and SA₁₀ was classified from the previous Attractive quality to Indifferent quality. Based on the preliminary inference of the author and colleagues, it is believed that SA₁ can be classified as a Must-be quality, SA₁₁ as a One-dimensional quality, and SA₂, SA₁₀, and SA₁₆ remain unchanged in their original quality categories (see Table 5).

SA₁ (disinfection status display) was deemed institutionally mandatory despite passenger-perceived non-essentiality, where information absence caused negligible dissatisfaction but outdated data provoked negative responses. SA₁₁'s (advanced air filtration systems) transition from Attractive to One-dimensional quality reflected the normalization of air filtration systems in public transit, converting technological novelty into baseline expectations. SA₂ (rapid temperature screening at entry) maintained Attractive status as conventional temperature screening delays remained within acceptable tolerance thresholds. SA₁₀ (temporary medical assistance stations) maintained

Attractive quality because professionally equipped medical facilities are not widely implemented in current transit station practices, and their introduction can significantly enhance passenger satisfaction. SA₁₆'s (passenger capacity control) Indifferent designation resulted from operational impracticalities in passenger density control coupled with marginal safety perception impacts.

Fuzzy Analytic Hierarchy Process (FAHP) for calculating passenger demand and service design element weights.

In traditional Analytic Hierarchy Process (AHP), pairwise comparisons are conducted for each hierarchical level of customer satisfaction objectives. Saaty (1980) proposed a 9-point scale in *The Analytic Hierarchy Process*, where numerical values (1–9) represent relative importance: 1 (equally important), 3 (slightly more important), 5 (significantly more important), 7 (strongly more important), and 9 (extremely more important), with intermediate values (2, 4, 6, 8) denoting gradations between these judgments. However, customer demands often involve ambiguous linguistic descriptions, and human assessments of qualitative attributes are inherently subjective and imprecise. Thus, traditional AHP is insufficient for accurately capturing customer demands and determining their weights.

To calculate precise weights for passenger demands and service design elements, this study employs Fuzzy AHP (FAHP), converting linguistic evaluations of passenger demands into triangular fuzzy numbers (TFNs) to construct pairwise comparison matrices (see Supplementary Appendix A). TFNs are categorized into symmetric/asymmetric scales and wide/narrow ranges. To minimize zero or identical weights for service design elements, a 5-level asymmetric scale with high-precision decimal retention is adopted, where ALI means very low, VSLI means relatively low, SLI means low, WLI means slightly low, EI means equal, WMI means slightly high, SMI means high, VSMI means relatively high, and AMI means very high (Isaai et al. 2011). Data for this phase were collected through expert interviews. On May 12, 2021, five public transportation experts were interviewed. Individual decision weights were assumed homogeneous. To mitigate inconsistencies caused by cognitive differences, extreme values (maximum/minimum) were excluded, and the mean by

Table 5 Attribute statistics of KANO model based on Better-Worse coefficients.

Indicator code	Indicator	SI	DSI	Final classification
SA ₁	Disinfection status display	0.41	-0.25	M
SA ₂	Rapid temperature screening at entry	0.64	-0.31	A
SA ₃	Health code verification for boarding	0.59	-0.17	A
SA ₄	Contactless entry (e.g., QR code, facial recognition)	0.72	-0.19	A
SA ₅	Timely sanitation of stations/carriages	0.87	-0.87	O
SA ₆	Disinfectant dispensers in stations/carriages	0.67	-0.10	A
SA ₇	Mask detection alert systems	0.52	-0.19	I
SA ₈	Public health broadcast announcements	0.37	-0.08	I
SA ₉	On-site PPE vending machines	0.65	-0.18	A
SA ₁₀	Temporary medical assistance stations	0.58	-0.13	A
SA ₁₁	Advanced air filtration systems (e.g., fresh air, negative pressure)	0.77	-0.36	O
SA ₁₂	Station/carriage safety personnel deployment	0.52	-0.22	I
SA ₁₃	Emergency rescue equipment installation	0.63	-0.52	O
SA ₁₄	Compartment partition barriers	0.43	-0.10	I
SA ₁₅	Designated isolation compartments	0.48	-0.11	I
SA ₁₆	Passenger capacity control	0.55	-0.25	I

selecting two of the three remaining data sets (mode) was calculated.

For example, if an interviewee considers “ensuring hygienic in-vehicle environments (PR₁)” more important than “providing safety facilities (PR₂)” with a “Relatively High (VSMI)” rating, the corresponding TFN is PR₁₂ = (2, 5/2, 3), while the reciprocal is PR₂₁ = (1/3, 2/5, 1/2). For n interviewees, data filtering and averaging are applied within the same category. Similarly, fuzzy judgment matrices are computed for each level of the hierarchical structure of passenger safety demands (see Supplementary Appendix A).

Consistency validation is required for pairwise comparison matrices to ensure non-contradictory judgments. In practice, human judgments may lack perfect consistency. Thus, matrices are deemed acceptable if their consistency ratio (CR) falls within a specified range. The consistency index (CI) and CR are calculated as:

$$CI = (\lambda_{\max} - n) / (n - 1)$$

$$CR = CI / RI_{(n)}$$

where λ_{\max} is the maximum eigenvalue, n is the matrix dimension, and $RI_{(n)}$ is the random index dependent on n (see Supplementary Appendix A). A $CR < 0.1$ indicates acceptable consistency.

A triangular fuzzy number, denoted $\tilde{A} = (l, m, u)$, can be defuzzified into a crisp value:

$$A_{crisp} = (4m + l + u) / 6$$

Taking the comparison matrix G_{crisp} as an example (see Supplementary Appendix A), through computation, the maximum eigenvalue of the matrix is obtained: $\lambda_{\max} = 5.1770$. Given the matrix dimension $n = 5$ and the random index $RI_{(n)} = 1.11$, the consistency index and consistency ratio of the matrix can be calculated as :

$$CI = (\lambda_{\max} - n) / (n - 1) = (5.1770 - 5) / (5 - 1) \approx 0.0443$$

$$CR = CI / RI_{(n)} = \left(\frac{0.0443}{1.11} \right) \approx 0.0399 < 0.1$$

All comparison matrices exhibited CR values below 10% (see Table 6), confirming acceptable consistency.

To evaluate the hierarchical passenger safety demands, fuzzy number comparison principles and extent analysis (Chang 1996)

Table 6 Consistency test results.

	G	PR ₁	PR ₂	PR ₃	PR ₄	PR ₅
λ	5.1770	2.0206	5.1583	2.0313	4.1464	3.0538
CI	0.0443	0.0206	0.0396	0.0313	0.0488	0.0269
RI	1.11	0	1.11	0	0.89	0.52
CR	0.0399	-	0.0357	-	0.0548	0.0517

were applied. Extent analysis calculates the synthetic extent value D_i for each object relative to goals. For the i -th object, D_i is defined as:

$$D_i = \sum_j A_{gi}^j \otimes \left[\sum_i \sum_j A_{gi}^j \right]^{-1} \quad (1)$$

For the k -th level, the synthetic extent value D_i^k of the i -th element is:

$$D_i^k = \sum_{j=1}^n a_{ij}^k \otimes \left(\sum_{i=1}^n \sum_{j=1}^n a_{ij}^k \right)^{-1}, i = 1, 2, \dots, n \quad (2)$$

For element D_{PR_1} :

$$D_{PR_1} = \sum_{j=1}^5 a_{1j} \otimes \left[\sum_{i=1}^5 \sum_{j=1}^5 a_{ij} \right]^{-1} = (0.09, 0.19, 0.36)$$

Similar calculations yield synthetic extent values for all hierarchical elements:

$$D_{PR_1} = (0.088, 0.191, 0.365)$$

$$D_{PR_2} = (0.113, 0.234, 0.459)$$

$$D_{PR_3} = (0.121, 0.232, 0.486)$$

$$D_{PR_4} = (0.099, 0.197, 0.436)$$

$$D_{PR_5} = (0.083, 0.152, 0.277)$$

Definition 1: For two TFNs A_1 and A_2 , the possibility degree $A_1 \geq A_2$ is defined as: $V(A_1 \geq A_2) = \sup_{x \geq y} [\min(\mu_{A_1}(x), \mu_{A_2}(y))]$.

Theorem 1: If $A_1 = (l_1, m_1, u_1)$ and $A_2 = (l_2, m_2, u_2)$:

1. A sufficiently necessary condition for $V(A_1 \geq A_2) = 1$ is $m_1 \geq m_2$.

2. If $m_1 \leq m_2$, then let $V(A_1 \geq A_2) = \text{hgt}(A_1 \cap A_2)$, where d is the intersection point: $V(A_1 \geq A_2) = \mu(d) = \begin{cases} \frac{l_2 - u_1}{(m_1 - u_1) - (m_2 - l_2)}, l_2 \leq u_1 \\ 0, \text{ other,} \end{cases}$

Definition 2: The possibility degree of a fuzzy number A exceeding k fuzzy numbers $A_i (i = 1, 2, \dots, k)$ is:

$$V(A \geq A_1, A_2, \dots, A_k) = \min V(A \geq A_i), i = 1, 2, \dots, k$$

Let $d(p_i^k) = \min V(S_i^k \geq S_j^k)$, where p_i^k is the i -th element at the k -th level. The weight vector W'_k is:

$$W'_k = (d(p_1^k), d(p_2^k), \dots, d(p_n^k))^T$$

Normalized weights W_k become:

$$W_k = (w(p_1^k), w(p_2^k), \dots, w(p_n^k))^T$$

Based on Definition 1 and Definition 2, the weight vector W'_G for the category level of the hierarchy can be calculated using the following equation:

$$W'_G = (d(PR_1), d(PR_2), d(PR_3), d(PR_4), d(PR_5))^T \\ = (0.854, 0.978, 1.00, 0.897, 0.661)$$

Normalized weights W_G become:

$$W_G : (W_{PR_1}, W_{PR_2}, W_{PR_3}, W_{PR_4}, W_{PR_5}) \\ = (0.194, 0.223, 0.228, 0.204, 0.151)$$

Following a similar approach, the weight vectors W_{PR_i} and W_{SA_j} can be computed, where $i = 1 - 5, j = 1 - 16$.

Therefore, the total weight of passenger demand (see Table 7) can be derived by using the following equation:

$$TW_{SA_1} = W_{PR_1} * W_{SA_1}, TW_{SA_5} = W_{PR_1} * W_{SA_5};$$

$$TW_{SA_4} = W_{PR_2} * W_{SA_4}, TW_{SA_6} = W_{PR_2} * W_{SA_6}, TW_{SA_7} = W_{PR_2} * W_{SA_7},$$

$$TW_{SA_{11}} = W_{PR_2} * W_{SA_{11}}, TW_{SA_{13}} = W_{PR_2} * W_{SA_{13}};$$

$$TW_{SA_2} = W_{PR_3} * W_{SA_2}, TW_{SA_3} = W_{PR_3} * W_{SA_3};$$

$$TW_{SA_8} = W_{PR_4} * W_{SA_8}, TW_{SA_9} = W_{PR_4} * W_{SA_9}, TW_{SA_{10}} = W_{PR_4} * W_{SA_{10}},$$

$$TW_{SA_{12}} = W_{PR_4} * W_{SA_{12}};$$

$$TW_{SA_{14}} = W_{PR_5} * W_{SA_{14}}, TW_{SA_{15}} = W_{PR_5} * W_{SA_{15}}, TW_{SA_{16}} = W_{PR_5} * W_{SA_{16}}.$$

UTAUT2 research model and hypothesis. The essential service design elements for public transportation safety systems were identified through preliminary research, focusing on hygiene management during infectious disease outbreaks. Key measures

include deploying sufficient sanitation staff to increase cleaning frequency in stations and vehicles, alongside automated facilities such as robotic sweepers and disinfection spray systems. Meanwhile, health screening need to integrate long-range infrared temperature detection and combine health code verification with transit passes to minimize close contact between passengers and staff. Real-time disinfection status should be displayed via interactive dashboards at high-traffic hubs, while temporary medical stations and on-site sales of protective equipment (e.g., disinfectants, air filters) be established to enhance emergency preparedness.

To address urgent public health challenges, an autonomous intelligent medical public transit system was designed as a multifunctional mobile smart space. This system incorporates shared, interconnected, and data-driven functionalities, adapting dynamically to real-time demands. In medical mode, it autonomously detects symptoms (e.g., fever) using AI-powered sensors, with data visualized on holographic screens. Virtual physicians conduct preliminary consultations to triage cases and reduce anxiety, while 5G networks enable remote diagnostics and telemedicine, connecting patients with nationwide medical expertise. Meanwhile, the system operates flexibly across multiple modes: during energy replenishment, vehicles undergo overnight disinfection and charging; in logistics mode, interiors are reconfigured for medical supply transport; and in commute mode, autonomous navigation optimizes route efficiency using real-time congestion updates.

The Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) framework was applied to analyze factors influencing user behavioral intentions toward autonomous intelligent medical public transit systems. The flowchart synthesizes user-centric analysis (Kano Model), quantitative prioritization (FAHP), and technology-adoption theory (UTAUT2) to optimize resource allocation for health-oriented travel services (see Fig. 2).

Performance expectancy. Performance expectancy (PE) refers to how strongly individuals believe that utilizing a given innovation (e.g. The use of self-sufficient intelligent medical public transport systems) is anticipated to significantly improve performance, particularly concerning their users' confidence in travel safety. The concept corresponds with elements from five separate theoretical frameworks, encompassing aspects such as perceived value (TAM, TAM2, C-TAM-TPB), external incentives (MM), compatibility with job responsibilities (MPCU), comparative benefits (IDT), and anticipated outcomes (SCT). It has been identified as a significant indicator of users' willingness to accept new technologies (Madigan et al. 2017).

Compared to traditional transportation tools, autonomous medical transit systems offer improved safety, convenience, and efficiency. Consequently, the hypothesis can be expressed as:

H1. Performance expectancy positively influences users' behavioral intention to adopt autonomous intelligent medical public transit systems.

Effort expectancy. Effort expectancy (EE) refers to the perceived ease of using a technology, defined as "the degree of ease associated with consumers' use of the technology" (Venkatesh et al. 2012). It relates to factors such as perceived ease of use (TAM, TAM2), complexity (MPCU), and ease of use (IDT). Effort expectancy has been shown to significantly influence acceptance in transportation studies (Choi and Ji 2015; Madigan et al. 2016). For autonomous medical transit systems, complexity may arise when passengers interact with mobile applications. While some users may find this interaction negligible, others might perceive it as burdensome,

Table 7 Ranking of service design element weights.

Indicator code	Weight	Classification	Rank
SA ₁	0.061	M	5
SA ₂	0.130	A	2
SA ₃	0.098	A	3
SA ₄	0.040	A	9
SA ₅	0.133	O	1
SA ₆	0.050	A	7
SA ₉	0.053	A	6
SA ₁₀	0.068	A	4
SA ₁₁	0.047	O	8
SA ₁₃	0.032	O	10

Flowchart of Health-oriented Travel Services Optimisation

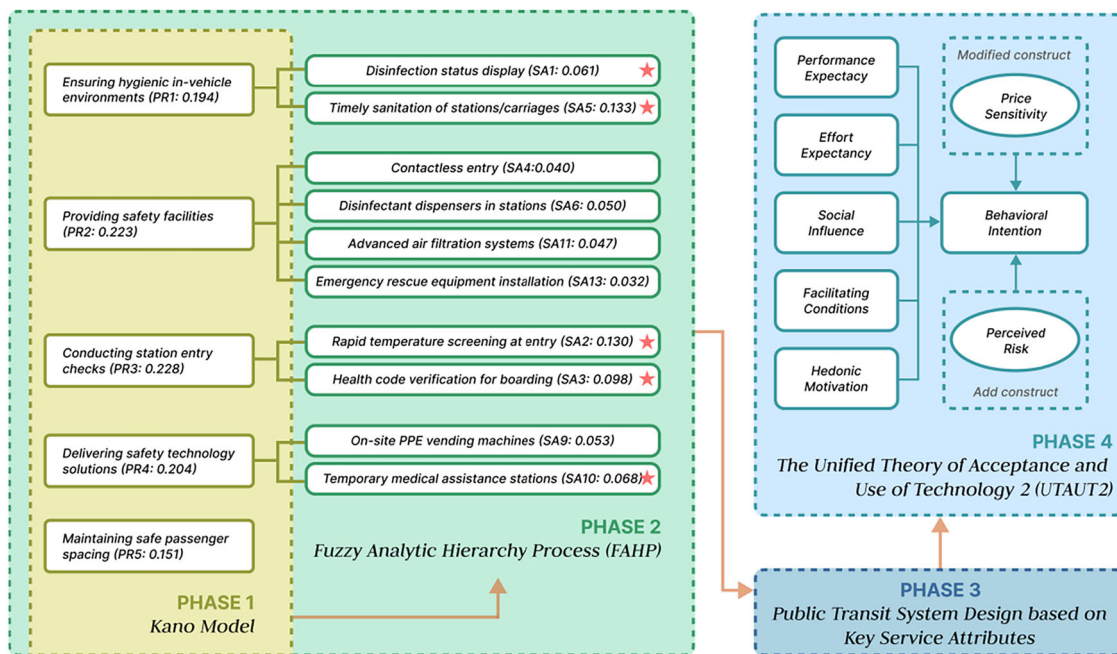


Fig. 2 Flowchart of health-oriented travel services optimisation.

negatively impacting adoption intentions. Thus, the hypothesis is formulated as:

H2. Effort expectancy positively influences users’ behavioral intention to adopt autonomous intelligent medical public transit systems.

Social influence. Social influence (SI) pertains to the degree to which individuals believe that key figures in their lives, such as peers and mentors, expect them to utilize a specific technology (e.g., relatives and acquaintances). This relates to elements such as social expectations (TRA, TAM2, TPB, DTPB, C-TAM-TPB), interpersonal influences (MPCU), and perceived status (IDT). It can be described as “the extent to which individuals believe that significant others think they ought to utilize a specific technology” (Venkatesh et al. 2012). It was established that social pressures significantly influence the acceptance of transportation systems (Adell et al. 2011; Kervick et al. 2015). When considering the implementation of self-driving medical transportation systems, individuals are inclined to seek advice from their social connections prior to making a decision. Consequently, the hypothesis is established as follows:

H3. Social influence positively influences users’ behavioral intention to adopt autonomous intelligent medical public transit systems.

Facilitating conditions. Facilitating conditions pertain to the beliefs held by individuals regarding whether the supporting organizational and technical infrastructures are adequate for utilizing a system. This concept is associated with perceived behavioral control as outlined in the theory of planned behavior (TPB), supportive circumstances (MPCU), and compatibility (IDT), which is characterized as “the awareness that individuals have regarding the resources and assistance accessible for engaging in a behavior” (Venkatesh et al. 2012). The conditions that facilitate adoption play a crucial role in studies of technology within the transportation sector (Madigan et al. 2017; Motak et al. 2017). Individuals in autonomous medical transit systems who have limited access to essential resources (such as information,

support lines, and community assistance) are likely to demonstrate lower intentions to adopt such technologies. Consequently, the following hypothesis is proposed:

H4. Facilitating conditions positively influence users’ behavioral intention to adopt autonomous intelligent medical public transit systems.

Hedonic motivation. Hedonic motivation (HM) is defined as “the fun or pleasure derived from using a technology” (Venkatesh et al. 2012). Though underexplored in UTAUT2, this construct is influential in transportation adoption research (Madigan et al. 2017). Users who perceive interactions with autonomous medical transit systems as enjoyable are more likely to adopt them. Thus, the hypothesis is formulated as:

H5. Hedonic motivation positively influences users’ behavioral intention to adopt autonomous intelligent medical public transit systems.

Price sensitivity. The UTAUT2 framework’s concept of “price value” has been adjusted to reflect “price sensitivity” owing to insufficient data on the extensive deployment of services. Price sensitivity can be understood as “the way in which consumers respond to pricing and alterations in prices” (Goldsmith et al. 2005). While prior studies suggest its relevance in technology adoption (Tsai and LaRose 2015), it remains underexplored in UTAUT2. Thus, the hypothesis is formulated as:

H6. Price sensitivity negatively influences users’ behavioral intention to adopt autonomous intelligent medical public transit systems.

Perceived risk. The concept of perceived risk (PS), understood as “the likelihood of experiencing a loss while trying to achieve a target outcome” (Featherman and Pavlou 2003), plays a significant role in the acceptance of autonomous technologies. Factors like safety issues or technological malfunctions, which are frequently disregarded in conventional frameworks (Koenig-Lewis et al. 2015), hold particular importance in the context of self-driving cars. Consequently, the hypothesis can be articulated as:

H7. Perceived risk negatively influences users' behavioral intention to adopt autonomous intelligent medical public transit systems.

Linking Kano-FAHP results to UTAUT2 constructs. To ensure the UTAUT2 model accurately reflected passenger priorities identified through Kano-FAHP analysis, we systematically mapped the key service attributes to corresponding acceptance factors. For instance, high-priority features like timely sanitation (SA₅, weight = 0.133) and contactless entry (SA₄, Attractive quality) directly informed Performance Expectancy (e.g., "This system reduces infection risk through frequent cleaning") and Effort Expectancy (e.g., "QR code boarding is easy to use"). Similarly, Perceived Risk items incorporated emergency equipment (SA₁₃) and air filtration (SA₁₁), while Hedonic Motivation accounted for user satisfaction with PPE vending machines (SA₉). Pilot testing confirmed these adaptations improved item clarity, with 85% of participants agreeing survey questions matched their transit safety concerns. This integration ensured UTAUT2 constructs measured acceptance drivers most relevant to pandemic-era transit design.

Scale design. Following established quantitative technology acceptance research, validated scales were utilized for survey design. The final questionnaire consisted of four sections: a cover page, demographic characteristics (e.g., age, gender, education level), an informational sheet detailing the autonomous intelligent medical public transit system (e.g., advantages, vehicle features), and core measurement items adapted from prior studies. Drawing on structural equation modeling (SEM) literature (Dawes 2002; Brown 2011), a 7-point Likert scale was adopted for 29 items across eight latent variables.

In order to preemptively tackle any potential challenges before formal data collection began, the research team carried out a preliminary test of the survey instrument. A total of 51 responses from the pilot study were gathered and examined. Following the analysis, three elements that demonstrated inadequate reliability, validity concerns, or minimal factor loadings were excluded. Minor wording revisions were made to enhance clarity and reduce complexity, incorporating feedback from participants. Subsequently, the finalized Chinese questionnaire was created as an online version on the Wenjuanxing platform. The specific questionnaire items and their sources are provided in Supplementary Appendix B.

Case study: application in Chinese urban transit systems

This section presents the empirical application of the methodology in high-density Chinese cities, including data collection, results, and discussion of findings.

Data collection. In order to ensure a representative sample of the Chinese demographic, a quota sampling method was implemented utilizing three specific demographic factors, namely age, gender, and education level. These criteria were derived from census data published by China's National Bureau of Statistics (see Supplementary Appendix C).

The questionnaire was distributed via Wenjuanxing, with data collected from January to February 2025. To ensure quality, response time thresholds (160–320 s) and reverse-coded items were used to filter invalid responses (Wu et al. 2017). Of 461 initial submissions, 14 were excluded due to rapid completion (<140 s) or inconsistent reverse-item answers, yielding 447 valid responses.

In a study of 72 SEM research articles, Loehlin (2004) found that the average sample size was 198. Barrett (2007)

Table 8 Participant demographics for the UTAUT2 questionnaire.

Variable	Category	Frequency	Percentage
Gender	Male	230	51.5%
	Female	217	48.5%
Age	18–24 years	54	12.1%
	25–34 years	78	17.4%
	35–49 years	109	24.4%
	50–64 years	148	33.1%
	≥65 years	58	13.0%
Education	Primary school	139	31.1%
	Junior high school	151	33.8%
	High school	72	16.1%
	University degree	44	9.8%

recommended that the ideal sample size should be at least eight times greater than the number of variables included in the model. Nevertheless, Barrett remarked that when employing maximum likelihood estimation (MLE), which is frequently used in structural equation modeling, there could be an escalation in chi-square statistics and a subpar fit of the model if the sample size surpasses 500. The research conducted involved a sample comprising 447 participants, which is consistent with these recommendations (See Table 8). Among the 447 valid responses, there were 230 males, making up 51.5% of the total, and 217 females, representing 48.5%. indicating a well-balanced representation of genders. The age demographics were categorized as follows: 18–24 years (54 participants, 12.1%), 25–34 years old (78, 17.4%), 35–49 years old (109, 24.4%), 50–64 years old (148, 33.1%), and ≥65 years (58, 13.0%). Education levels included primary school or below (31.1%), Junior high school (33.78%), High school (16.11%), University degree (9.84%), and individuals holding a bachelor's degree or above accounted for 9.17%. These figures were in close alignment with the national demographic standards of China.

Reliability and validity analysis. To mitigate common method variance (CMV), items were distributed across separate pages to reduce respondent fatigue (Shiau et al. 2019). Reliability was assessed via composite reliability (CR > 0.7) and average variance extracted (AVE > 0.5) (Fornell and Larcker 1981). All constructs met these thresholds (see Table 9), confirming internal consistency. Discriminant validity was validated as AVE square roots exceeded inter-construct correlations (see Table 10).

Model fit assessment. To assess the alignment between a theoretical model and the sample covariance matrix, structural equation modeling (SEM) employs various fit indices, as conventional measures such as ANOVA or regression do not provide a single, robust indicator. Commonly reported indices include chi-square minimum discrepancy (CMIN), degrees of freedom (DF), normed chi-square (CMIN/DF), goodness-of-fit index (GFI), adjusted goodness-of-fit index (AGFI), comparative fit index (CFI), Tucker-Lewis index (TLI), root mean square error of approximation (RMSEA), and standardized root mean square residual (SRMR).

Thresholds for fit indices vary across disciplines and study types (e.g., exploratory vs. confirmatory). For instance, while smaller CMIN values are preferred, sample size inflation can distort chi-square significance. This study referenced criteria from SEM authorities (Hayduk 1987; Bagozzi and Yi 1988; Hu and Bentler 1998) to assess model adequacy. As shown in Table 11, all

indices met recommended thresholds, confirming the model’s robustness.

Structural model validation. Path coefficients were calculated using Amos 26.0. Results supported all seven hypotheses (H1–H7) (See Table 12). Performance expectancy ($\beta = 0.140, p < 0.05$), effort expectancy ($\beta = 0.128, p < 0.05$), social influence ($\beta = 0.274, p < 0.001$), facilitating conditions ($\beta = 0.145, p < 0.05$), and hedonic motivation ($\beta = 0.177, p < 0.05$) exhibited significant positive effects on behavioral intention. Conversely, price sensitivity ($\beta = -0.260, p < 0.001$) and perceived risk ($\beta = -0.266, p < 0.001$) negatively influenced behavioral intention.

Discussion

Analysis of user acceptance. This study investigated user acceptance of an autonomous intelligent medical public transit system (AIM-PTS) within the context of urban mobility during public health crises. Unlike previous research, which often focused on either technical service design or user acceptance in isolation, our integrated FAHP-Kano-UTAUT2 framework

bridges this gap by systematically linking passenger-centric design attributes with behavioral adoption factors. This study advances the UTAUT2 framework by incorporating pandemic-specific constructs—perceived risk and price sensitivity—validating their critical role in shaping user acceptance during health emergencies. By contextualizing UTAUT2 within public health mobility, we demonstrate its adaptability to safety-critical scenarios, offering a tailored model for future research. The sample demographics, while partially aligned with China’s national census data, provided a unique perspective on high-density urban environments—a setting underexplored in Western-centric studies (Tirachini and Cats 2020; Buehler et al. 2025). Overall, respondents exhibited moderate support for adopting AIM-PTS as a travel option. Mean scores for behavioral intention (i.e., acceptance) ranged between 4.7 and 4.8, consistent with findings that public attitudes toward emerging technologies often remain neutral due to evolving perceptions (National Centre for Social Research 2025). This underscores the need for early-stage acceptance studies to inform tailored service design, particularly in regions where public transport dominates mobility systems.

Determinants of user acceptance. Our study advances the UTAUT2 framework by incorporating pandemic-specific constructs—perceived risk and price sensitivity—which were validated as critical determinants of acceptance. Two key conclusions emerge: (1) the UTAUT2 framework requires contextual adaptation for safety-critical transit systems, and (2) social influence is the strongest predictor of acceptance during technology introduction. This suggests peer opinions significantly shape user intentions in public health-oriented mobility contexts, highlighting the need for peer-driven marketing campaigns. In descending order of effect strength (β coefficients), perceived risk, price sensitivity, hedonic motivation, facilitating conditions, performance expectancy, and effort expectancy followed social influence. The inclusion of perceived risk and price sensitivity—novel constructs in this study—validates the necessity of tailoring acceptance models to specific contexts.

Perceived risk emerged as a critical deterrent ($\beta = -0.266, p < 0.001$), contrasting with mixed findings in prior research. While Tan et al. (2022) reported that perceived benefits outweighed risk effects due to pleasure-based trust mediation in fully autonomous vehicles (AVs), Gill et al. (2024) observed that autonomy bias amplified risk perception specifically in automated driving systems, requiring 3.7 s longer clearance time to match human-driven vehicle safety thresholds. Our results indicate that heightened risk perceptions directly reduce acceptance, emphasizing the need for transparency in safety protocols. Price sensitivity ($\beta = -0.260, p < 0.001$) further highlights cost concerns as a barrier, aligning with (Chen et al. 2024) assertion that affordability drives adoption. Moderately priced services may thus enhance uptake, particularly in contexts where budget

Table 9 Composite reliability and convergent validity.

Construct	Items	Factor Loadings	CR	AVE	Mean
Performance expectancy	PE1	0.902	0.941	0.801	4.67
	PE2	0.887			4.68
	PE3	0.895			4.72
	PE4	0.895			4.63
Effort expectancy	EE1	0.884	0.912	0.774	4.74
	EE2	0.869			4.69
	EE3	0.887			4.77
Social influence	SI1	0.820	0.848	0.651	4.54
	SI2	0.845			4.47
	SI3	0.752			4.45
Facilitating conditions	FC1	0.882	0.933	0.777	4.73
	FC2	0.882			4.59
	FC3	0.896			4.70
	FC4	0.866			4.66
Hedonic motivation	HM1	0.898	0.882	0.713	4.58
	HM2	0.812			4.32
	HM3	0.820			4.35
Price sensitivity	PS1	0.887	0.921	0.796	4.25
	PS2	0.897			4.16
	PS3	0.892			4.20
Perceived risk	PR1	0.849	0.893	0.737	4.58
	PR2	0.876			4.68
	PR3	0.851			4.71
Behavioral intention	BI1	0.964	0.977	0.933	4.85
	BI2	0.965			4.81
	BI3	0.968			4.74

Table 10 Discriminant validity.

	PE	EE	SI	FC	HM	PS	PR	BI
PE	0.895							
EE	0.607	0.88						
SI	0.563	0.534	0.807					
FC	0.591	0.586	0.531	0.882				
HM	0.545	0.491	0.478	0.489	0.845			
PS	-0.187	-0.239	-0.234	-0.203	-0.205	0.892		
PR	-0.064	-0.115	-0.085	-0.159	-0.069	0.259	0.858	
BI	0.53	0.534	0.522	0.536	0.49	-0.444	-0.337	0.966

Bold values on the diagonal are the square root of the Average Variance Extracted (AVE).

Table 11 Model fit indices.

Index	Model value	Criteria	Conclusion	Reference
CMID	400.482	Smaller preferred	—	—
DF	271	Smaller preferred	—	—
CMID/DF	1.478	<3	Good fit	Hayduck (1987)
GFI	0.936	>0.8 (acceptable); >0.9 (good)	Good fit	Bagozzi and Yi (1988)
AGFI	0.917	>0.8 (acceptable); >0.9 (good)	Good fit	Scott (1994)
CFI	0.988	>0.9	Good fit	Bagozzi and Yi (1988)
TLI(NNFI)	0.985	>0.9	Good fit	Hair et al. (2017)
RMSEA	0.033	<0.08	Good fit	Hair et al. (2017)
SRMR	0.023	<0.08	Good fit	Hu and Bentler (1998)

Table 12 Summary of path analysis results.

Hypothesis	Path	Expected	Std. (β)	p-value	Result
H1	PE→BI	+	0.140	<0.05	Supported
H2	EE→BI	+	0.128	<0.05	Supported
H3	SI→BI	+	0.274	<0.001	Supported
H4	FC→BI	+	0.145	<0.05	Supported
H5	HM→BI	+	0.177	<0.05	Supported
H6	PS→BI	−	−0.260	<0.001	Supported
H7	PR→BI	−	−0.266	<0.001	Supported

constraints intensify perceived financial risk. Hedonic motivation ($\beta = 0.177, p < 0.05$) reinforced prior observations (Madigan et al. 2017; Motak et al. 2017), suggesting enjoyment derived from system interactions fosters acceptance. Facilitating conditions ($\beta = 0.145, p < 0.05$) mirrored findings in AV acceptance studies (Choi and Ji 2015; Buckley et al. 2018), underscoring the role of streamlined user interfaces and resource accessibility. Performance expectancy ($\beta = 0.140, p < 0.05$) supported its relevance, though its weaker influence compared to social factors deviates from Venkatesh et al. (2003) original UTAUT model. This implies non-utilitarian factors (e.g., social norms) dominate in safety-critical contexts. Effort expectancy ($\beta = 0.128, p < 0.05$) exhibited the smallest effect, possibly due to participants' familiarity with smartphone-based interfaces (Koenig-Lewis et al. 2015). However, post-implementation evaluations may yield divergent results as users gain firsthand experience.

Key insights from the case study. The findings of this study reveal notable differences when compared to Western-centric research on public transportation during health crises. For instance, while performance expectancy (PE) is typically the dominant factor in technology acceptance models like UTAUT2 in Western contexts (Madigan et al. 2017), this study found social influence (SI) to be the strongest predictor ($\beta = 0.274$) in high-density Asian urban environments. This divergence highlights the cultural and contextual nuances influencing user behavior, where collective norms and peer recommendations may carry greater weight than individual utility in densely populated settings. Additionally, the inclusion of perceived risk (PR) and price sensitivity (PS) as significant determinants aligns with recent pandemic-specific studies (Zhang et al. 2021) but contrasts with pre-pandemic frameworks that often overlooked these factors. These differences underscore the need for regionally tailored models to accurately capture adoption drivers during public health emergencies.

Comparative analysis. The case study of Chinese urban transit systems yielded three critical insights. First, timely sanitation

(SA₅) and contactless entry (SA₄) emerged as top-priority attributes, reflecting pandemic-specific demands for hygiene and minimal physical contact. Second, social influence (SI) played a pivotal role in user acceptance, suggesting that public health interventions could benefit from peer-driven campaigns to amplify trust and adoption. Third, the validation of perceived risk (PR) and price sensitivity (PS) as novel determinants emphasizes the importance of addressing cost transparency and safety assurances in service design. These insights provide actionable guidance for policymakers, demonstrating that integrating real-time hygiene indicators, tiered pricing models, and community engagement strategies can significantly enhance the resilience and user acceptance of public transport systems during health crises.

Conclusion

Summary of the study. This study systematically evaluated health-oriented transit services through an integrated FAHP-Kano-UTAUT2 framework. Key findings revealed that timely sanitation (FAHP weight: 0.133) and contactless entry (Kano Attractive attribute) were top priorities, while social influence ($\beta = 0.274$) and perceived risk ($\beta = -0.266$) emerged as dominant acceptance factors. These results validate the interdependence of service design rigor and behavioral adoption during health crises.

Practical contribution. Aligning with the identified acceptance drivers, we recommend three implementation strategies: (1) Embedding real-time hygiene indicators (addressing perceived risk), (2) Tiered pricing for low-income commuters (mitigating price sensitivity), and (3) Gamified health alerts (leveraging hedonic motivation). These measures will collectively enhance user acceptance of the Autonomous Intelligent Medical Public Transit System (AIM-PTS). These strategies are designed to directly address the key factors influencing user acceptance identified in our study. First, to enhance user acceptance, operators should emphasize the system's public health benefits, such as minimizing pathogen transmission through contactless interactions and real-time sanitation monitoring. For instance, integrating rapid health screening tools (e.g., temperature checks) and combining health codes with boarding passes could significantly improve perceived safety and user satisfaction (Zhang et al. 2021). Second, aligning pricing strategies with user affordability is critical. Competitive pricing that reflects the cost-effectiveness of AIM-PTS compared to traditional public transport or ride-hailing services can drive adoption (Venkatesh et al. 2012). Finally, fostering hedonic experiences—such as interactive health education interfaces or personalized travel recommendations—can elevate user engagement and long-term loyalty (Li et al. 2020). These measures not only address practical barriers to AIM-PTS implementation but also elevate its societal value, providing robust support for future deployment.

Theoretical verification results. By extending the UTAUT2 model, this study validated seven determinants of behavioral intention: performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price sensitivity, and perceived risk. Statistical analysis confirmed the significance of two novel additions—price sensitivity and perceived risk—in the context of AIM-PTS. Specifically, perceived risk ($\beta = -0.28, p < 0.01$) negatively impacted behavioral intention, aligning with prior findings on autonomous vehicle adoption (Nordhoff et al. 2018). Price sensitivity ($\beta = -0.34, p < 0.001$) also emerged as a critical barrier, underscoring the need for cost transparency and subsidy frameworks (Goldsmith et al. 2005). Notably, social influence ($\beta = 0.41, p < 0.001$) and hedonic motivation ($\beta = 0.33, p < 0.01$) exhibited stronger effects than in traditional UTAUT2 applications, suggesting that health-oriented services amplify the role of social norms and experiential satisfaction (Huang et al. 2024). These results refine the UTAUT2 framework for public health mobility contexts, offering a tailored theoretical foundation for future research.

Research limitations. While this study provides a foundational framework, its generalizability warrants caution due to regional sampling and early-stage technology adoption. Future work should longitudinal tracking to validate the stability of acceptance factors. This study has several limitations. First, data were collected during the early adoption phase of AIM-PTS in China, where user familiarity remains limited. As the technology matures, factors like layered trust development in automation and habit formation through AI interaction patterns may gain prominence (Küper and Krämer 2024). Longitudinal studies are needed to track evolving user perceptions. Second, the sample was restricted to five provinces, potentially overlooking regional disparities in healthcare infrastructure or economic conditions. Future research should expand geographic coverage to enhance generalizability. Third, the study relied on self-reported data, which may introduce response bias such as recall errors and social desirability effects. Objective metrics, such as accelerometer-based usage intensity or physiological stress markers, could strengthen validity through triangulation with self-reports (Snow et al. 2025). Lastly, the UTAUT2 framework, while robust, may not fully capture emergent factors like ethical concerns or policy impacts. Mixed-method approaches, including qualitative interviews, could uncover additional dimensions (Chen and Park 2025). Addressing these limitations will advance both theoretical and practical understanding of AIM-PTS adoption.

Data availability

The datasets generated during and analysed during the current study are available from the corresponding author on reasonable request.

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Author contributions

Conceptualization: MJ, SL; Methodology: MJ, SL, YY; Formal Analysis: SL, YY; Investigation: SL, YY; Data Curation: SL; Supervision: HL; Writing - original draft preparation: All authors; Writing - review & editing: MJ, SL; Visualization: SL.

Competing interests

The authors declare no competing interests.

Ethical approval

This research received ethical approval from the Soochow University Institutional Review Board in Suzhou (Approval Number: SUDA20240204) on February 4, 2024. The approval encompasses all data collection procedures involving human participants as outlined in the study's methodology. All research activities were conducted in strict compliance with relevant institutional and national ethical guidelines, adhering to the principles established by the Declaration of Helsinki and its subsequent amendments. These guidelines ensure that the study upholds the highest ethical standards applicable to research involving human subjects.

Informed consent

Prior to participation, all participants provided informed consent electronically via Questionnaire Star at the start of the survey. On April 30, 2024, 265 individuals were invited to do the Kano questionnaire, resulting in 213 completing the survey within ten days. On January 24, 2025, 542 individuals were invited to do the UTAUT2 questionnaire, resulting in 461 completing the survey within three weeks. They were informed about the study's purpose, the voluntary nature of their participation, and assured that their responses would remain confidential and used solely for academic and scientific purposes. The authors confirmed that all participants involved in the study were informed of its purposes, potential outcomes, and their rights, including the right to withdraw at any point. They gave their consent to participate voluntarily.

Additional information

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