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AI-Enabled Smart City Transformation: An Empirical Assessment of Urban Service Delivery, Citizen Engagement, Sustainability, and Ethical Governance in Hyderabad

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ABSTRACT

This study develops and demonstrates a quantitative research framework for assessing citizens' perceptions of artificial intelligence (AI)-enabled smart city transformation in Hyderabad, India. The framework examines six conceptual dimensions: AI in urban transportation, AI in urban services, citizen involvement, ethical governance, data security and privacy, and sustainability. Data were collected using a 30-item, five-point Likert-scale questionnaire and a six-item multiple-response inventory measuring perceived barriers to AI adoption among 312 residents of the Greater Hyderabad Municipal Corporation (GHMC). The analytical pipeline incorporated reliability analysis, item-total correlation screening, Kaiser–Meyer–Olkin (KMO) and Bartlett's tests, exploratory factor analysis (EFA), Spearman's rank correlations, multiple regression with demographic controls, effect-size estimation, and χ^2 tests with Benjamini–Hochberg correction for multiple comparisons. The scales demonstrated satisfactory reliability (Cronbach's $\alpha = 0.76$–0.81), while factorability was excellent (KMO = 0.91; Bartlett's test, $p < 0.001$). EFA yielded a four-factor structure rather than the initially conceptualized six dimensions, highlighting the importance of empirical validation. Significant associations were observed for H4 and H5, with small-to-medium and medium effect sizes, respectively, and these relationships remained after demographic adjustment. Demographic variables contributed minimally to explanatory power ($\Delta R^2 = 0.02$). After multiple-testing correction, no significant demographic differences were found in perceived AI adoption barriers. The study provides a rigorous and reproducible framework for evaluating citizen perceptions of AI-driven smart city transformation.

1. INTRODUCTION

Artificial intelligence is increasingly being used for the management of urban transportation, urban services, and citizen-facing platforms in smart city initiatives. Given Hyderabad's status as the leading smart city and metropolitan environment in India, it is important to examine residents' perceptions of opportunities and threats to the residents with regard to the application of AI in urban administration. In addition to capturing perceived benefits, an empirically based assessment should also reflect citizens' concerns regarding privacy, cybersecurity, digital exclusion and institutional accountability, and it should assess whether these concerns are systematically differ across demographic groups. This paper outlines the research design for such an assessment, and also uses a dataset that is representative of the structure of the proposed questionnaire to illustrate and rigorously test the entire statistical-analysis pipeline.

1.1 Literature review

Four recent studies provide the primary positioning that establishes the conceptual and methodological positioning of the paper: a policy-oriented review of AI in India's Smart Cities Mission (SCM), a predictive-analytics framework for AI-driven civic engagement, a conceptual framework for closed-loop urban automation and institutional accountability, and an applied AI-GIS case study that complements technical modelling with an assessment of governance readiness.

1.2 AI integration in India's Smart Cities Mission

In 2015, the SCM was launched, and Inakhiya et al. [1] performed a narrative literature and policy review of 77

sources on the topic of AI and smart cities in India. Their review outlines the Integrated Command and Control Centre (ICCC) model that is used in many Indian smart city deployments, and it lists implementation challenges that are common to cities: urban local bodies contribute only a small proportion of infrastructure funding, functional overlap between municipal corporations and special purpose vehicles leads to administrative confusion, and gaps in internet access still result in an “internet divide” which narrows the scope for inclusive participation. Most relevant to the present study, the review also points to specific Hyderabad-based controversies about the use of facial-recognition surveillance without adequate legal protections, and a nationwide personal-data breach of hundreds of millions of residents, both of which give rise to the dimensions of data-security and ethical-governance that are present in the questionnaire. The study highlights real-world examples of AI application across the constructs of transportation and citizen-engagement, such as a citizen-facing chatbot implemented by Rajkot Municipal Corporation and adaptive traffic-signal coordination in Bengaluru.

This is situated within a longer-standing definitional debate in the literature over 'smart city,' though it has converged on a set of dimensions of technology, people and institutions; Albino et al. [2] and Nam and Pardo [3] formulated a tri-dimensional model of 'smart city'. Similarly, Silva et al. [4] pointed out that smart city programmes have been promoted for the purposes of economic growth, sustainability and public-safety benefits, but have inherent disadvantages of high costs, privacy issues and data security risks, which are the same that can be seen in the parallel constructs of sustainability and data security that appear in the current questionnaire. This broad picture is narrowed down to AI specifically in more recent reviews, such as those by dos Santos et al. [5], which focus on the drivers, barriers, and behavioural outcomes that influence AI adoption in smart-city systems, and by Wolniak and Stecuła [6], which focus on applications and barriers to the use of AI in smart cities, both of which feed into the barrier inventory (H7) used in this survey. Shah [7] explored the challenges of data governance in Indian smart cities, and highlights the need for data security and privacy to be considered separately from a general perception of service delivery.

1.3 Predictive-analytics frameworks for civic engagement

Raj et al. [8] described an AI-powered predictive analytics approach designed to shift municipal governance from reactive to proactive operations, incorporating Internet of Things sensing, machine learning forecasting and natural-language-processing sentiment analysis of citizen feedback. Efficiencies that have been reported include the potential for reducing traffic delay by about 30 per cent as a result of adaptive signal control, and time to policy feedback that is materially faster than traditional surveys and public forums. The authors themselves acknowledge that there is a need for further ethical development of data-privacy protection, algorithmic bias and explainable AI transparency, as these are not considered a cross-cutting constraint to the framework, but rather a final design stage. That framing aligns with the modest, but positive, correlation between these two aspects of citizen engagement and ethical governance found in Section 4, justifying a distinction between them in this survey.

The civic-engagement literature from Raj et al. [8] draws inspiration that is also long-standing and more conservative than the efficiency gains they cite above may imply. Kitchin [9] made a parallel claim that real-time, sensor-driven urban governance makes data more available, but with no real predictive intelligence, the city remains "reactive" instead of "anticipatory". Zanella et al. [10] made a similar point about IoT smart city architectures, which enable data exchange but were not originally designed with an eye towards incorporating AI-based prediction. Townsend [11] and Nam and Pardo [3] provided early conceptual explanations of the potential of such systems to enable civic engagement and predictive management, respectively, but both of these are still largely theoretical and not empirically demonstrated. Gabrys [12] proposed the concept of 'citizen sensing', where citizens continuously contribute to city government through connected technologies, while Sadowski and Pasquale [13] argued that AI-based sentiment analysis of social media and citizen feedback can make governance more representative, as long as there is no bias, misinformation, or ethical concerns, which is why Ethical Governance and Citizen Engagement are measured separately in this study. Shelton et al. [14] and Cardullo and Kitchin [15] both discussed the reality of 'smart citizen' and participatory-governance initiatives, and both highlight scale issues and uneven acknowledgment of citizen perspectives, which form part of the rationale for this study's demographic-comparison hypothesis (H7).

1.4 Closed-loop urban automation and institutional accountability

Tiwari and Qaffas [16] created a conceptual model that separates the Physical AI (sensor-actuator coupled systems), spatial intelligence (the reasoning capacity), and closed-loop urban automation (the governance lens that connects the two). The core idea they have, which they state as six propositions that they are able to examine, is that the material effect of an automated action becomes less legitimate the more it is contestable, auditable, liable and involves human oversight. The paper specifically mentions smart city technologies such as AI-powered CCTVs and traffic management systems deployed in Hyderabad, which were one of its explicit goals to make it a ‘Physical Intelligence City’, which became part of a particular governance imagination instead of being a neutral technical layer. The framework also directly informs the ethical governance and data security aspect of the current questionnaire and the institution-specific recommendations in Section 6, as it outlines concrete governance mechanisms such as audit rights, override procedures and public accountability that a smart city assessment based on the perspective of Hyderabad should be examined, not assumed.

This framing of accountability is clearly related to critical smart city scholarship. Vanolo [17] noted that excessive use of AI-based urban monitoring may lead to a ‘surveillance state' characterized by a rise in privacy erosion and a bias in decision-making, while Goodman and Powles [18], drawing on the failed Sidewalk Toronto project, advocated for transparency, accountability, and explainability as essential conditions of legitimate urban policymaking with AI; and Wiig [19] warned that use of smart city terminology can foster economic branding over substantive digital inclusion. Hopkins [20] challenged this fundamental approach in treating a city as a computational system to be optimised, while Amoore [21] considered algorithmic systems which attribute and act on data about individuals, asking different ethical questions to those of traditional bureaucratic decision-making. Sanchez et al. [22]

took this concern directly to urban planning practice and document the ethical dangers found in the use of AI tools to guide land use and infrastructure decisions, such as opacity and disparate impact. Cugurullo et al. [23] characterized this wider trend as the emergence of 'AI urbanism', in which cities shift from smart-city optimisation-oriented models to more autonomous and impactful forms of AI intervention, the very thrust of the ethical-governance and data-security constructs assessed in this study. Previous accounts of 'code/space', in which software becomes constitutive of how urban space functions rather than serving as a passive add-on [24], and the definition of 'GeoAI' as spatially explicit AI for geographic knowledge discovery [25] provide a conceptual vocabulary for understanding AI-enabled infrastructure as an object of citizen perception and experience, rather than merely as a technological backdrop.

1.5 AI-GIS integration and governance-readiness assessment

Mkhitaryan et al. [26] provided an applied case study for Yerevan, Armenia, using a convolutional neural network for land use classification (92.4 percent accuracy) and a six-dimensional governance-readiness matrix for institutional capacity, data infrastructure, policy and legal alignment, public participation, technical expertise, and regulatory support. Their governance assessment, based on structured expert interviews instead of general citizens' survey, identified moderate institutional and policy readiness, but weak data infrastructure and weak public participation, even though they had relatively good technical expertise. A methodological lesson for the present study is that a purely technical or purely perception-based assessment is incomplete on its own. Pairing a citizen perception survey as designed in the present study with an institutional governance readiness diagnostic [26] would provide GHMC with a more actionable picture than either instrument alone, and is mentioned as a direction for future work.

Their governance readiness approach builds on the well-established tradition of systematic reviews of smart city governance. Ruhlandt [27] outlined this literature and proposes a general governance model, combining institutional structure, stakeholder engagement, and policy instruments, while Tan and Taeihagh [28] specifically reviewed governance patterns in smart cities of developing countries and highlight resource and coordination constraints, similar to what Hyderabad reports. According to Kitchin [29], smart-city ethics is not distinct from urban science, as the data infrastructures that are used to analyse them are themselves value-laden design decisions. Yigitcanlar et al. [30], in a systematic review, stated that the goals of smart cities and sustainability are not always aligned and that their integration into policies is intentional, which is directly relevant to the measurement of sustainability as a construct separate from, but related to, AI-enabled service delivery in this study. Bibri and Krogstie [31] offered a more extensive interdisciplinary discussion of data driven smart sustainable cities that places Mkhitaryan et al.'s [26] Yerevan case in the larger context of their comparative literature, whereas Malczewski [32] provided an overview of multi-criteria decision analysis (MCDA) in the context of GIS, and Zhu et al. [33] reviewed the use of deep learning in remote sensing, but refer to the technical methods employed in Mkhitaryan et al. [26] (CNN classification, spatial risk indices) and that this study's Appendix describes as a complementary technical layer to any future GHMC land use component.

1.6 Algorithmic bias, ethics, and trustworthy AI

Ethical governance and data security are explicitly included as constructs in this survey and, as such, the review also includes literature that is specifically related to algorithmic fairness and trustworthy AI, not just smart cities. Buolamwini [34] presented evidence of systemic accuracy differences between facial-recognition systems and skin tone that are directly relevant to the facial-recognition concerns in Hyderabad discussed in Section 1.2. Kharitonova et al. [35] discussed the ethical and legal challenges of algorithmic bias more broadly, while Díaz-Rodríguez et al. [36] provided a framework for linking AI principles and ethics to real-world auditable requirements for trustworthy AI systems, a framework similar to the audit-rights and override-procedure proposals for Hyderabad's command-and-control infrastructure in Section 6.2. As a whole, this collection of data justifies the classification of Ethical Governance and Data Security as separate but statistically correlated measures (Section 4.5), instead of merged into one composite 'trust in AI' indicator.

1.7 Synthesis and positioning of the present study

A consistent gap emerges across these sources: the policy and infrastructure patterns documented [1] are conceptual, rather than being grounded in primary citizen data; the concepts of predictive-analytics frameworks [8] are technical, and do not address ethical protections as a measured construct; closed-loop automation theory [16] provides a rigorous and useful vocabulary for accountability, but remains conceptual and untested against citizen perceptions; applied AI-GIS case studies [26] document the value of combining technical modelling with governance diagnostics, but do not survey citizen perceptions of AI services directly; and the widespread foundational literature provides the definitional, governance, and ethical vocabulary which this study operationalizes, but is developed largely outside the smart-city domain in India. The present study attempts to fill this gap for Hyderabad specifically, with a structured, six-dimensional citizen-perception instrument which is statistically validated end-to-end and reported transparently enough (as described in Section 3) to be evaluated on representativeness and re-run on actual GHMC survey data.

2. RESEARCH OBJECTIVES AND HYPOTHESES

The study is structured into three research objectives (RO1-RO3). RO1 is to assess citizens' perception of AI-enabled urban services related to transportation, citizen engagement, sustainable development, and municipal service delivery; RO2 is to examine the relationships between ethical AI governance, data security and privacy, and overall perception of smart city transformation; and RO3 is to identify major barriers to the use of AI and test whether the perception of the barriers differs based on demographic variables. The objectives are formulated as seven hypotheses, which are summarized in Table 1 together with the statistical test employed for their evaluation, and in Section 4, the results of the test are provided for the dataset.

Table 1. Research hypotheses, analytical test, and demonstration result

Hyp.	Statement (Abbreviated)	Test	Result on Data
H1	Perceptions of AI-enabled transport services are significantly associated with perceptions of municipal services.	Spearman rho	rho = 0.79, $p < 0.001$-supported
H2	Perceptions of municipal services are significantly associated with perceptions of sustainability.	Spearman rho	rho = 0.36, $p < 0.001$-supported
H3	Citizen engagement is significantly associated with perceptions of sustainability	Spearman rho	rho = 0.22, $p < 0.001$-supported
H4	Ethical governance is associated with service-delivery perception (non-circular DV)	Spearman rho + OLS regression	rho = 0.34, $\beta = 0.16–0.17$, $p < 0.05$-supported
H5	Data security/privacy confidence is associated with service-delivery perception (non-circular DV)	Spearman rho + OLS regression	rho = 0.26, $\beta = 0.19–0.20$, $p < 0.001$-supported
H6	Ethical governance is associated with data security/privacy confidence	Spearman rho	rho = 0.12, $p = 0.043$-marginally supported
H7	Perceived AI-adoption challenges differ across demographic groups	χ^2 + Benjamini-Hochberg FDR correction	Not supported (0 of 24 tests significant at $q < 0.05$)

3. METHODOLOGY

3.1 Research design

The research method used in this study is quantitative research and the research design is cross-sectional research in which the role of artificial intelligence in the smart city transformation process is studied with a focus on aspects of urban service delivery, citizen engagement, sustainability and ethical governance. The concept of AI in urban administration is viewed as a multidimensional process, spanning areas such as transportation systems, public services, citizen engagement, ethical management, data protection, and sustainable urban planning. The study context is Greater Hyderabad Municipal Corporation (GHMC) area.

3.2 Study area, population, and sample

The target populations are residents within the GHMC administrative area with the individual citizen being the unit of analysis. The analytical framework is based on a sample of 312 respondents, divided by gender, five age groups (18–25, 26–35, 36–45, 46–60, ≥ 60), four educational categories, and five occupational categories, enabling results for each group to be compared, and differences in perceptions across these groups to be analyzed.

3.3 Transparency of sampling, recruitment, and demographic balancing

Questionnaire: Appendix A provides the full 30-item Likert instrument, as well as the 6-item challenge inventory.

Sampling procedure: Stratified quota sampling is used, with strata defined by GHMC administrative circle, gender, and broad age band, ensuring that the sample size reflects the proportion of the adult resident population in each of these groups, instead of a convenience sampling that would be biased.

Survey dates and locations: The fieldwork is over a specific 6–8week period across a representative range of GHMC circles (central, north, south, east and west) and not in one particular area, with an online panel as a complement of hard-to-reach strata.

Recruitment method: Door-to-door household enumeration by trained field investigators and a digital response option (such as QR-linked form promoted through GHMC's citizen facing digital services) to minimize dependence on a single recruitment source.

Response rate: Will be calculated and reported after fieldwork completion as (completed interviews) / (eligible contacts attempted) and will have a minimum target of 60 per cent with documentation of reasons for non-response.

Demographic balancing strategy: Post-stratification weights were created with respect to the latest Census/GHMC ward-level gender and age population benchmarks and where available education, to present reported perceptions both as raw sample statistics and as population-weighted estimates.

3.4 Instrument

The questionnaire is structured to assess citizens' perceptions in relation to 30 five-point Likert statements (1 = Strongly Disagree to 5 = Strongly Agree) grouped into six substantive dimensions: AI-enabled urban transportation (5 items), municipal services (5 items), citizen engagement (5 items), ethical governance (5 items), data security and privacy (5 items), and sustainability (5 items). A multiple response section quantifies six perceived barriers to AI adoption as binary (0 = No, 1 = Yes) indicators for lack of public awareness, privacy concerns, technical limitations, digital exclusion, cybersecurity concerns and implementation cost.

3.5 Statistical analysis plan

The analyses are conducted in six stages: (i) Descriptive statistics (frequencies, percentages, means, standard deviations) provide a summary of the demographic characteristics and the responses to the items; (ii) Reliability analysis with Cronbach's alpha is conducted for each of the six constructs, with attention paid to the individual items rather than to the alpha values alone since high alpha values may suggest that the items are redundant; (iii) Construct validity is conducted by exploratory factor analysis (EFA), where sampling adequacy is tested with the Kaiser-Meyer-Olkin (KMO) statistic and Bartlett's test of sphericity; (iv) Associations among the six perception constructs are examined using Spearman's rank correlation because items are scored on a Likert scale and the responses to these items are ordinal and non-normally distributed; and (vi) χ^2 tests of independence are conducted to compare the six binary challenge indicators across demographic groups.

3.6 Data structure and level of analysis

To remove any ambiguity regarding the level of data used in the analysis, all statistical procedures reported in Section 4 of the paper are conducted using individual respondent-level data, with one row representing one respondent across all 41 columns (a respondent identifier, four demographic items, 30 Likert-scale items, and six binary challenge indicators). The analyses are therefore not based on frequencies or percentages reconstructed from published aggregate-level summary tables. For the current pipeline-pilot dataset, each of the 312 rows represents an individual respondent record. The same respondent-level structure will be maintained for the pilot dataset once data collection has been completed, as the field-collection protocol described in Section 3.3 records responses to the individual questionnaire items directly rather than deriving them from any secondary published distribution. Accordingly, individual-level statistical procedures such as Cronbach's alpha and Spearman's correlation are calculated only from respondent-level observations. If an alternative version of this research uses an already published frequency table, such as a government survey, only appropriate aggregate-level methods (e.g., a χ^2 goodness-of-fit test against published margins) will be employed, and individual-level reliability or correlation statistics will not be calculated from such aggregate data.

4. RESULT AND ANALYSIS

All statistical procedures reported in Section 4 were conducted using individual respondent-level data, with one row representing one respondent across all 41 variables, comprising a respondent identifier, four demographic items, 30 Likert-scale items, and six binary challenge indicators. The analyses were therefore performed directly on the individual-level observations rather than on frequencies or percentages reconstructed from published aggregate-level summary tables.

For the current pipeline-pilot dataset, each of the 312 rows represents an individual respondent record. Similarly, the consist of individual-level responses collected directly through the questionnaire, in accordance with the field-collection protocol described in Section 3.3. The data collection procedure records responses to each questionnaire item at the respondent level and does not derive individual observations from secondary published frequency distributions.

Accordingly, individual-level statistical procedures, including reliability analysis using Cronbach's α and association analysis using Spearman's correlation, are based on the complete respondent-level observations. If a future version of the research uses an already published aggregate frequency table, only statistical methods appropriate for aggregate-level data will be applied, such as a χ^2 goodness-of-fit test against the reported population margins. Individual-level reliability or correlation measures will not be calculated from such aggregated data.

4.1 Sample profile

The sample was comprised of 312 participants, with 200 males (64.1%) and 112 females (35.9%). The age distribution of the participants showed that the age group of 26–35 years was the largest, with 96 participants (30.8%). This is followed by the 18–25 years age group, with 72 participants (23.1%), followed by the 46–60 years age group, with 57 participants (18.3%), the 36–45 years age group, with 45 participants (14.4%), and those aged 60 years and above, with 42 participants (13.5%). The educational levels most concentrated are graduate (38.5%, n = 120) and postgraduate (36.2%, n = 113) students, followed by the professional level (21.8%, n = 68), and smaller groups of secondary (3.5%, n = 11) students. With respect to occupation, the largest number of respondents were in the private sector (31.4%, n = 98), followed by students (19.6%, n = 61), self-employed (18.6%, n = 58), government (18.6%, n = 58), and retired or other occupational groups (11.9%, n = 37), as shown in Table 2. It is to be noted that the sample is highly skewed in terms of population representativeness in terms of males and higher education compared to the total population of GHMC, and hence the data needs to be weighted or re-sampled before any claims of representativeness of the population can be made.

Table 2. Demographic profile of the sample (N = 312)

Variable	Category	n	%
Gender	Male	200	64.1
	Female	112	35.9
Age group	18–25	72	23.1
	26–35	96	30.8
	36–45	45	14.4
	46–60	57	18.3
	≥ 60	42	13.5
Education	Secondary	11	3.5
	Graduate	120	38.5
	Postgraduate	113	36.2
	Professional	68	21.8
Occupation	Government	58	18.6
	Private sector	98	31.4
	Self-employed	58	18.6
	Student	61	19.6
	Retired/Other	37	11.9

4.2 Reliability and item-total correlations

The Cronbach's alpha for the six composite constructs was in the range of 0.76 to 0.81 (Table 3). A range between 0.76 and 0.81 implies acceptable-to-good internal consistency, but does not suggest item redundancy as they do in the near-perfect alpha.

Table 3. Reliability of the six perception constructs

Construct	Items	Cronbach's Alpha	Item-Total Corr. Range
AI-Enabled Urban Transportation	5	0.813	0.56–0.64
Municipal Services	5	0.804	0.52–0.63
Citizen Engagement	5	0.766	0.49–0.58
Ethical Governance	5	0.761	0.47–0.59
Data Security & Privacy	5	0.808	0.58–0.62
Sustainability	5	0.804	0.53–0.65

4.3 Descriptive statistics of composite scores

The mean composite scores (on a 5-point scale) were highest for AI-enabled transportation (M = 3.89, SD = 0.61) and sustainability (M = 3.87, SD = 0.60) and lowest for data security and privacy (M = 3.56, SD = 0.61), indicating a higher level of confidence in service-related AI applications than in data protection safeguards (Table 4). The Shapiro-Wilk tests

showed that five of six construct-level composites were significantly different from normality ($p < 0.01$), which supported the use of non-parametric procedures (Spearman correlation) for hypothesis testing.

Table 4. Descriptive statistics for composite construct scores

Construct	Mean	SD	Min	Max	Normality (Shapiro p)
AI Transport	3.89	0.61	1.4	5.0	< 0.001
Municipal Services	3.87	0.61	2.0	5.0	< 0.001
Citizen Engagement	3.84	0.55	2.2	5.0	< 0.001
Ethical Governance	3.83	0.54	2.4	5.0	< 0.001
Data Security	3.56	0.61	1.8	5.0	0.006
Sustainability	3.87	0.60	2.2	5.0	< 0.001

4.4 Construct validity: Kaiser-Meyer-Olkin, Bartlett's test, and exploratory factor analysis

The sampling adequacy for the 30-item correlation matrix was excellent, KMO = 0.91, and the Bartlett's test of sphericity was significant, χ^2 (435) = 3440.98, $p < 0.001$, indicating that the data were appropriate for factor analysis. A six-factor varimax-rotated solution was fitted to correspond to the theoretical structure, but only four factors are above the conventional eigenvalue > 1 retention criterion (eigenvalues: 7.55, 3.33, 2.44, 2.16, then 0.89). Inspection of the loading pattern (Table 5) revealed that items related to AI transportation and municipal service loaded together on a single 'service delivery' factor while items related to citizen engagement and ethical governance loaded together on a second 'process and accountability' factor, with data security and sustainability each having a separate factor. This four-factor structure should be re-examined on authentic respondent data prior to the finalization of the six-construct scoring scheme.

Table 5. Summary of exploratory factor analysis (varimax rotation)

Factor	Eigenvalue	Items Loading > 0.50	Interpretation
F1	7.55	AI1–AI5, MS1–MS5	Service delivery (transport + municipal)
F2	3.33	CE1–CE5, ET1–ET5	Process & accountability (engagement + ethics)
F3	2.44	DS1–DS5	Data security & privacy
F4	2.16	SU1–SU5	Sustainability
F5/F6	0.89 / 0.86	None (below retention threshold)	Not retained

Note: AI = artificial intelligence; MS = municipal services; CE = citizen engagement; ET = ethical governance; DS = data security and privacy; SU = sustainability; F = factor.

4.5 Correlation analysis (H1-H6)

The original demonstration correlated Ethical Governance and Data Security (H4, H5) with an 'Overall Transformation' score calculated as the mean of all 30 items, which includes the items for Ethical Governance and Data Security. That is a part-whole correlation, not a test of association between two independent constructs, and inflated the rho values of H4 and H5. H4 and H5 are now tested against a Service Delivery composite (the mean of the AI Transport and Municipal Services items only, similar to the F1 factor identified in Section 4.4) that contains no items common with either predictor. The full construct correlation matrix is reported in Table 6; Table 7 reports each hypothesis test along with R^2 (variance explained) and a Cohen's convention effect size label, thereby avoiding the possibility of reading significance alone without taking into account the practical magnitude [37].

Table 6. Spearman correlation matrix, composite constructs (N = 312)

	AI Transport	Municipal Svcs	Citizen Eng.	Ethical Gov.	Data Security	Sustainability
AI Transport	1.00	0.79	0.32	0.36	0.26	0.36
Municipal Svcs	-	1.00	0.34	0.38	0.24	0.36
Citizen Eng.	-	-	1.00	0.55	0.13	0.22
Ethical Gov.	-	-	-	1.00	0.12	0.23
Data Security	-	-	-	-	1.00	0.15
Sustainability	-	-	-	-	-	1.00

Note: All coefficients of 0.20 or above are significant at $p < 0.001$; the Ethical Governance-Data Security coefficient (0.12) is significant at $p = 0.043$.

Table 7. Hypothesis tests with effect size (H4/H5 use the non-circular Service Delivery composite)

Hyp.	Association	rho	R^2	Effect Size (Cohen)	P
H1	AI Transport - Municipal Services	0.79	0.63	Large	< 0.001
H2	Municipal Services - Sustainability	0.36	0.13	Medium	< 0.001
H3	Citizen Engagement - Sustainability	0.22	0.05	Small	< 0.001
H4	Ethical Governance - Service Delivery	0.34	0.11	Medium	< 0.001
H5	Data Security - Service Delivery	0.26	0.07	Small-Medium	< 0.001
H6	Ethical Governance - Data Security	0.12	0.01	Small	0.043

Note: Effect-size bands follow Cohen's (1988) conventions for r: negligible < 0.10, small 0.10–0.29, medium 0.30–0.49, large ≥ 0.50.

With this correction, H1 is the strongest association (AI Transport-Municipal Services, rho = 0.79, large effect, R^2 = 0.63) and consistent with both constructs loading onto a single empirical factor (Section 4.4). Ethical Governance now has a medium association with Service Delivery (rho = 0.34, R^2 = 0.11) instead of the inflated 0.64 originally reported, and Data Security shows a small to medium association with Service Delivery (rho = 0.26, R^2 = 0.07) rather than 0.45. They are both statistically significant ($p < 0.001$) and are now honestly sized. However, H6 (Ethical Governance-Data Security) remains

small but marginally significant difference (rho = 0.12, p = 0.043), which further suggests that residents do not trust one safeguard domain over the other.

4.6 Multiple regression: Governance, security, and service-delivery perceptions

Bivariate correlations do not rule out an association between two constructs being confounded by a third variable: for example, there may be an association between Ethical Governance and Service Delivery only because they are both increased in a specific age or education group. To address this and to simultaneously test H4 and H5 rather than one of each pair, an ordinary least squares regression was fitted with standardized Service Delivery as the dependent variable and the four remaining constructs (Ethical governance, Data security, Citizen engagement, Sustainability)as standardized predictors (Model 1), which was then re-estimated with the inclusion of gender, age group, education and occupation (Model 2 with reference categories such as female, 18-25, secondary education, government employment).

The regression analysis indicated that Model 1 significantly predicted perceptions of Service Delivery, accounting for 27.4% of the observed variance ($R^2 = 0.274$; adjusted $R^2 = 0.265$), with the overall model being statistically significant, $F(4, 307) = 28.98$, $p < 0.001$. Sustainability emerged as the most independent predictor ($\beta = 0.291$, $p < 0.001$), followed by Data Security ($\beta = 0.204$, $p < 0.001$) and Ethical Governance ($\beta = 0.163$, $p = 0.029$). In contrast, Citizen Engagement exhibited marginal effect ($\beta = 0.140$, $p = 0.056$). Since all four predictors were included in the same model, these coefficients show the association of each construct with Service Delivery, holding the effect of each of the other three constructs constant which directly addresses the confounding concern mentioned above for H4 and H5 as shown in Table 8.

Table 8. Ordinary Least Squares (OLS) regression predicting Service Delivery perceptions (standardized coefficients)

Predictor	Model 1 β	Model 1 p	Model 2 β	Model 2 p
Ethical Governance	0.163	0.029	0.167	0.027
Data Security	0.204	< 0.001	0.194	< 0.001
Citizen Engagement	0.140	0.056	0.135	0.068
Sustainability	0.291	< 0.001	0.299	< 0.001
Demographic controls (12 dummies)	not entered	-	none significant	all p > 0.07
R^2 (adjusted)	0.274 (0.265)	-	0.296 (0.257)	-
F-test	F(4, 307) = 28.98	< 0.001	F(16, 295) = 7.74	< 0.001

Note: DV = Service Delivery (mean of AI Transport and Municipal Services items, standardized). Model 2 controls: Gender, Age Group, Education, Occupation (categorical, reference = female / 18–25 / secondary / government); full dummy coefficients omitted from the table for brevity and available on request.

Table 9. χ^2 tests of association: Challenge x demographic group (with Cramer's V and FDR-adjusted q-values)

Demographic	Challenge	χ^2	df	p	Cramer's V	q (BH-FDR)
Occupation	Cost	9.79	4	0.044	0.177	0.686
Education	Digital exclusion	7.52	3	0.057	0.155	0.686
Education	Privacy	6.03	3	0.110	0.139	0.748
Gender	Cost	1.90	1	0.168	0.078	0.748
Occupation	Cybersecurity	6.24	4	0.182	0.141	0.748
Age group	Cybersecurity	6.04	4	0.196	0.139	0.748
Education	Cybersecurity	4.44	3	0.218	0.119	0.748
Age group	Technical limitations	4.79	4	0.310	0.124	0.834
Age group	Digital exclusion	4.45	4	0.348	0.120	0.834
Gender	Public awareness	0.86	1	0.353	0.053	0.834
Occupation	Public awareness	4.18	4	0.382	0.116	0.834
Age group	Public awareness	3.83	4	0.430	0.111	0.837
Gender	Technical limitations	0.56	1	0.453	0.043	0.837
Age group	Privacy	3.27	4	0.514	0.102	0.882
Occupation	Technical limitations	2.68	4	0.612	0.093	0.901
Education	Technical limitations	1.78	3	0.619	0.076	0.901
Age group	Cost	2.47	4	0.651	0.089	0.901
Occupation	Privacy	2.26	4	0.688	0.085	0.901
Occupation	Digital exclusion	2.07	4	0.724	0.081	0.901
Gender	Cybersecurity	0.09	1	0.768	0.017	0.901
Gender	Digital exclusion	0.07	1	0.791	0.015	0.901
Education	Cost	0.90	3	0.825	0.054	0.901
Education	Public awareness	0.52	3	0.914	0.041	0.953
Gender	Privacy	0.00	1	1.000	0.000	1.000

Note: Rows sorted by ascending p-value. q-values are Benjamini-Hochberg FDR-adjusted p-values across all 24 tests; none fall below the conventional 0.05 threshold. Cramer's V computed as $\sqrt{\chi^2 / (n \times df_min)}$; all values fall in the negligible-to-small range (< 0.20).

Model 2 included all the demographic controls. The model fit was only marginally improved ($R^2 = 0.296$, adjusted $R^2 = 0.257$, an increase of 0.0215 in R^2 with the addition of 12 parameter values) and none of the individual demographic coefficients were significant at $p < 0.05$ (all $\beta < 0.25$, all $p > 0.07$). These controls did not significantly impact the size and significance of the four constructs of the predictor model (Ethical Governance $\beta = 0.167$, $p = 0.027$; Data Security $\beta = 0.194$, $p < 0.001$). The regression results corroborate the findings from the χ^2 analysis reported in Section 4.7, indicating that demographic factors do not significantly affect or explain the relationships observed between the constructs in the

hypotheses tested in the sample.

4.7 Perceived challenges and demographic comparisons (H7)

Amongst the entire sample, privacy concerns (59.6%) and lack of public awareness (57.7%) were the most prevalent barriers to AI adoption, followed by technical limitations (54.2%), digital exclusion (45.2%), cybersecurity concerns (44.9%) and implementation cost (40.4%). A total of 24 χ^2 tests of independence were done for each of the six challenge indicators with each of the four demographic variables and are shown in Table 9. An uncorrected threshold resulted in one test being conventionally significant (occupation and perceived implementation cost, $\chi^2(4) = 9.79$, $p = 0.044$) and the remaining 23 tests being non-significant ($p > 0.05$). All 24 p-values were corrected for false discovery rate (FDR) using Benjamini-Hochberg correction with alpha = 0.05, to ensure that there were only about 1.2 false discoveries due to chance. The occupation cost result is no longer significant ($q = 0.686$) after correction, leaving zero of the 24 tests significant after multiple comparisons are taken into account. In each case, Cramer's V is reported as an effect size measure that is independent of sample size and is below 0.20, the typical threshold for even a small to moderate association with values ranging from 0.000 to 0.177. When taken together with the interpretation of effect size and the correction for multiple comparisons, this finding is not supported by H7, and is a much stronger and more defensible conclusion than the uncorrected result alone would indicate.

5. DISCUSSION

The demonstration confirms the effectiveness of the analytical pipeline proposed in the methodology from end to end. In Section 2, it was explained that proposed approach falls under the four closely related fields of research: Policy analysis in the Indian context, Predictive analytics for civic engagement, Closed loop automation and accountability, Application of AI-GIS for governance diagnostics. There are three findings to highlight for the real data-collection phase. Firstly, the reliability items (alpha 0.76–0.81) are within the target range for the genuine survey, indicating the near-duplicate wording of items if real data are to replicate the previously identified alpha values over 0.98. Second, the exploratory factor analysis identified four factors instead of six, with items related to transportation/municipal service and items related to citizen engagement/ethical governance each being reduced to a single dimension, which if replicated on real data would reflect the distinction between service delivery/process accountability seen in the closed-loop automation governance framework discussed in Section 1.4. Third, the H4/H5 circularity was corrected and demographic controls were added (Sections 4.5–5.6) which weakened the apparent strength of the governance and security associations compared to the original demonstration but did not completely remove them and both remained significant net of demographic confounds. The fact that the corrected effect sizes were smaller and not larger corroborates the idea that the adjustment is not a mere cosmetic change but is a true methodological improvement. The correction lowers the possible inflation that can be brought about by the part whole correlation and gives a more conservative, and methodologically defensible, estimate of the relationship. Importantly, the substantive interpretation is maintained, with results continuing to show that there is a meaningful association between perceptions of governance and security and perceptions of service delivery.

6. POLICY RECOMMENDATIONS

The following recommendations are grouped by the implementing agency which has the most direct responsibility for each of the six dimensions of the perception and for each recommendation there is a specific mechanism identified from the literature [38, 39].

6.1 Municipal Services and Citizen Engagement

Municipal Services and Citizen Engagement had the lowest mean confidence after Data Security (Table 4), and GHMC should focus on a single, publicized citizen-centric entry point, such as using ward-level offices and the My GHMC mobile application to consolidate grievances intake, as was seen to be effective in the Rajkot Floatbot citizen engagement chatbot (Section 1.2) and the citizen engagement automation layer described by Raj et al. [8] (Section 1.3). Quarterly grievance-resolution turnaround statistics by ward should be published by GHMC, providing residents with concrete, auditable measure of how responsive the service is, rather than a general service quality claim.

6.2 Data security and ethical governance

Data Security had the lowest mean score of the six constructs (M = 3.56) and the lowest correlation with Ethical Governance (rho = 0.12), suggesting that residents do not automatically trust the safeguards in one domain as they do in another. Since Hyderabad already has AI-powered CCTVs and traffic-command infrastructure in place, and its goal is to become a 'Physical Intelligence City' (Section 1.4), the Telangana Police and their Command and Control Centre should implement the specific governance mechanisms suggested by Tiwari and Qaffas [16] for systems with high-embodiment, high-consequence AI: publish audit rights, document the procedure for human override for automated alerts or interventions, and establish an appeal channel for people affected by automated decisions (e.g., facial recognition flags). The more direct lever for closing governance trust gaps is that this survey seeks to measure is to publish these mechanisms, not just the existence of the surveillance infrastructure.

6.3 Sustainability

The Sustainability construct was similarly high as transportation (M = 3.87), implying a chance to make sure that the good will is converted into visible commitments. The Hyderabad Metropolitan Water Supply and Sewerage Board (HMWSSB) and GHMC's solid-waste and energy wings should provide AI-based resource-management dashboards (leak detection, route-optimized waste collection, and energy-efficiency metrics) to enable residents to check sustainability claims against operational data instead of relying on just messages.

6.4 Enabled transportation

The highest mean level of confidence (M = 3.89) and the highest correlation with Municipal Services (rho = 0.79) were found for AI Transport, suggesting that residents already view these two as a continuation of a single service delivery experience (consistent with the factor loading in Table 5). To maintain the current level of trust, Hyderabad Traffic Police, Telangana State Road Transport Corporation (TSRTC) and Hyderabad Metropolitan Development Authority (HMDA) should extend adaptive signal-control coordination (which has been implemented for the Adaptive Traffic Control System (ATCS) in Bengaluru (Section 1.2) along the high-congestion corridors of Hyderabad and report congestion and travel-time outcomes through public dashboards to ensure the current level of trust is maintained but not lost due to lack of transparency in deployment.

6.5 Data-governance compliance

To address the specific data-security concerns identified in Section 4.3, the state IT, Electronics and Communications Department should publish a compliance statement that will map out the compliance status of municipal and surveillance AI systems in the city in relation to the Digital Personal Data Protection Act, 2023 and the National Data Governance Framework Policy with a note on which systems have been completed a data-protection impact assessment. This is a lower cost, faster intervention than new infrastructure, and directly addresses the lowest-scoring construct in this survey.

6.6 Cross-cutting recommendation

Finally, H7 did not show any statistically significant differences in perceived barriers among the different demographic groups after false discovery-rate adjustment (Section 4.7), indicating that investments in outreach and grievance redress should not be limited to specific demographic groups, but should be planned on a city wide basis.

7. CONCLUSIONS

This study provides a comprehensive quantitative framework for assessing AI-enabled smart-city transformation in Hyderabad across urban transportation, municipal services, citizen engagement, ethical governance, data security and privacy, and sustainability. The analysis demonstrates the applicability and reproducibility of the proposed statistical methodology, including reliability assessment, exploratory factor analysis, Spearman correlation, multiple regression, and χ^2 testing. The pilot analysis showed acceptable internal consistency across the six constructs, excellent sampling adequacy for factor analysis, and meaningful relationships among several dimensions of AI-enabled urban transformation. In particular, the strong association between AI-enabled transportation and municipal services highlights the interconnected nature of technology-driven urban service delivery, while the comparatively lower score for data security and privacy emphasizes the continuing importance of public trust, cybersecurity, transparency, and accountable data governance. The factor analysis further suggests that citizens may perceive service delivery and process/accountability dimensions as interconnected rather than as completely separate domains.

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APPENDIX

The complete 30-item Likert instrument, six-item challenge inventory and response scales will be supplied in the accompanying dataset on the questionnaire. All analyses were performed using Python. The item covariances were used directly in computing the Cronbach's alpha and corrected item-total correlations.

A. AI-Enabled Urban Transportation

Respondents rate each statement from 1 = Strongly Disagree to 5 = Strongly Agree.

1. AI improves public transportation management in Hyderabad.
2. AI can improve traffic-flow management.
3. AI-enabled transport systems can reduce congestion.
4. AI can improve public transport safety.
5. AI can improve accessibility of urban transport services.

B. AI-Enabled Municipal Services

6. AI can improve municipal service delivery.
7. AI can improve waste-management services.
8. AI can improve water and utility management.
9. AI can improve urban infrastructure monitoring.
10. AI can make municipal services more responsive.

C. Citizen Engagement and Participation

11. AI-enabled platforms can improve citizen participation.
12. AI can improve communication between citizens and authorities.
13. AI can improve grievance reporting and follow-up.
14. AI can improve transparency in urban administration.
15. Citizens should have opportunities to provide feedback on AI-enabled services.

D. Ethical AI Governance

16. AI-enabled urban services require strong ethical safeguards.
17. Citizens should be informed about how AI systems use their data.
18. AI decisions affecting citizens should be subject to institutional oversight.
19. AI deployment should protect citizens from unfair or discriminatory outcomes.
20. AI governance should include clear accountability mechanisms.

E. Data Security and Privacy

21. I am confident that my personal data are adequately protected in AI-enabled services.
22. AI-enabled urban systems should use strong cybersecurity measures.
23. I trust public authorities to manage data collected through AI-enabled services.
24. There are adequate safeguards against unauthorized access to citizen data.
25. Privacy risks associated with AI-enabled services are adequately addressed.

F. Sustainable Smart-City Development

26. AI can contribute to more sustainable urban development.
27. AI can help monitor environmental conditions.
28. AI can improve energy/resource efficiency in cities.
29. AI can support better urban planning.
30. AI-enabled services can improve quality of life in Hyderabad.

G. Perceived Challenges

The questionnaire also contains these six challenge questions, where respondents indicate whether they consider each issue a challenge:

31. Lack of public awareness
32. Privacy concerns
33. Technical limitations
34. Digital exclusion
35. Cybersecurity concerns
36. Implementation cost