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Towards Scalable and Sustainable Urban Digital Twins: Causal Mapping of Implementation Barriers

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Abstract

Urban Digital Twins (UDTs) are becoming more recognized as important enablers to facilitate data-driven decision-making in smart city environments. Governments, industry, and research organizations have stood committed and increased funding. However, a complex web of interdependent barriers prevents the large-scale deployment of UDTs. An elaborate literature review on studies published from 2021 to 2025 found twenty-five barriers which were modelled using fuzzy DEMATEL to find their causal interrelationships. The exploratory qualitative-quantitative causal research design was developed using a purposive sample of twelve experts. A two-round elicitation process was adopted to capture expert uncertainty and barrier interdependency. The findings from the fuzzy DEMATEL reveal nine causal barriers and sixteen effect barriers. Analysis shows how reducing barriers from high-leverage cause-groups can reduce downstream effects considerably. This facilitates UDT implementations that are scalable and sustainable. The findings also provide actionable information for policymakers, urban designers, and system designers.

Keywords: Adoption Barriers, Fuzzy DEMATEL, Smart Cities, Sustainable Cities and Communities, Urban Digital Twin.

1. Introduction

Cities are very complex systems linking transportation, energy, water, housing, public health and governance with one another. To manage such complexities, decision-making tools that integrate various data sources, simulate dynamic interactions and assess the impact of transitions must be used (Weil et al., 2023). With this context, Urban Digital Twins (UDTs) represent a new way to better understand and manage cities in a more systematic and predictive way (Zhu & Jin, 2025). A virtual representation of a city that is constantly updated based on real world data is referred to as an Urban Digital Twin. Unlike traditional simulation techniques or static digital models, a UDT is continuously linked to the physical city through sensors, administrative information, and operational systems (Zhu & Jin, 2025). This incorporation helps the digital model to accurately reflect on present-day realities, assess various alternatives, and evaluate possible solutions before their application in the real world. According to the literature, UDTs have been used to answer many policy questions, such as how traffic flows will evolve under new mobility policies (Sacoto-Cabrera, Perez-Torres, Tello-Oquendo & Cerrada, 2025), how energy demand will be affected by climate extremes (Mazzetto, 2024), or how infrastructure failures will cascade through urban systems (Weil et al., 2023). It is essential to differentiate UDTs from related concepts. Conventional urban models usually have a sectoral focus, relying on historical or periodic data updates. UDTs, in contrast, contain real-time or close and real-time data, support cross-sectoral analysis, and enable continual feedback between the physical and digital environments (Sacoto Cabrera et al., 2025). As a result, UDTs count as essential elements of smart city applications that use adaptive, data-driven, and forward-looking decision support. The integration of UDTs continues to be limited in practical smart cities, despite an insightful conceptual appeal and growing academic interest. Numerous projects continue to exist solely as trials or demonstrations, and only a handful have successfully integrated on a citywide scale on a long-term basis (Mazzetto, 2024). The difference between what is possible in theory and reality shows that there are several barriers to adoption. Barriers can be technical as well as related to organisational structure, financing capacity, governance arrangements and coordination among stakeholders (Weil et al. 2023). As such, grasping these barriers is critical for cities' transition from trial digital twin projects to solid and scalable urban solutions. From a sustainability perspective, the successful implementation of UDTs is most closely aligned with Sustainable Development Goal 11, which is Sustainable Cities and Communities. SDG 11 attempts to make cities inclusive, safe, resilient and sustainable. It boots improved urban planning, infrastructure resilience, environmental management and participatory decision making (Selvaraj et al., 2025). These goals will be supported when UDTs help cities to anticipate risks, evaluate trade-offs, and optimise the performance of essential urban systems (Yang et al. 2025). When adoption barriers continue to exist, cities will not be able to make full use of these capabilities. This limits the contribution of UDTs to Sustainable urban development. This research contributes to SDG 11 by systematically identifying and structuring the barriers to UDT adoption, as well as offering a pathway for cities to overcome such barriers. The paper not only concerns the practical functioning, but also the conditions for workable implementation coordination, prioritisation and strategic planning (Azadi et al., 2025). This study helps with urban decision-making, resource allocation, and long-term planning for sustainable cities by identifying which barriers have the most influence on adoption outcomes. Consequently, the research is directed by the research questions.

R1) What are the barriers that hinder implementation of Urban Digital Twins in smart cities?

R2) What actions should policymakers and urban planners prioritize for overcoming barriers to the adoption of Urban Digital Twin for smart cities?

Consequently, the present research enhances our understanding of the adoption of UDT as a complex urban governance problem and offers policy-relevant insights to urban planners and city administrators who aim to leverage digital twin technologies in sustainable cities.

The remainder of this paper is organized as follows: the literature review is presented in Section 2, the methodology in Section 3, results and discussion in Section 4, research implications in Section 5, and the conclusion in Section 6.

2. Literature Review

2.1 Definition and Evolution of Urban Digital Twins

Urban digital twins (UDTs) are data driven, city wide replicas that use real time sensor streams, computational models, and sophisticated analytics to aid urban planning, monitoring, and decision-making processes. Recent surveys have highlighted that UDTs lean on IoT, machine learning/AI, and cyber physical systems as the core enabling technology for smart city optimisation and services (Huzzat et al., 2025). The aforementioned technologies collectively deliver the necessary data acquisition, computational intelligence, and physical virtual coupling to create city scale digital twins that can serve multiple urban functions from traffic management to energy balancing while still accommodating future smart city applications.

2.2 Conceptual Background

A sense-compute-actuate loop from a cyber physical systems (CPS) perspective lays the low latency feedback backbone of city scale twins (Weil et al., 2023). The socio-technical systems (STS) viewpoint stresses the need to align technological development with organisational and institutional factors, informing governance models that accommodate diverse stakeholder groups (Ferré Bigorra et al., 2022). According to Mazzetto, systems of systems (SoS) constitute' conceptualization of the urban setting to be a federation of semi-autonomous subsystems (transport, energy, water, waste) that are coordinated through a common orchestration layer. As the theories above would suggest, the smart city digital twin designs widely adopt a three-layer reference architecture data, services, applications.

2.3 Evidenced based benefits of Urban Digital Twins

According to multiple case studies, traffic simulation experiments can ease congestion and improve flow and travel time (Alvi et al., 2025). Bibliometric evidence suggests that real-time modelling of cross infrastructure dependencies holds significant promise. In particular, it could improve resilience to extreme weather events (El

Agamy et al., 2024). According to Mazzetto (2024) energy optimisation use cases reveal twin driven demand response delivers reductions in district level electricity consumption but the exact percentage varies between implementations. The continuous air quality monitoring through the use of digital twins can enable more timely public health actions.

2.4 Current Research Trends in Urban Digital Twin Development

The current research focuses on four interrelated themes. The research on data fusion and interoperability aims to integrate heterogeneous IoT streams, open data portals, and legacy GIS layers. The edge cloud orchestration architectures or hybrid AI IoT frameworks aim to minimize communication latency and enable near real time analytics. The use of explainable AI (XAI) for twin insights is gaining momentum in order to make model-driven recommendations intelligible to planners. Ultimately, studies on participatory government are examining crowdsourced data collection, and deliberative platform via which we may co create twin scenarios (Bahreldin et al., 2025).

2.5 Scalable Adoption Barriers of Urban Digital Twins

2.5.1 Study Selection Criteria

Between the years 2021 until 2025, 25 barriers of UDT were identified in smart cities. An initial literature search was conducted on Google Scholar from 2001 to 2025 using the keyword phrase: "barriers to Urban Digital Twin in smart cities." Further, from the results, only Scopus-indexed journal articles were retained. Only studies that clearly reported barriers to UDT adoption were included while vague, duplicative and opinion-based factors were filtered out. To achieve only enhanced understanding of barriers contributing to the adoption challenges unique duplicate findings removed.

2.5.2 Literature-based Barrier Identification

Past literatures show that many barriers affect the adoption of urban digital twin. The window of 2021-2025 has been chosen with care to take cognizance of the latest technology, infrastructure and policy development trends and issues emerging in smart cities. The absence of globally accepted data models as well as ontologies which limits seamless subsystem integration (Weil et al., 2023), limited HPC, storage and low latency networking, which impede real-time operation (Mazzetto, 2024), and sensor actuator heterogeneity, which hampers fidelity of physical digital link (Zali et al., 2024) are technical barriers. The manifestation of governance challenges arises due to institutional fragmentation delineations and obscured ownership that obstruct coherent policy formulation (Weil et al., 2023). Misalignment between public-private partnerships and low levels of trust have constrained joint financing. As documented by Mohamed et al. (2025), there are privacy concerns on data collection but there is limited evidence on further citizen acceptance. The strategic weaknesses are related to a strong focus on the physical infrastructure at the expense of the economic, social and behavioural (Ferré Bigorra et al., 2022) and a modelling at multiple scales, which compromises cross-domain accuracy (Zali et al., 2024). Ultimately, hurdles such as skill shortages, financing constraints, and accumulated technical debt may hinder the long-term sustainability of twin initiatives (Bahreldin et al., 2025). The barriers identified from the literature review is given in table 1.

2.6 Research gaps

Despite an abundance of reporting on barriers, three substantive gaps remain. The first thing to note is that causal inter dependency analysis of barriers is mostly absent; the majority of studies refer to barriers as isolated factors overlooking feedback loops which shape the adoption ecosystem (Zali et al., 2024). The limited evidence-based policies allocation is due to the scarcity of quantitative prioritization of barriers (Weil et al., 2023). In the domain of UDT, the application of fuzzy DEMATEL, a superior decision analytic approach capable of addressing expert uncertainty and portraying cause effect relationships, is limited. To close the gaps, an appropriate level of methodological framework is needed that can clarify the layered structure of barriers and offer actionable prioritisation for city stakeholders.

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3. Research Methodology

3.1 Research Design

This study adopts an exploratory qualitative–quantitative causal research design to investigate the interrelationships among barriers hindering the adoption of Urban Digital Twins (UDTs) in smart cities. The design's exploratory nature is appropriate in so far as UDT adoption is an emerging field with intricate relationships among technology, organization, policy, governance and social factors. By uncovering the directional causes and impacts of the different barriers, the study aims to inform decision-makers' choices and allow for targeted intervention strategies. The expert knowledge is captured in qualitative terms through linguistic assessments. The same assessments are converted into numerical influence values in the quantitative part using fuzzy set theory in combination with matrix-based causal analysis.

3.2 Expert Panel Selection and Sampling Technique

3.2.1 Sampling Technique

The research used purposive (or judgmental) sampling which is used when dealing with DEMATEL studies that are based on domain expertise rather than representative probabilistic. Experts were chosen through their expert experience, specialization, and direct experience on smart-city initiatives.

3.2.2 Sample Size and Composition

A panel of 12 experts (See table 2) constituted the multistakeholder group which had at least five years of experience working in smart-city development. The composition of the panel was consciously constructed to mitigate disciplinary bias whilst capturing the multi-dimensionality of UDT adoption across technical, policy, governance, and socio-technical domains. This multidisciplinary variety ensures that the causal ratings for UDT adoption barriers are based on complementary expertise, ranging from technical feasibility, institutional readiness, governance arrangements and human aspects.

3.3 Data Collection Procedure

The data was collected through a structured expert elicitation process over two stages. Each of the experts was required to rate the degree of influence of every pair among 25 barriers identified through a linguistic scale (See table 3) from 0 (no influence) to 4 (very high influence). This two-round evaluation process was used to improve judgment reliability and mitigate random bias. A gap of around 14 days was kept for experts to think about their first assessments for the rounds. The judgments of each expert (2 rounds) were aggregated to obtain the final influence scores of that particular expert across a consolidated 25 × 25 direct-relation matrixes.

3.4. Rationale for Using Fuzzy DEMATEL

Fuzzy DEMATEL is highly appropriate in this case since the constraints to Urban Digital Twin (UDT) adoption are interrelated and dynamic rather than independent decision criteria. Conventional multi-criteria decision-making techniques like analytical hierarchy process (AHP) and technique for order of preference by similarity to ideal solution (TOPSIS) presume independence among criteria. Moreover, they do not formally model interrelationships and feedback. On the other hand, DEMATEL utilizes the elements of direct and indirect influence. It produces a total relation matrix which distinguishes driving (cause) barriers from dependent (effect) barriers. The fuzzy extension of DEMATEL based on triangular fuzzy numbers (TFNs) allows an expert to express their judgments regarding influences in linguistic terms facilitating the handling of uncertain, subjective and imprecise judgments which are common in socio-technical evaluation problems. By doing so, it reduces the information loss that may occur during the aggregation process and improves the stability of influence estimates (Abdullah & Lim, 2018; Appasamy, 2026).

3.5 Methodological Validity and Suitability

Fuzzy DEMATEL has already applied in smart city planning, infrastructure development, technology adoption, risk assessment, and governance analysis, exhibiting strong methodological validity in studying complex systems characterized by feedback loops and interdependencies. For instance, DEMATEL has been employed for the analysis of barriers and determinants in smart city development while revealing the causal linkages among influencing factors (Makki & Alqahtani, 2024; Braga et al., 2021). Moreover, triangular fuzzy numbers are utilized in fuzzy extensions, capable of portraying expert judgment amidst uncertainty and recognizing cause-effect structures within the realm of multi-criteria decision problems (Abdullah & Lim, 2018). Fuzzy DEMATEL improves the understanding of the high leverage barriers and can be helpful to different stakeholders like policymakers, urban planners, and system designers to accelerate the Urban Digital Twin journey.

3.6 Fuzzy Linguistic Scale and Corresponding Triangular Fuzzy Numbers

The expert panel assessed the pairwise influence of each barrier using a five-point linguistic scale (See table 3). Each linguistic term is linked to an influence score (used for reporting) and a triangular fuzzy number (TFN) that captures the minimum, most-likely, and maximum values of the expert's perception.

3.6.1 Membership function of a TFN

For a generic triangular fuzzy number (TFN) $T = (A, B, C)$with $A \leq B \leq C$, the membership degree $\mu_T(x)$is defined as:

$$\mu_T(x) = \begin{bmatrix} 0, & x < A \\ \dfrac{x - A}{B - A}, & A \leq x \leq B \\ \dfrac{C - x}{C - B}, & B \leq x \leq C \\ 0, & x > C \end{bmatrix} \tag{1}$$

The function rises linearly from 0 at the lower bound A to 1 at the most-likely value B, then decreases linearly back to 0 at the upper bound C.

3.6.2 Rationale for using TFNs

The TFNs (See table 3) are adopted because they reflect single-point expert judgement (each expert supplies one representative estimate for every pairwise comparison, while the TFN captures that estimate together with realistic lower- and upper-bounds); they provide computational convenience since addition, multiplication, and other arithmetic operations are straightforward, which simplifies the fuzzy DEMATEL steps such as normalisation and total-relation-matrix construction; and they enjoy strong alignment with prior research—triangular fuzzy numbers have long been employed for linguistic scales and fuzzy pairwise comparisons in multi-criteria decision-making, from the seminal fuzzy AHP work of Van Laarhoven & Pedrycz (1983) to the extensive reviews of fuzzy MCDM methods by Kahraman *et al.* (2015).

3.7 Fuzzy DEMATEL Procedure

This study adopts a fuzzy DEMATEL–based decision-making approach to identify and analyse the causal relationships among barriers to Urban Digital Twin (UDT) adoption in smart-city contexts. The method is well-suited for handling uncertainty and subjectivity in expert judgements while revealing complex cause-effect inter-dependencies.

Step 1 – Identification of barriers

A comprehensive literature review has to be conducted to identify the barriers relevant to the study context. This step establishes the evaluation framework and does not involve numerical computation.

Step 2 – Fuzzy Direct-Assessment Matrix (FDAM)

Experts performed pairwise evaluations to assess the extent to which barrier i influences barrier j using a five-point linguistic scale, which was mapped to triangular fuzzy numbers (TFNs). For the *k-th* expert, the fuzzy influence rating is defined as:

$$x_{ij}^{(k)} = \left(A_{ij}^{(k)}, B_{ij}^{(k)}, C_{ij}^{(k)}\right) \tag{2}$$

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where i denotes the influencing barrier, j the influenced barrier, and k the expert. The resulting fuzzy direct-assessment matrix for expert k is of order $m \times m$, with diagonal elements set to zero to exclude self-influence.

Step 3 – Initial Direct-Relation Matrix (IDRM)

The TFNs are defuzzified using the centroid method:

$$d_{ij}^{(k)} = \frac{A_{ij}^{(k)} + B_{ij}^{(k)} + C_{ij}^{(k)}}{3} \tag{3}$$

Aggregating across the Kexperts give the crisp value:

$$d_{ij} = \frac{1}{K} \sum_{k=1}^{K} d_{ij}^{(k)} \tag{4}$$

The **initial direct-relation matrix** is:

$$D = [\, d_{ij} \,]_{m \times m} \tag{5}$$

Step 4 – Normalization of the IDRM

To guarantee convergence, the matrix $D$is normalized by:

$$\alpha = \max\left(\frac{1}{max_i \, \sum_j d_{ij}}, \frac{1}{max_j \, \sum_i d_{ij}}\right) \tag{6}$$

The **normalized direct-relation matrix** is:

$$N = \alpha D \tag{7}$$

Step 5 – Total Relation Matrix (TRM)

The total-relation matrix, capturing both direct and indirect effects, is obtained as:

$$T = N\,(I - N)^{-1} \tag{9}$$

where $I$is the $m \times m$identity matrix.

Step 6 – Prominence and Relation

Row and column sums of Tprovide the total influence given (R_i) and received (C_i) by each barrier:

$$R_i = \left\{\sum_{j=1}^{n} t_{ij}\right\}_{n \times 1} \tag{9}$$

$$C_i = \left\{\sum_{i=1}^{n} t_{ij}\right\}_{1 \times n} \tag{10}$$

Prominence and Relation are then computed as:

$$\text{Prominence}_i = R_i + C_i \tag{11}$$

$$\text{Relation}_i = R_i - C_i \tag{12}$$

A positive Relation ($R_i - C_i$) value designates a cause-group (driving) barrier, while a negative value indicates an effect-group (dependent) barrier.

Step 7 – Cause-effect diagram

Barriers are plotted on a two-dimensional graph with Prominence on the vertical axis and Relation on the horizontal axis. The diagram visualises the causal structure and separates the cause-group from the effect-group. The steps of fuzzy DEMATEL process are given below in Figure 1.

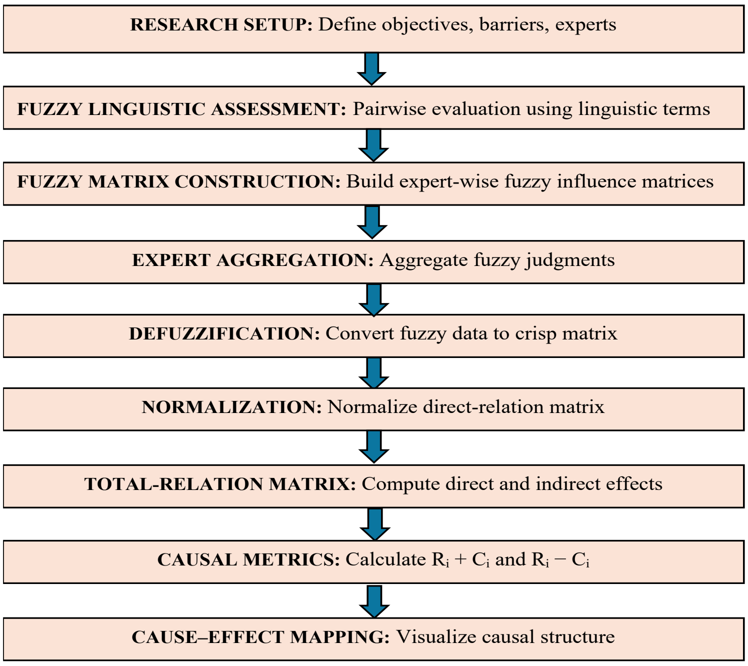

Figure 1 Flowchart of Fuzzy DEMATEL Process

3.8 Empirical Case Study

The fuzzy DEMATEL approach described in Section 3.7 was applied to a large-scale smart-city pilot in India to uncover the most influential barriers that hinder the adoption of an Urban Digital Twin (UDT). The case study illustrates how the procedural steps translate into a concrete decision-making workflow and validates the method's usefulness for real-world smart-city planning.

Stage 1 – Data collection and barrier identification

Step 1 - Identification of barriers: During this phase, data collection was limited to identifying barriers pertaining to UDT use. As indicated in Section 2.5.1, an extensive literature search was carried out to compile an initial set of barriers, which was then screened and thereafter assembled to 25 barriers. As discussed in Section 3.3, the experts were asked to provide their ratings in two distinct rounds. For each expert, the two sets of ratings were aggregated (e.g., averaged) to produce one fuzzy direct-assessment matrix per expert for Stage 2. There was no aggregation across experts at this stage.

Stage 2 – Fuzzy DEMATEL analysis

Step 2 – Fuzzy Direct-Assessment Matrix (FDAM): As described in Section 3.3, the selected experts provided ratings in two separate rounds, allowing them to reflect on their initial assessments. For each expert, the two sets of ratings were consolidated (e.g., by averaging) to produce a single fuzzy direct-assessment matrix per expert. In data filling procedure, each expert evaluated the degree to which barrier i influences barrier j using a five-point linguistic scale. These linguistic judgments were mapped to triangular fuzzy numbers (See table 3) in accordance with Equation (2). Diagonal elements were fixed at zero to eliminate self-influence.

Step 3 – Initial Direct-Relation Matrix (IDRM): The consolidated fuzzy matrices were defuzzified using the centroid method as in Equation (3) and subsequently aggregated across all twelve experts via Equation (4). This process resulted in a single crisp direct-relation matrix by Equation (5) that represents the collective causal perceptions of the expert panel (Refer to Table 4).

Step 4 & Step 5 – Normalization of the IDRM and Total relation matrix (TRM): To ensure mathematical convergence, the direct-relation matrix was scaled using the normalisation factor defined in Equation (6), resulting in the Normalised Direct-Relation Matrix by Equation (7). The normalised matrix was then employed to compute the Total-Relation Matrix using Eq. (8), which captures both direct and indirect influence pathways among the twenty-five barriers panel (Refer to Tables 5 and 6).

Step 6 – Prominence and Relation: Row (R_i) and column (C_i) totals of the total-relation matrix were calculated to obtain the overall influence each barrier exerts on the system (Eq. (9)) and the influence it receives from other barriers (Eq. (10)). Prominence values $(R_i + C_i)$ were derived using Eq. (11), while relation values $(R_i - C_i)$ were computed using Eq. (12). Barriers with positive relation scores were classified into the cause-group, whereas those with negative relation scores were assigned to the effect group. (See tables 7, 8 and 9)

Step 7 – Cause-effect diagram: The calculated prominence and relation values were plotted on a two-dimensional graph, with prominence on the vertical axis and relation on the horizontal axis. (See Figure 3).

Stage 3 – Result verification

The outcomes of the fuzzy-DEMATEL analysis were validated through follow-up consultations with the expert panel, which comprised professionals from urban-planning, data-engineering, smart-city governance, and policy domains. In addition, the identified cause-effect relationships were cross-checked against recent scholarly literature on Urban Digital Twins and smart-city systems to ensure both theoretical soundness and contextual relevance. The validated findings were then communicated to key urban-development stakeholders to facilitate managerial interpretation and to inform evidence-based policy formulation. This verification process enhances confidence in the robustness of the results and supports their practical application for prioritising interventions that address the most critical barriers to UDT adoption in smart-city environments.

4. Results And Discussion

Urban Digital Twins (UDT) adoption for smart city ecosystems is a complex multi-layered process in the context of closely coupled network of interdependencies. Using the literature, we identified 25 barriers and, we applied Fuzzy DEMATEL technique on these barriers to evaluate their relative influence as well as cause-effect relationship. In the methodology, the prominence score ($R_i + C_i$), shows the overall importance of a constraint, while relation score ($R_i - C_i$) distinguishes cause barriers (positive values), which mainly have an effect on the system, from effect barriers (negative values), which are mainly affected by the system; their absolute value ($R_i - C_i$) also shows strength of their impact, thus guiding to identify the most critical barriers. Among the 25 barriers, nine were classified as cause barriers and sixteen as effect barriers.

Cause-group ranking (highest → lowest): Data Acquisition & Actuation Constraints (B3) > Real-Time Data Communication Latency (B25) > Urban Critical-Infrastructure Threats (B17) > Funding & Financial Resource Constraints (B11) > Sensor Data Overload & Processing Bottlenecks (B20) > Under-Developed Infrastructure & Real-Time Capabilities (B2) > Cybersecurity Problems (B10) > Technical Debt Issues (B12) > Scalability of Urban Digital Twins (B19).

Effect-group ranking (highest → lowest): Data Quality & Harmonisation Issues (B4) > Trust & Public Acceptance Issues (B14) > Lack of Collaborative Interdisciplinary Approaches (B23) > Data Visualisation & Information Display Limitations (B6) > Modelling, Simulation & Decision-Support Limitations (B5) > Interoperability & Semantic Standards Problems (B1) > Multi-Scale Modelling & Integration Challenges (B13) > Incomplete Modelling of Urban Systems (B16) > Limited Citizen & Stakeholder Engagement (B21) > Economic & Social City-Function Integration Difficulty (B15) > Limited Real-World Implementation & Evaluation (B24) > Governance, Organizational & Social Structure Issues (B8) > Public–Private Partnership Coordination Issues (B9) > Socio-Technical Coordination Issues (B22) > Legal Uncertainty & Accountability Issues (B18) > Lack of Skilled Human & Capital Resources (B7).

Addressing the barriers that cause problems will help lower the effects of the problems themselves. Also, in practice, this can, 1) lower cost of a more cost-effective intervention, 2) useful in resource screening and 3) trusted and scalable implementation of UDTs for smart cities. The following sub-sections present the discussion for the barrier sets and their real-world implications for policymakers and urban planners.

4.1 Discussion of cause-group barriers

The fuzzy DEMATEL hierarchy suggests that Data Acquisition & Actuation Constraints (B3) represents the most fundamental barrier to large-scale Urban Digital Twin (UDT) implementation. The enactment of digital twins at city-wide scale appears to be further impeded by the heterogeneous nature of sensor deployments and non-standards actuator interfaces, which together obviate the possibility of a unified, synchronized cyber physical representation Batty (2018). The subsequent systemic trigger, which involves latency in real-time data communication (B25) respectively, increases the impact of B3 by time delay effect. Limited bandwidth, network congestion, and inadequate edge cloud integration reduces the timeliness of simulations used for traffic management, emergency response as well as energy distribution (Qi & Tao, 2018). Urban Critical Infrastructure Threats (B17) further reinforce this cascade as the interdependence of transport, water, power and health subsystem means the twin is vulnerable to cascading failures which in turn undermines stakeholder confidence and restricts expansion (Ouyang, 2014). Funding and Financial Resource Constraints (B11) is a strong constraint that prevents investment in sensor networks, high performance computing, and skilled personnel. Consequently, no measures were taken in view of the past technical difficulties. The issues of sensor data overload and processing bottlenecks (B20) together with underdeveloped infrastructure and real-time capabilities (B2) complicate the problem by overloading analytics pipelines and by lacking edge computer resources. Cybersecurity Problems (B10) and Technical Debt Issues (B12) are reinforcing constraints that widen the attack surface and reduce adaptability. The scalability of urban digital twins becomes a downstream barrier that encapsulates all the consequences of the unresolved root-level constraints (which are discussed above). These additional consequences include latency, infrastructural attack threats, funding, processing and security shortages. This demonstrates the need for a uniform data and actuator interface, a hybrid edge cloud deployment strategy, at least one dedicated funding stream, security by design, and systematic technical debt reduction through an integrated mitigation strategy.

4.2 Discussion on effect-group barriers

Findings of fuzzy DEMATEL analysis reveal that UDT (Urban Digital Twin) adoption exhibits significant data-centric and socio-technical weaknesses which mainly arise from upstream technical and infrastructural constraints. Barrier B4, Data Quality and Harmonisation Issues, which ranks the highest rank among the effect-group barriers, implies that twins are highly reliant on the availability of consistent, interoperable, and up-to-date datasets sourced from multiple urban agencies. When barriers related to foundational causes – such as limitations in data gathering, interoperability gaps, and a less than fully developed real time infrastructure – persist, then fragmentation and inconsistency in data become inevitable. This, in turn, will lead to unreliable outputs from twins, which can weaken confidence in the results of analyses. B14, Trust and Public Acceptance Issues, ranks second among the barriers. It is a downstream socio-technical consequence of inadequate data governance, transparency and reliability of systems. Perceptions of data misuse, opaque decision-making, and uncertainty of system accuracy shape public trust. For this reason, even technologically advanced twins may be resisted if citizens and other stakeholders do not regard them as secure, transparent and socially beneficial. Structural fragmentation across urban planning, engineering, data science and policy due to Lack of Collaborative Interdisciplinary Approaches (B23) is third in line. Inefficient institutional-specific practices restrict knowledge integration, the growth of modelling inconsistencies, and hold back the holistic representation of urban complexity within the model. The follow-on barriers (B6) Data Visualisation & Information Display Limitations, (B5) Modelling, Simulation & Decision Support Limitations and (B1) Interoperability & Semantic Standards Problems indicate that the availability of data does not provide operational value. Decision makers need intuitive visual analytics interfaces, semantically aligned data structures, and validated simulation models to meaningfully translate digital twin outputs into urban interventions. The mid-tier barriers Multi-Scale Modeling & Integration Challenges (B13), Incomplete Modeling of Urban Systems (B16), Limited Citizen & Stakeholder Engagement (B21), and Economic & Social City Function Integration Difficulty (B15) occur when the fundamental data quality and modeling issues are not resolved. In turn, this limits the ability of the twin to depict interconnected subsystems spanning spatial, temporal, economic and social realms. Ultimately, less significant yet important obstacles such as limited real-world implementation and evaluation (B24), governance and organizational issues

(B8), public-private partnership coordination issues (B9), socio-technical coordination issues (B22), legal uncertainty and accountability issues (B18), and lack of skilled human and capital resources (B7) typically arise at later stages of implementation. At this point, unresolved technical and data-centric constraints have already impeded large-scale deployment (Ruhlandt, 2018). The between-group structure indicates that many social, governance and institutional challenges commonly cited are systemic outcomes of upstream causes group constraints. As a result, it is essential to address these root level drivers to mitigate the downstream effects and enable the sustainable, trustworthy and scalable adoption of Urban Digital Twins in smart cities.

5. Implications

5.1 Theoretical implications

By employing fuzzy-DEMATEL, the study moves beyond traditional barrier lists and reveals a causal network in which a handful of cause-group barriers—principally data acquisition, real-time latency, and funding—exert disproportionate influence over a wide array of downstream effect-group obstacles. This empirically validates systems-thinking and complexity-theory perspectives for Urban Digital Twin (UDT) adoption, refines digital-twin theory by separating technical drivers from socio-technical outcomes, and demonstrates that many frequently cited governance and trust issues are emergent rather than isolated. The resulting hierarchical model integrates data-governance, interoperability, and interdisciplinary coordination into a transferable causal framework that can be applied to other large-scale cyber-physical systems such as smart grids and transportation networks.

5. 2 Policy and managerial implications

To address the root cause barriers, municipalities should enact a city wide sensor deployment mandate with open API standards and launch a public private "Smart Sensor Network" fund (B3); adopt a low latency broadband policy (fibre to the edge, 5G slicing, QoS thresholds) to keep communication latency at near-real-time or sub-100 ms levels suitable for operational urban decision-making (B25); embed twin driven risk assessments and cross agency oversight boards into critical infrastructure resilience plans (B17); create a dedicated Digital Twin Innovation Fund financed by municipal bonds, supranational or national innovation grants, and PPP cost sharing, linked to performance based KPI targets (B11); implement hierarchical streaming data policies with edge pre-processing and container orchestrated analytics to curb sensor overload (B20); upgrade the municipal ICT backbone to high-capacity, multi-gigabit-scale and sub 100 ms latency while requiring "digital first" procurement of real time ready hardware (B2); mandate a city wide recognised international cybersecurity framework (e.g., NIST-CSF or ISO/IEC 27001) with regular penetration testing and a dedicated Digital Twin Cyber Response Unit (B10); manage technical debt through modular API first architectures, a municipal technical debt register, and CI/CD pipelines (B12); and embed scalability targets in system architecture blueprints, supported by research consortia developing federated twin models and a staged deployment approach (B19). Concurrently, because Data Quality & Harmonisation (B4) remains the most influential effect barrier, cities must establish comprehensive data governance frameworks, pursue transparent, participatory design to boost trust and stakeholder engagement (B14, B21), fund interdisciplinary consortia and shared ontology repositories to resolve interoperability and multi scale modelling challenges (B23, B1, B13), deploy standardized visual analytics platforms and validated decision support models (B6, B5, B15), and formalise PPP contracts, clarify legal accountability, and create specialised training programmes to overcome residual governance, legal, and skill gaps (B8, B9, B18, B7). Together, these coordinated actions provide a clear roadmap for dismantling the primary barriers and achieving robust, city-wide adoption of Urban Digital Twins.

6. Conclusion

The urban digital twins create a big opportunity for data-driven decision-making in smart cities but implementation is hindered by a web of interrelated challenges. By reviewing the literature from 2021-2025, twenty-five major barriers were identified and subsequently analyzed with the fuzzy DEMATEL approach in order to determine their causal relationships. The research employed an exploratory qualitative-quantitative causal design which was aimed at accounting for expert judgment uncertainty and dependency between the barriers. A structured two-round elicitation with twelve purposively selected experts was carried out. The results of fuzzy-DEMATEL indicated the existence of nine cause-group barriers and sixteen effect-group barriers. By explicitly quantifying the causal interdependencies, the analysis shows that strategically targeted interventions at the root cause level can significantly reduce the cascading effects of secondary obstacles. Specifically, standardising sensor and actuator interfaces, deploying low latency communication infrastructure, securing dedicated and sustained financing, and adopting modular, secure system architectures are high leverage actions that enhance scalability and reliability while strengthening UDTs' contribution to Sustainable Development Goal 11 by enabling more resilient, data driven, and sustainable urban communities.

Future research should expand the static fuzzy DEMATEL analysis into a framework that is dynamic and multi-method. This framework can integrate probabilistic approaches (e.g., Bayesian networks) or system dynamics modelling to simulate the temporal propagation of barrier effects and to undertake scenario-based policy testing. Longitudinal case studies of real world UDT pilots across diverse governance contexts (Europe, Asia, Africa) will validate whether overcoming the barriers due to identified causes (such as data acquisition and latency, as well as funding) successfully mitigates downstream effect barriers (such as data quality and public trust). Linking this causal network and multi-objective optimisation - specifically Pareto-front analysis can quantify trade-offs among cost, carbon and social equity, steering UDT adoption in the direction of SDG 11 and leading to implementable policy recommendations. Open-source semantic standards for interoperability, human-centred visual analytic tools and approaches to blockchain based data governance should also be complementarily investigated to address technical, legal and usability hurdles. Taken together, these will produce an evidence-based roadmap for the scalable, trustworthy deployment of Urban Digital Twins in smart cities.

8. References:

[1] Abdullah, L. A. Z. I. M., & Lim, H. (2018). A Decision making method with triangular fuzzy numbers for Unraveling the Criteria of E-Commerce. WSEAS transactions on computers, 17, 126-135.

[2] Alvi, M., Dutta, H., Minerva, R., Crespi, N., Raza, S. M., & Herath, M. (2025). Global perspectives on digital twin smart cities: Innovations, challenges, and pathways to a sustainable urban future. Sustainable Cities and Society, 106356.

[3] Appasamy, S. (2026). A Study on DEMATEL Approach Under Uncertainty Environments. Spectrum of Operational Research, 29-39.

[4] Azadi, S., Kasraian, D., Nourian, P., & Wesemael, P. V. (2025). What have urban digital twins contributed to urban planning and decision making? From a systematic literature review toward a socio-technical research and development agenda. Smart Cities, 8(1), 32.

[5] Bahreldin, I., Samir, H., Maddah, R., Hammad, H., & Hegazy, I. (2025). Leveraging advanced digital technologies for smart city development in Saudi Arabia: opportunities, challenges, and strategic pathways. International Journal of Low-Carbon Technologies, 20, 834-847.

[6] Batty, M. (2018). Digital twins. Environment and Planning B: Urban Analytics and City Science, 45(5), 817-820.

[7] Braga, I. F., Ferreira, F. A., Ferreira, J. J., Correia, R. J., Pereira, L. F., & Falcão, P. F. (2021). A DEMATEL analysis of smart city determinants. Technology in Society, 66, 101687.

[8] Deng, T., Zhang, K., & Shen, Z. J. M. (2021). A systematic review of a digital twin city: A new pattern of urban governance toward smart cities. Journal of management science and engineering, 6(2), 125-134.

[9] El-Agamy, R. F., Sayed, H. A., AL Akhatatneh, A. M., Aljohani, M., & Elhosseini, M. (2024). Comprehensive analysis of digital twins in smart cities: a 4200-paper bibliometric study. Artificial Intelligence Review, 57(6), 154.

[10] Ferré-Bigorra, J., Casals, M., & Gangolells, M. (2022). The adoption of urban digital twins. Cities, 131, 103905.

[11] Huzzat, A., Anpalagan, A., Khwaja, A. S., Woungang, I., Alnoman, A. A., & Pillai, A. S. (2025). A comprehensive review of digital twin technologies in smart cities. Digital Engineering, 100040.

[12] Kahraman, C., Onar, S. C., & Oztaysi, B. (2015). Fuzzy multicriteria decision-making: a literature review. International journal of computational intelligence systems, 8(4), 637-666.

[13] Makki, A. A., & Alqahtani, A. Y. (2024). Analysis of the barriers to smart city development using DEMATEL. Urban Science, 8(1), 10.

[14] Mazzetto, S. (2024). A review of urban digital twins integration, challenges, and future directions in smart city development. Sustainability, 16(19), 8337.

[15] Mittal, G., Bansal, R., Fahlevi, M., & Aziz, A. L. (2025). Mapping the research patterns on fuzzy decision-making trial and evaluation laboratory technique in marketing: A bibliometric analysis. Social Sciences & Humanities Open, 12, 101691.

[16] Mohamed, M., Mohamed, D., & Maatouk, M. M. (2025). PRIVACY-PRESERVING DIGITAL TWIN TECHNOLOGIES FOR SMART CITIES: BALANCING UTILITY AND DATA PROTECTION. International Journal on Information Technologies & Security, 17(4).

[17] Ouyang, M. (2014). Review on modeling and simulation of interdependent critical infrastructure systems. Reliability engineering & System safety, 121, 43-60.

[18] Qi, Q., & Tao, F. (2018). Digital twin and big data towards smart manufacturing and industry 4.0: 360 degree comparison. Ieee Access, 6, 3585-3593.

[19] Ruhlandt, R. W. S. (2018). The governance of smart cities: A systematic literature review. Cities, 81, 1-23.

[20] Sacoto-Cabrera, E. J., Perez-Torres, A., Tello-Oquendo, L., & Cerrada, M. (2025). IoT, AI, and Digital Twins in Smart Cities: A Systematic Review for a Thematic Mapping and Research Agenda. Smart Cities, 8(5), 175.

[21] Selvaraj, V., Nivethikha, R., Yi, L., Rao, M. S., Balaraman, R., & Jain, A. (2025). Digital twins and urban SDGs simulating smart cities for sustainable development. Int J Environ Sci, 8(3), 849-59.

[22] Van Laarhoven, P. J., & Pedrycz, W. (1983). A fuzzy extension of Saaty's priority theory. Fuzzy sets and Systems, 11(1-3), 229-241.

[23] Weil, C., Bibri, S. E., Longchamp, R., Golay, F., & Alahi, A. (2023). Urban digital twin challenges: A systematic review and perspectives for sustainable smart cities. Sustainable Cities and Society, 99, 104862.

[24] Yang, S., Macatulad, E. G., Biljecki, F., & Dane, G. (2025). Can Urban Digital Twins Support the Realization of Sustainable Development Goal 11? Identifying Key Social and Technical Challenges. ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences, 10, 129-136.

[25] Zali, N., Soltani, A., Najafi, P., Qajari, S. E., & Mehrju, M. (2024). Digital Twins for Smarter Iranian Cities: A Future Studies Perspective. Computational Urban Science, 4(1), 43.

[26] Zhu, M., & Jin, J. (2025). Data-driven urban digital twins and critical infrastructure under climate change: A review of frameworks and applications. Urban Planning, 10.