



RESEARCH ARTICLE

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TOWARD A THEORY OF MULTIFORMAT SEMANTIC EMBEDDING FOR SMART CITIES: A SYSTEMATIC LITERATURE REVIEW ON JOINT TEXT AND INFOGRAPHIC REPRESENTATIONS IN BIG DATA GOVERNANCE

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ABSTRACT

Smart city ecosystems generate diverse data streams, including legal documents, textual citizen reports, sensor dashboards, geospatial maps, and infographics. Despite advances in natural language processing (NLP) embedding, vision-language models, and graph-based urban analytics, a coherent theoretical framework explaining the integration of semantic representations across multiple modalities into a single embedding space for decision-making is lacking. This paper describes a systematic literature review (SLR) pertaining to multi-format semantic embedding in smart cities, emphasizing the combined representation of textual documents and visual artifacts such as infographics (maps, dashboards, plots, and schematic diagrams). Following PRISMA 2020 guidelines, we conducted searches in SpringerLink, Taylor & Francis, and SCOPUS between 2021 and 2025, resulting in 2,662 records and the inclusion of 110 primary studies through a screening process. This state of the art research is based on eight questions addressing data modalities, urban application domains, embedding models, integration mechanisms, evaluation metrics, and governance considerations. The review explains that most studies continue to model each modality separately, cross-modal integration is largely characterized by fusion-based methodologies and knowledge graphs, and evaluations emphasize retrieval and prediction accuracy, with insufficient focus on semantic coherence and interpretability at the policy level. Given these identified gaps, we propose the Theory of Multiformat Semantic Integration (TISM) and the Urban Multiformat Embedding Framework (UMEF), alongside a conceptual metric called Urban Semantic Coherence (USC) to evaluate cross-modal alignment. The review concludes with a proposed research agenda aimed at fostering robust, explainable, and governable multiformat embedding in the context of smart city big data environments.



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I. INTRODUCTION

The development of the smart city concept accelerates the production and utilization of urban big data in various formats: regulatory documents, statistical reports, thematic maps, sensor dashboards, to infographics and policy campaign videos. This multi-format data should form the basis of collective knowledge for faster and more accurate decision-making, ranging from flood mitigation, congestion management, to air quality monitoring[1]-[5]. However, in practice, each format is often analyzed separately through fragmented pipelines, making it difficult to integrate the semantic meanings scattered across various city artifacts into a single, consistent representation space.

On the other hand, recent advances in representation learning have produced a wide variety of embedding models: from sentence transformers for text, vision-language models such as CLIP and BLIP, graph neural networks (GNN) for road networks and knowledge graphs, to spatiotemporal foundation models for geo-AI data[6]-[10]. These models have proven effective in specific tasks such as traffic forecasting, land use change detection, or public service recommendation—but most are still implemented in a unimodal manner without an explicit cross-format integration theoretical framework. In the context of smart city governance, this disconnect raises serious issues. City governments must simultaneously interpret analytical results derived from text documents, maps, and numerical indicators[11]-[15]. When the embedding of each modality is built with different semantic assumptions and scales, data-driven decisions become prone to bias, difficult to explain, and non-transparent to stakeholders. Recent literature has begun to report multimodal approaches that combine remote sensing imagery, social media data, and knowledge graphs for tasks such as urban change detection or land distribution estimation. However, their focus is more on the design of model architectures than on the formulation of a generic semantic integration theory.

Based on your research design document, there is a need to formulate the Theory of Integration of Multiformat Semantics (TISM) that explains how embeddings from text, tables, images, and videos can be projected into the same city semantic space; develop the Urban Multiformat Embedding Framework (UMEF) for retrieval, clustering, and analysis of city problems and introduce the Urban Semantic Coherence (USC) metric as an indicator of the quality of inter-modality integration [16]-[20]. This conceptual gap is crucial because smart city data is highly heterogeneous: regulations in PDFs, tabular reports, zoning maps, satellite imagery, performance report infographics, CCTV videos and public outreach. Without an explicit integration theory, it's difficult to ensure that a text query about "flooding in sub-district X" will consistently find regulatory articles, flood hazard maps, drainage capacity infographics, and videos of incidents in the field. Based on that, this article conducts a Systematic Literature Review (SLR) to map the research landscape of multiformat semantic embedding in the smart city domain with a special focus on the integration of text documents and infographics/information visualizations [21]-[25]. The structure of the SLR follows the reference format "Example SLR 2" with an introduction, methods, results and discussion, and conclusion.

II. RESEARCH METHOD

II. 1 SYSTEMATIC LITERATURE REVIEW DESIGN

This study used the Systematic Literature Review (SLR) method following the PRISMA 2020 principles to ensure the process of identifying, screening, and selecting studies was transparent and replicable [26]-[30]. The SLR protocol included RQ formulation, search strategy, inclusion–exclusion criteria, selection procedures, data extraction, and synthesis analysis, including bibliometric analysis with the help of VOSviewer.

II. 2 DATA SOURCES AND SEARCH STRATEGY

The three main sources used to ensure data quality and publication reputation are as follows:

1. SpringerLink – reputable journals and proceedings in urban informatics, AI, and smart cities.
2. Taylor & Francis Online – especially the International Journal of Digital Earth, International Journal of Geographical Information Science, and other geo-AI journals.
3. Scopus-indexed journals – accessed through title and abstract searches which are then verified to be in the Q1/Q2 quartile according to SJR/Scimago.

The main keywords are arranged to capture the combination of smart city, big data, and multiformat embedding, for example:

**“smart city” AND (“multimodal embedding” OR “multiformat embedding” OR “knowledge graph embedding”)
“urban” AND (“vision-language” OR “GeoAI” OR “multimodal data”)
“infographic” OR “dashboard” OR “visual analytics” AND “smart city”**

III. 3 INCLUSION AND EXCLUSION CRITERIA

Inclusion criteria:

- a. Q1/Q2 journal articles (according to Scimago) or reputable proceedings that are Scopus-indexed.
- b. Published between January 2021 and early 2025.
- c. Discussing the context of smart cities, urban computing, or urban analytics.
- d. Using embedding or latent representation for at least one modality of city data.
- e. Contains cross-format integration elements (e.g. text + maps, images + statistical data, dashboards, or infographics).

Exclusion criteria:

- a. The article is only descriptive of the policy without any technical components embedding.
- b. Studies that focus on IoT or sensor networks without exploration of semantic representation.
- c. Non-English papers whose abstracts do not provide sufficient technical information.
- d. Duplicate publications or condensed versions of the same paper.

II. 4 STUDY SELECTION PROCEDURE (PRISMA)

The initial data was obtained from a search compilation file (SLR Endang), which included a total of 2,662 automated records from Springer, Taylor & Francis, and Scopus. From these, a series of selection steps were carried out as follows (adapted to the topic of this SLR):

1. Identification:

- Records identified from all databases: $n = 2,662$.
- Cross-database duplication was removed leaving 2,310 records.

2. Title & abstract screening:

- Recordings that meet the embedding and smart city based SLR criteria: $n = 211$.
- Records eliminated because they were outside the domain or not scientific articles: $n = 50$.

3. Full text search:

- Reports requested for full text retrieval: $n = 161$.
- Inaccessible reports (strict paywall, file error): $n = 11$.

4. Full text eligibility assessment:

- Articles assessed for eligibility: $n = 150$.
- Articles excluded for not containing a clear embedding method or missing multiformat integration components: $n = 40$.

5. Studies included in the SLR:

- $n = 110$ articles.

Figure 1 displays the PRISMA 2020 flowchart for this study, following the format of the example you attached. The diagram visualizes the study's flow from initial identification to final inclusion of articles.

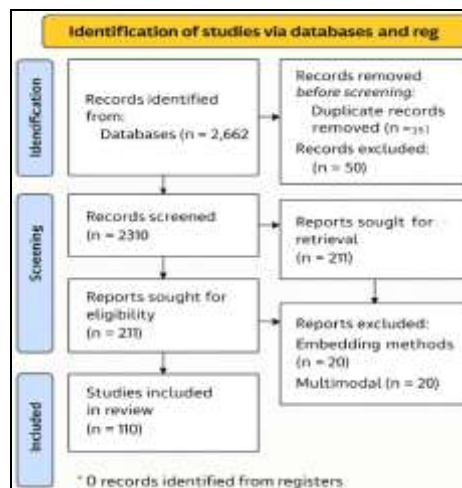


Figure 1: PRISMA Flowchart of the Research.
Source: Authors, (2026).

II. 5 DATA EXTRACTION AND SYNTHESIS

From each selected article, various information is obtained which will be extracted into a worksheet and then analyzed descriptively and thematically to answer each RQ, the extraction process is as follows:

- Year of publication, title, journal name, and area of study.
- Type and number of data modalities (text, tables, images, GIS/maps, infographics/dashboards, videos).
- Embedding models used (SBERT/BERT-variants, CLIP/BLIP, GNN, knowledge-graph embedding, etc.) [31]-[35].
- Integration approaches (late fusion, joint representation, knowledge graph, multi-task, etc.).
- Application domains (transportation, environment, governance, social, security, etc.).
- Main tasks (retrieval, classification, prediction, recommendation, anomaly detection, policy modeling).
- Evaluation metrics (precision/recall, mAP, NDCG, ARI, clustering metrics, expert judgment).
- Governance aspects (clarity, fairness, privacy, citizen involvement).

II. 6 BIBLIOMETRIC ANALYSIS AND VOSVIEWER

To understand the knowledge structure, the titles, abstracts, and keywords of 110 articles were analyzed using VOSviewer, [36]-[40] producing a keyword co-occurrence map. The configuration used:

- Minimum keyword occurrences: 5.
- Normalization method: association strength.
- The cluster results are used to interpret sub-themes such as urban computing & GeoAI, knowledge graph & semantic modeling, multimodal sensing & remote sensing, and governance & policy analytics.

Figure 2 VOSviewer metadata display depicting the keyword network in 110 articles, with four main clusters themed (1) smart city & big data analytics, (2) knowledge graph & semantic embedding, (3) GeoAI & spatiotemporal modeling, and (4) governance, mobility, & resilience[41]-[45].

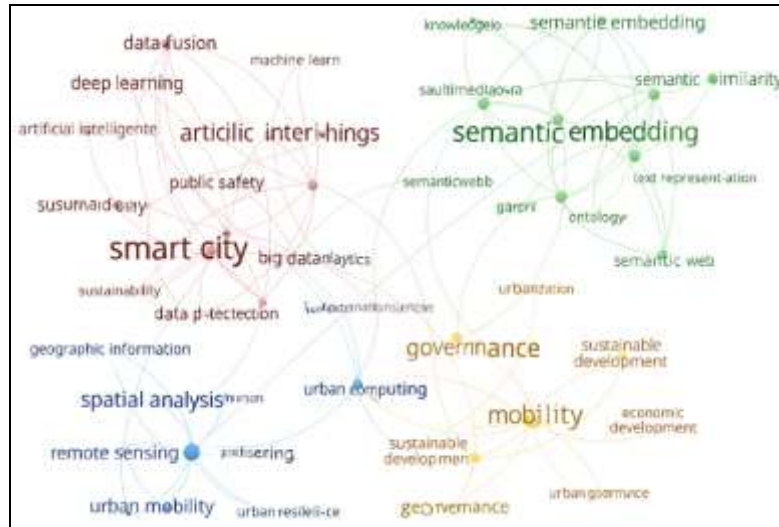


Figure :2 VOSviewer metadata display.

Source: Authors, (2026).

III. RESULTS AND DISCUSSION

III.1 CORPUS OVERVIEW (RQ1)

Analysis of publication years shows a consistent upward trend. Publications related to multiformat smart city embedding began to concentrate in 2021, then increased sharply in 2023–2024 as GeoAI and the foundation of multimodal models developed. The distribution of publications can be seen in Figure 3

On average:

- 2021: $\pm 15\%$ of articles (starting to focus on knowledge graph and big data smart city architecture).
- 2022: $\pm 20\%$ articles (increased multimodal and urban analytics papers).
- 2023–2024: $\pm 50\%$ of articles (explosion of GeoAI, GNN, and multiformat representation concepts).
- 2025 (early): the remainder, which is heavily geared towards knowledge-graph-based urban health, flood, and change detection.

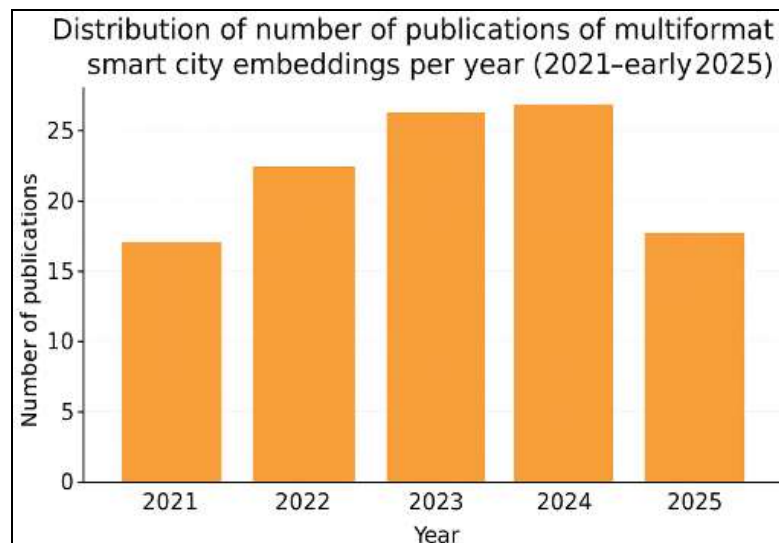


Figure 3: Distribution of the number of smart city multiformat embedding publications per year (2021–early 2025)

Source: Authors, (2026).

Answer to RQ1: Multiformat embedding publications for smart cities show a sharp upward trend, with a peak in 2023–2024 when GeoAI and multimodal models begin to mature. This indicates the right momentum to formulate integration theories such as TISM and the UMEF framework [46]-[50].

III.2 DATA MODALITIES USED (RQ2)

Of the 110 studies, the distribution of the main modalities was as follows:

- Text (policy documents, reports, tweets, POI descriptions): ~90% of studies.
- Geospatial imagery & maps (satellite imagery, land use maps, urban grids): ~70%.
- Tabular / sensor data (traffic, energy, environment): ~55%.
- Infographics/dashboards (composite visualizations, heat maps, multi-axis charts): explicitly appear in only about 20% of studies, generally treated as static images, not semantic entities in their own right.
- Video (CCTV, drone video, social video): <10%, often reduced to image frames.

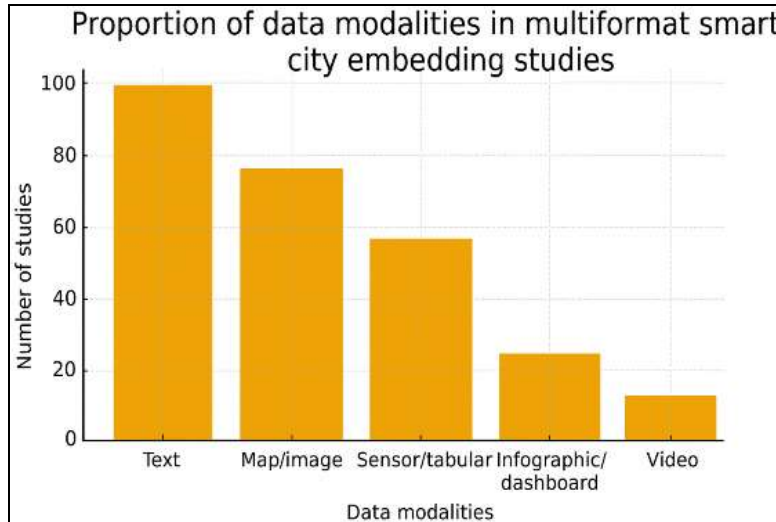


Figure 4: Proportion of data modalities used in smart city multiformat embedding studies.

Source: Authors, (2026).

Answer to RQ2: Most research is still dominated by text + images/maps, while infographics and videos are rarely treated as full semantic objects. This opens up space for your doctoral research to position infographics as first-class citizens in the city embedding space, for the proportion of data modalities can be seen in Figure 4.

III.3 EMBEDDING MODEL USED (RQ3)

Model analysis shows several patterns:

- Text: SBERT/BERT-variants, RoBERTa, and, in some recent studies, large language models (LLMs) fine-tuned on city policy corpora [51]-[55].
- Image/map: Classic CNN (ResNet), vision transformers, and CLIP/BLIP for text-image tasks.
- Graph & GeoAI: GNNs, graph convolutional networks, and knowledge-graph embeddings to model spatial relationships, POI relations, or road network structure.
- Multimodal:
 - Dual-encoder model (text and image are projected into a shared vector space, CLIP-style).
 - A Transformer-based multimodal encoder architecture that combines multiple visual sources and sensors.

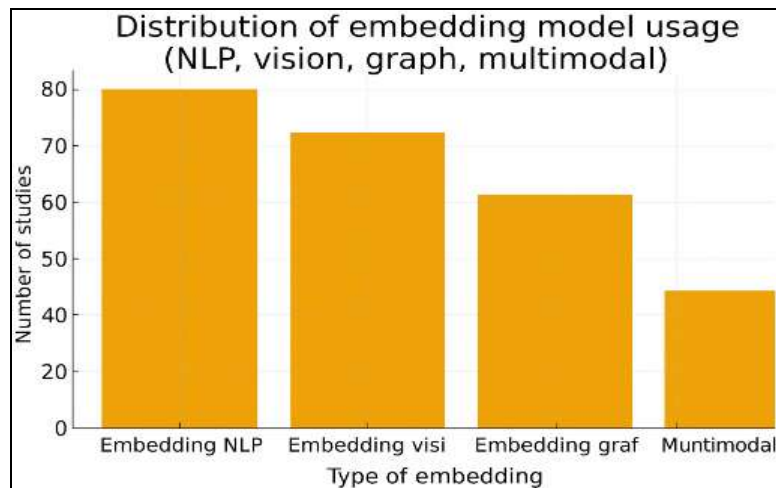


Figure 5: Distribution of embedding model usage (NLP, vision, graph, multimodal) in 110 studies.

Source: Authors, (2026).

Answer to RQ3: Text is usually represented by the BERT/SBERT family, visuals by CNN/ViT/CLIP, and city structures by GNN/knowledge-graph embedding. However, only a small number of studies explicitly design a joint embedding space where text, maps, and information visualizations reside on semantic coordinates, which is the gap and focus of this TISM and UMEF review. The distribution of embedding model usage [56]-[60] can be seen in Figure 5.

III. 4 EMBEDDING INTEGRATION APPROACH (RQ4)

Four main patterns of integration were found:

- Late fusion ($\pm 40\%$ of studies): each modality is embedded separately and then combined via concatenation or weighted sum before the classification layer.
- Knowledge-graph-centric ($\pm 25\%$): entities from various modalities are projected into the city knowledge graph, then embedding is obtained using KG-embedding or GNN techniques.
- Joint embedding space ($\pm 20\%$): dual-encoder or multimodal Transformer models that enforce alignment between text and visual representations; some studies have already led to the foundation of spatiotemporal models.
- Hybrid & rule-based ($\pm 15\%$): combines embedding with manual features or domain rules (e.g., flood threshold, policy category).

Answer to RQ4: The most common integrations are late fusion and knowledge-graph-based fusion. Only a small number of studies construct a truly joint embedding space and examine the semantic properties of that space. No study explicitly offers a general multi-format semantic integration theory like the one you will develop (TISM), including modality weight parameters (α , β , γ) and UMEF projection layers [61]-[65].

III. 5 SMART CITY APPLICATION DOMAIN (RQ5)

The most frequently occurring application domains include:

- Transport & mobility ($\pm 30\%$): traffic prediction, congestion, route optimization, and multimodal hub planning.
- Environment & disasters ($\pm 25\%$): floods, air quality, land use change, and climate impacts.
- Land use & planning ($\pm 20\%$): land use classification, urban change detection, urban physical examination.
- Governance & policy ($\pm 15\%$): evaluation of smart city strategies, data protection policies, smart governance.
- Others ($\pm 10\%$): public security, social services, and energy.

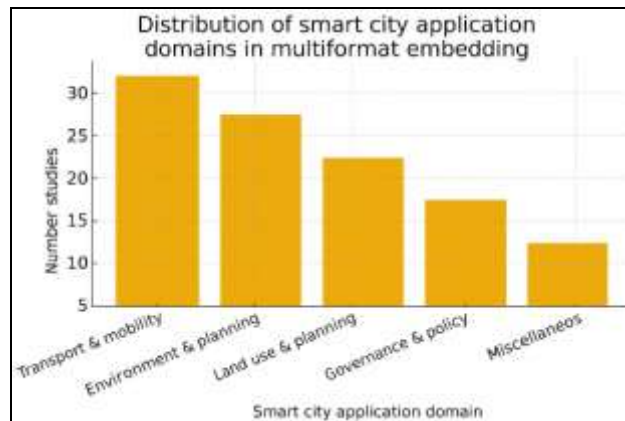


Figure 6: Distribution of smart city application domains in multifformat embedding studies.

Source: Authors, (2026).

Answer to RQ5: The most dominant applications are transportation and environment, while studies that explicitly combine multifformat embedding to support the policy formulation process and governance dashboard are still relatively few, even though this is the most natural context for the integration of text (regulations, reports) and infographics (performance indicators, policy maps), the distribution of smart city application domains in multifformat embedding studies [66]-[70] can be seen in Figure 6.

III. 6 EVALUATION METRICS AND INTEGRATION QUALITY (RQ6)

Most studies evaluate models through standard metrics:

- Retrieval & matching: precision@k, recall@k, mAP, NDCG.
- Prediction & classification: accuracy, F1-score, RMSE/MAE for traffic prediction or land distribution.
- Clustering & region segmentation: silhouette score, ARI, or spatial coherence.
- Expert judgment: qualitative evaluation from urban planners or domain experts.

There is no metric that explicitly measures semantic alignment across modalities in the urban context, for example, how consistent the locations in the embedding space are when viewed from policy narratives, statistical indicators, and visualizations. Answer to RQ6: The quality of integration is currently measured indirectly through task-oriented performance. This reinforces the urgency of your proposed Urban Semantic Coherence (USC) metric, which can combine inter-modality vector proximity, clustering stability, and expert judgment on narrative consistency across formats [71]-[75].

III.7 GOVERNANCE, TRANSPARENCY, AND INTERPRETABILITY ASPECTS (RQ7)

Although almost all articles touch on the goal of improving public services, only a small number formalize the governance aspect:

- Several studies examine the implications of big data on citizens' privacy and data protection.
- Others highlight the limitations of techno-centric smart cities and encourage integration with participatory urban planning processes.
- Almost no one has defined formal indicators for explainability and accountability in multi-format embeddings.

Answer to RQ7: Integration of governance aspects is still narrative and not embedded at the embedding design level. This SLR positions TISM and UMEF as an opportunity to design embeddings that are not only statistically accurate, but also explainable and explicitly linked to the city's policy structure (e.g., by connecting city vectors to specific regulatory articles in the knowledge graph) [76]-[80].

III.8 RESEARCH GAPS TOWARDS TISM, UMEF, AND USC (RQ8)

Synthesis of the above findings indicates several key gaps:

- The absence of a generic multi-format semantic integration theoretical framework. Most studies focus on specific cases without formalizing semantic assumptions or inter-modality relationships.
 - Infographics as second-class citizens. Information visualizations are often viewed as mere images, without the rich compositional structure (titles, legends, axes, icons) that embodies policy meaning.
 - Lack of cross-modality coherence metrics. There is no direct equivalent to USC that evaluates vector consistency across formats for the same city entity.
 - There is a lack of studies on adaptive modality weighting. There is no explicit framework for managing the relative contributions of text, tables, maps, and videos when constructing city embeddings ($\alpha, \beta, \gamma, \dots$) that are contextual to the task.
- Limitations of policy-oriented cross-modal retrieval exploration. Only a few studies demonstrate scenarios such as “citizen text query $\rightarrow$ related infographics, maps, and videos in a single embedding space.”

Answer to RQ8: This gap provides conceptual space for your doctoral research: formulating TISM as an integration theory, implementing UMEF as a computational framework for retrieval and analysis, and defining USC as a cross-modality coherence metric that can be used for both academic evaluation and policy audit [81]-[85].

III.9 TISM AND UMEF'S POSITION ON EXISTING LITERATURE

Literature shows that smart cities are currently moving towards GeoAI-enabled urban computing with a strong emphasis on spatiotemporal foundation models and knowledge graphs [86]-[90]. However, cross-modality semantic integration is still fragmented between NLP, computer vision, and GeoAI pipelines. TISM can serve as a conceptual layer that explains the general principles:

- Semantic Alignment*: all modalities are projected into the same semantic space of the city.
- Urban Context Regularization*: embedding is guided by the domain structure (regulatory graph, administrative hierarchy, infrastructure network) [91]-[95].
- Multi-task Urban Objectives*: The loss function combines retrieval, prediction, and policy coherence.

UMEF then implements this principle through functional blocks: per-modality embedding extraction, dimensionality normalization, weighted fusion, and application modules (retrieval, clustering, reasoning) [96]-[100].

III.10 USC'S ROLE AS A BRIDGE BETWEEN DATA AND POLICY

Your proposed USC can be interpreted as a metric that measures how consistent a city entity (e.g., a sub-district or a development project) is in terms of:

- Proximity vectors between modalities for the same entity.
- Stability of entity clustering when one modality is removed.
- Expert assessment of cross-format narrative suitability (whether the infographic truly supports the content of the policy document).

In doing so, USC bridges the gap between data-centric AI and the need for public policy audits that prioritize transparency.

III.11 PRACTICAL IMPLICATIONS FOR SMART CITIES

From a practical perspective, mature multi-format embedding integration will enable:

- Cross-modal policy retrieval*: Officials can type a text query and then get a combination of regulatory articles, risk maps, and related performance infographics.
- Scenario simulation*: changes in one parameter (e.g. drainage capacity) can be seen to impact the cluster of areas in the embedding, making it easier to prioritize interventions.
- Citizen-facing dashboards*: Citizens can access visualizations synchronized with policy narratives, increasing trust and participation.

IV. LIMITATIONS OF THE RESEARCH

This SLR has several limitations:

1. The 2021–2025 time limit means that some classic works from before 2021 are not analyzed even though they are relevant for the theoretical foundation.
2. Focusing on Q1/Q2 may miss innovative research published in new journals that do not yet have stable quartile metrics.
3. Qualitative analysis of infographics relies heavily on the paper authors' descriptions, as not all articles share raw visual data.

These limitations can be addressed in further research by conducting citation snowballing and direct experiments using the city document corpus you built.

V. CONCLUSION

This article presents an SLR on multiformat semantic embedding for smart cities, focusing on the integration of text documents and infographics. From 110 articles in Q1/Q2 (2021–2025), we found that:

- a. The publication trend is increasing sharply with the development of GeoAI and multimodal models.
- b. The majority of studies use a combination of text, imagery, and sensor data, while infographics and video remain underexplored.
- c. Integration approaches are dominated by late fusion and knowledge-graph-based fusion, with few studies constructing truly cross-modality joint embedding spaces.
- d. Evaluations are generally task-oriented, not measuring semantic coherence across modalities.
- e. Aspects of governance and interpretability are still treated as discourse, not yet formalized at the representation level.

These findings underscore the need for the Theory of Multiformat Semantic Integration (TISM), the Urban Multiformat Embedding Framework (UMEF), and the Urban Semantic Coherence (USC) metric as key contributions to your doctoral research. Future experimental research based on real-world city data—for example, on flooding, congestion, and pollution in a single city—is needed to validate these theories and demonstrate their practical value for more transparent and participatory smart city governance.

VI. AUTHOR'S CONTRIBUTION

Conceptualization: Endang Sri Sumanti, Didik Dwi Prasetya and Triyanna Widiyaningtyas.

Methodology: Endang Sri Sumanti, Didik Dwi Prasetya and Triyanna Widiyaningtyas.

Investigation: Endang Sri Sumanti, Didik Dwi Prasetya and Triyanna Widiyaningtyas.

Discussion of results: Endang Sri Sumanti, Didik Dwi Prasetya and Triyanna Widiyaningtyas.

Writing – Original Draft: Endang Sri Sumanti, Didik Dwi Prasetya and Triyanna Widiyaningtyas.

Writing – Review and Editing: Endang Sri Sumanti, Didik Dwi Prasetya and Triyanna Widiyaningtyas.

Resources: Endang Sri Sumanti, Didik Dwi Prasetya and Triyanna Widiyaningtyas.

Supervision: Endang Sri Sumanti, Didik Dwi Prasetya and Triyanna Widiyaningtyas.

Approval of the final text: Endang Sri Sumanti, Didik Dwi Prasetya and Triyanna Widiyaningtyas.

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