Articulating Morphological and Semantic Data in Heritage Modelling. A Conceptual Multilayer Framework for AI-Assisted Decision Support in Architectural Heritage

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Abstract

Current digital practices allow a faithful acquisition of the volumetries of heritage objects, but they struggle to integrate the spatial and cultural logics that generated the architecture. In the era of artificial intelligence (AI), an epistemological step back appears necessary to rethink heritage modelling methods when they combine scattered data arising, simultaneously, from the quantitative reproduction of geometries, the qualitative integration of the design process, and semantic appropriation. Building on a systemic approach to architectural heritage, this article proposes a conceptual and methodological framework aimed at producing hierarchised knowledge from heterogeneous data. The data are organised within a multilayer matrix: (1) a morphological layer, describing the physical, geometric and configurational characteristics of the built fabric; (2) a semantic layer, integrating historical knowledge, uses, cultural values, and architectural rules; (3) a relational layer, supported by AI, that articulates morphological and semantic information through explainable morpho-semantic relationships. This organisation constitutes a structured heritage dataset embedded within a reproducible and systematically structured processing pipeline, spanning from data acquisition to knowledge generation. Within this framework, AI is not envisaged as a substitute for historical expertise, but as a transversal reasoning operator capable of identifying inter-layer regularities, making correlations explicit, and inferring interpretable architectural rules opening the way to interpretive and predictive modelling. Rather than presenting an operational decision-support system, the proposed framework establishes the conceptual and methodological foundations for future AI-assisted heritage applications. The proposed approach thus models heritage documentation as a dynamic decision-support system, contributing to the analysis of historical data, to digital reverse engineering, and to the methodological foundations of conservation and valorisation strategies.

Keywords: heritage modelling, multilayer system, artificial intelligence, decision support, morpho-semantic data.

Introduction

Decision-making in the field of architectural heritage takes place in a context of uncertainty marked by partial and heterogeneous data. It relies on evolving knowledge that guides the processes of interpretation. In step with the reconfiguration of the notion of heritage, in which each building may be regarded as a heritage-in-becoming with respect to the issues of reuse and life cycle, digital technologies have profoundly transformed the practices of documentation, representation, and design. Advances in three-dimensional acquisition (terrestrial laser scanning, photogrammetry) now produce geometric and volumetric representations of buildings (Remondino & Campana, 2014). Furthermore, the rise of artificial intelligence (AI) opens new perspectives for the analysis and exploitation of these data, enabling the processing of complex sets and the identification of regularities within informational structures that are multidimensional (Naifer, 2025), while also tending to reduce the ambiguities and polysemy inherent in heritage objects (Bermès & Moiraghi, 2020). However, heritage modelling remains marked by a predominance of geometric data at the expense of the semantic, historical, and cultural dimensions. In response to this, recent research points to a transition towards multilayer models articulating different categories of information (Maietti et al., 2021; Simeone et al., 2021), set within a systemic approach (L. V. Bertalanffy, 1968) in which the building is understood as a dynamic system composed of interacting elements. The integration of heritage data nonetheless comes up against their heterogeneity and their inscription within multiple temporalities, generating an epistemological tension between the normalisation requirements needed for computational exploitation and the preservation of semantic and interpretive richness.

Against this background, the present study does not introduce or experimentally validate a fully operational AI-assisted decision-support system. Instead, it proposes a conceptual and methodological framework intended to structure heterogeneous heritage information and establish the theoretical foundations for future AI-assisted decision-support applications.

The problem addressed in this article is therefore organised around three questions: how can heterogeneous heritage data be structured, articulated, and integrated to render the intrinsic complexity of the built object? How can strictly geometric approaches be moved beyond in favour of models integrating semantic, relational, and evolving dimensions? Finally, to what extent can such a conceptual modelling framework provide the methodological foundations for devices that constitute relevant operational supports for heritage decision-making?

The aim of this research is to rethink the modelling of architectural heritage by developing a conceptual and methodological framework capable of integrating and connecting multidimensional data within a coherent multilayer information model that is intended to support the future development of AI-assisted decision-support systems rather than to present an implemented solution. The goal is to move beyond a logic of static representation towards a dynamic informational system, able to make explicit the relations between the building's different dimensions and to support interpretive scenarios. Accordingly, the contribution of this work lies primarily in the formalisation of the modelling framework, the organisation of the morpho-semantic information architecture, and the methodological principles governing AI integration.

The discussion is structured in five parts: (1) the theoretical framework and the state of the art of modelling approaches; (2) a conceptual framework apprehending the building as a dynamic system; (3) the methodological process, from data acquisition to the construction of the multilayer model; (4) a conceptual validation of the proposed framework together with a discussion of its methodological implications and future evaluation strategy; (5) the limitations and perspectives of the research.

Literature Review and Theoretical Framework

This theoretical framework articulates heritage decision-making, modelling devices, and systemic approaches. It brings out the interdependencies between knowledge production, data structuring, and decision-support processes, while making explicit the positioning of this research.

Heritage Decision-Making

Heritage decision-making operates under a regime of uncertainty linked to the incompleteness and heterogeneity of data as well as to the plurality of interpretations. It rests on evolving knowledge that conditions the trade-offs according to a logic of "bounded rationality," "reflective conversation," and "complex thought" (Simon, 1969; Schön, 1983; Morin, 1990). The building is not apprehended as a fixed object, but as a dynamic entity whose transformations must be envisaged through interpretive scenarios that guarantee the overall coherence of the system. Heritage decision-making may take the form of design scenarios simulating differentiated intervention trajectories, spatial recommendations, a system of constraints and alerts operating as a filter of decisional coherence, and/or procedural and substantive guidance (Cao et al., 2025). The implementation of decisional guidance supports collective deliberation, postulating that heritage decision-making requires situated, revisable, and co-constructed responses.

Digital Modelling of Heritage

Digital technologies have renewed documentation practices, notably through three-dimensional acquisition (laser scanning, photogrammetry) allowing high-precision surveys (Remondino & Campana, 2014). These data renew documentation by feeding modelling processes such as Scan-to-BIM and HBIM which structure geometric information and associate descriptive attributes with the elements of the building (Fuchs et al., 2004; Murphy et al., 2013; Maietti et al., 2021). These approaches remain dominated by a geometric and parametric logic in which the semantic, historical, and relational dimensions remain weakly integrated (Simeone et al., 2021).

This predominance of the quantifiable induces a methodological bias limiting the explanatory capacity of the models. The absence of robust metrics for quantifying non-measurable or hard-to-formalise aspects such as cultural values particularly hinders the integration of these dimensions into computational frameworks. The integration of AI opens new perspectives for exploitation but tends at the same time to normalise representations by reducing the polysemy inherent in heritage objects (Bermès & Moiraghi, 2020).

Multilayer Modelling and Systemic Approaches to Architectural Heritage

For several decades, architectural modelling has apprehended the building through a systemic approach, as a system articulating its material, informational, and cultural dimensions. This orientation is rooted in the cybernetics of Wiener (1948) and continues in the work of Alexander (1964) who propose a decomposition of the architectural fact into recurrent "patterns," structured in relational networks. This perspective is extended by the experiments of Pask and Price, in which architecture is conceived as an interactive system founded on communication and feedback (Pask, 1969; Claeys & Roobaert, 2022). It is enriched by the intentional and symbolic approaches of Norberg-Schulz (1965), which emphasise the signifying dimension of space.

This lineage is formalised by the general systems theory of Ludwig Von Bertalanffy (1968), which conceives of the building as an open system. Buckminster Fuller (1969) develops a holistic vision of architecture as an interconnected system associating ecology, technology, and environment, while Nicholas Negroponte (1970) introduces the idea of an architectural design founded on human–machine interaction. The complexity approaches developed by Edgar Morin (1977) highlight the interdependence of the system's levels of analysis, while Bill Hillier and Julienne Hanson (1984) formalise spatial configuration as a measurable relational organisation.

In this continuation, the notion of layer is reconfigured as a dynamic relational element. A layer may be defined as an organised level of information, functions, or properties participating in a single system while retaining a relative autonomy. A multilayer system therefore does not denote a mere linear superposition of strata, but a relational organisation in which the layers may intersect, partially overlap, or interact according to different scales and temporalities. In computer science, this notion refers to the hierarchised architectures founded on modular decomposition (Parnas, 1972); in architecture, Stewart Brand (Brand, 1994) draws on it to differentiate the components of the building according to their temporalities of evolution; in planning and landscape, Ian McHarg (McHarg, 1969) uses it as a tool for the analytical superposition of heterogeneous data. This evolutionary reading is extended by John Frazer (Frazer, 1995) and by the research on the living machines of Nancy and John Todd (Todd, 1994).

At the intersection of these approaches, the layer may be defined as an intermediate structuring unit at once functional, relational, and temporal enabling the organisation and interpretation of the complexity of built systems. Recent developments extend this orientation towards interoperable informational systems (the SSIM model) (Yuan et al., 2026), marking the shift from an object-centred modelling to a relation-centred modelling (Bos et al., 2025). Machine learning indeed confirms the emergence of implicit multilayer organisations founded on the granularity of architectural elements and their interactions (Cera et al., 2025).

Positioning and Contributions of the Research

Despite these advances, current approaches remain fragmented and struggle to integrate coherently the interactions between the dimensions of the built fabric, between morphology and semantics. This gap limits the understanding of the building as a dynamic system and constrains the development of decision-support tools. This research proposes a systemic and multilayer approach aimed at articulating these dimensions within an integrated model, in which AI plays a mediating role by ensuring the linking and interpretation of the morphological and semantic dimensions, with a view to supporting decision-making (*cf*. Fig. 1).

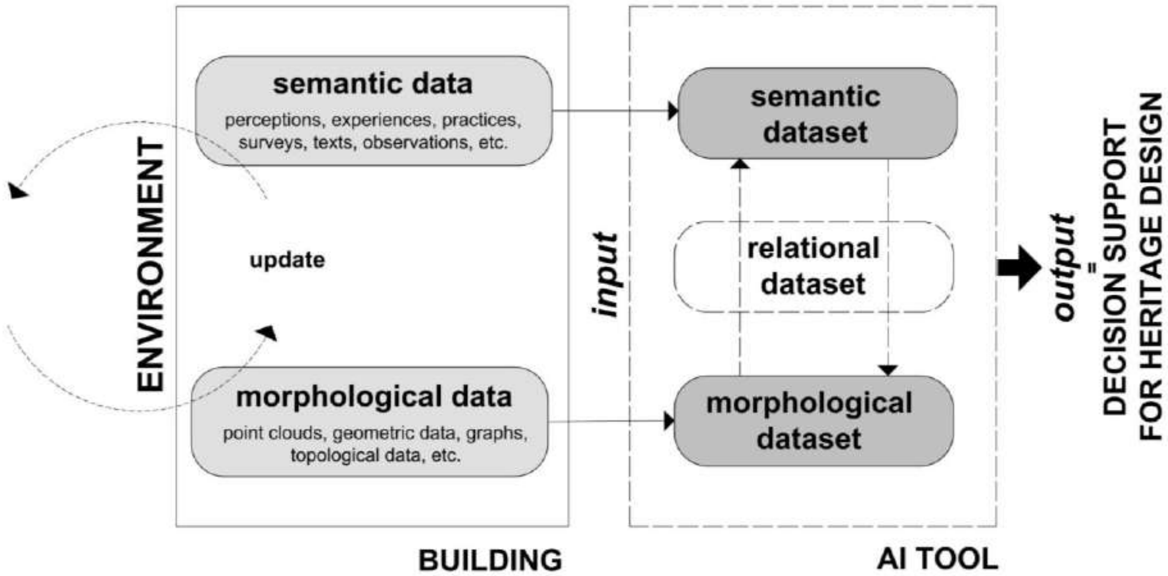

Fig. 1 : General principle of the heritage decision-support device: from the building to the AI tool

Conceptual Framework: Understanding the Real Phenomenon

The Heritage Building as a Dynamic System

Understanding the architectural heritage phenomenon constitutes a founding step of the modelling process: "each heritage object is unique and calls upon knowledge, ancestral know-how, and contemporary expertise" (Hervy et al., 2015, p. 3). This is particularly the case within an AI-assisted systemic logic. This approach requires the constitution of a rich, diversified, and structured data corpus to allow a multidimensional analysis (Hervy et al., 2015; Abidi et al., 2024).

The apprehension of this complexity is organised around the notion of layer. On the one hand, a morphological, technical, and material dimension and, on the other, a semantic dimension linked to cultural representations, values, and conceptions of the world. This division into sub-layers calls for a controlled understanding of a complex system, which can be achieved only through its decomposition into independent sub-systems (Alexander, 1964, p. 42-43). This decomposition requires a rigorous recomposition of the inter-layer relations. This dynamic of synthesis aims to restore the overall coherence of the building, to overcome the biases of current tools still too often restricted to the quantitative and to apprehend architecture fully as a system articulating morphology, spatial configuration, and semantic meaning.

Multidimensional Modelling

In the architectural domain, the design and analysis of a building resemble a process of data processing and interpretation aimed at producing new knowledge (Claeys & Naifer, 2022). The physical and spatial characteristics of the built fabric (geometries, proportions, orientation) become truly meaningful only once integrated into an analytical framework able to reveal their structure and interactions. To carry out this conceptual transition, the building is decomposed hierarchically, from its overall scale down to the elementary architectural elements (storeys, spaces, walls, etc.). This structuring transforms a continuous object into analytical units that are described, compared, and related (Murphy et al., 2013).

Morphological Data

The constitution of the analysis system requires the aggregation of a rigorous data corpus. This approach relies first on classic documentation (surveys *in situ*, plans, sketches) (Fuchs et al., 2004), enriched by historical and archaeological sources in order to restore the dynamics of transformation of the space (Abidi et al., 2024). In parallel, three-dimensional digitisation technologies (terrestrial laser scanning, photogrammetry) refine this collection. They generate high-resolution 3D models that facilitate the morphological and material study of the built fabric (Murphy et al., 2013). Finally, these volumes of spatial data can feed analytical approaches such as *space syntax* (Hillier & Hanson, 1984), allowing the architectural configuration to be studied through the accessibility, connectivity, and social organisation of the spaces.

Semantic Data

Despite recent advances, the work remains fragmented, limiting the continuity, traceability, and overall reuse of qualitative knowledge (Hervy et al., 2015). To remedy this lack of an integrated methodology, the acquisition and structuring of semantic data emerge as a central challenge. These rest on approaches combining heterogeneous sources (archives, literature, archaeology), ontological modelling, and automatic extraction (Wang & Zhang, 2025).

These methods rest on the constitution of corpora (literature, archives, archaeological data), their pre-processing (normalisation, cleaning), and then the establishment of a reference ontology often inspired by the CIDOC CRM (International Committee for Documentation - Conceptual Reference Model) structuring the entities (objects, places, actors, events) and their relations. Advanced language models then extract triples (subject/predicate/object), integrated into graph-oriented databases (such as Neo4j) to generate interconnected knowledge graphs. Finally, although partially automated, this technological flow requires human validation to guarantee the quality, coherence, and interoperability of the data, ensured by their formalisation in the RDF (Resource Description Framework) standard (Doerr, 2003; Tzitzikas et al., 2022; Wang & Zhang, 2025).

From Data to Knowledge: Positioning AI

The management of architectural data is part of a cognitive continuum formalised by the classic "data, information, knowledge" model (Shannon, 1948; Ackoff, 1989; Le Deuff, 2014). This operational process unfolds in three interconnected phases: (1) the collection of raw facts derived from surveys and documentary sources (Paquet, 2006); (2) their analytical processing, which transforms these data into contextualised information; and finally (3) the computational modelling that translates these elements into structured knowledge, capable of revealing the interactions within the architectural system (Sowa, 1984; Rowley, 2007).

Any intelligent algorithm processes input data to produce output data (Roobaert & Claeys, 2024b; Naifer, 2025). Inputs may be numeric, audio, video, or textual; outputs may be continuous, categorical, sequential, structured, ranking, or probabilistic. In accordance with this computational framework, the qualitative characteristics of the building must be subjected to numerical coding. For example, symmetry is translated into a binary variable (0 or 1) and orientation is expressed in degrees (from 0 to 360°) relative to a reference axis. These variables are not independent but linked by causal interactions: the modification of one element may affect others, revealing a complex relational structure (Alexander, 1964).

In this configuration, AI is not a substitute for the expert but a cognitive tool enabling the exploration of the "conceptual order" and the "inter-layer regularities" within large databases that human intuition alone can no longer process (Alexander, 1964, p. 7). Human interpretation remains decisive in defining the domain rules that the machine will have to assimilate (Alexander, 1964, p. 109). Setting itself apart from generative models (such as GANs), often marked by a certain opacity, the approach proposed here favours a decomposition into successive sub-models of machine learning (*machine learning* – ML). This recourse to supervised models guarantees an explainability, a relational legibility, and a traceability of results that are indispensable to the requirements of the heritage context (Naifer, 2025, p. 68).

Faced with the inherent scarcity of heritage data, this research draws on a multimodal and multi-objective approach inspired by the work of Stanislas Chaillou (Chaillou, 2019). The system is segmented into autonomous sub-models, each operating on a specific layer of the built fabric. This granularity makes it possible to isolate and adjust each component independently, thereby ensuring control over the overall functioning of the device. This decisional pipeline draws on three of the major families of non-deep learning: (1) supervised; (2) unsupervised; and (3) reinforcement learning, selected according to the nature of the available data and the degree of human involvement required (Mitchell, 2013; Serrano, 2021; Roobaert & Claeys, 2024a, 2024b). This classification preserves the methodological clarity necessary for the scientific validation of heritage scenarios.

Methodology: A Multilayer Informational System

General Approach

The methodology is part of a systemic and multilayer approach aimed at modelling architectural heritage in the form of a dynamic information system capable of integrating heterogeneous data and supporting decision-making. It rests on the postulate that the understanding of a building cannot be reduced to its geometric description alone but requires the articulation of morphological and semantic dimensions, whose interactions govern the overall behaviour of the system.

To operationalise this hypothesis, the approach is structured in four interdependent steps: (1) the acquisition of morphological and semantic data, combining architectural surveys, historical documentary sources, and digital models; (2) the processing, analysis, and structuring of these heterogeneous corpora in order to formalise them into entities, variables, and relations within a coherent framework; (3) multilayer modelling, structured around three components: a morphological layer (physical and geometric characteristics), a semantic layer (meanings, uses, and historicity), and a relational layer. This last operates as an interface of analytical mediation charged with deciphering the complex relations between form and meaning; (4) the construction of an integrated informational model formalising the data into structured entities and relations.

This operational framework makes it possible to make the inter-layer dynamics explicit. It moves beyond mere static representation and leads to the construction of an evolving system capable of qualifying the current state of the building and exploring its trajectories of transformation.

Data Acquisition

Morphological Data

The input data mobilised for the morphological and spatial analysis describe the physical and functional organisation of the building. They aggregate, on the one hand, the spatial characteristics derived from plans, in situ surveys, or segmentation into units (rooms, convex spaces, etc.) and, on the other hand, the accessibility relations (doors, passages, stairs, vertical transitions, etc.) as well as the structure of the circulations connecting them (corridors, galleries, movement axes) (Fuchs et al., 2004; Murphy et al., 2013; Naifer et al., 2023). The exploitation of this information can rely on analysis using *space syntax* (Hillier & Hanson, 1984), transforming them into genuine matrices of spatial analysis rather than mere descriptive documents (Fuchs et al., 2004; Murphy et al., 2013; Naifer et al., 2023).

Semantic Data

Semantic data refer to the set of interpretive information that confers meaning on spatial and morphological configurations: functions assigned to spaces, activity systems, social uses, as well as cultural, symbolic, and historical values. They also incorporate ontological categories and conceptual relations enabling knowledge to be structured (typologies of spaces, public/private statuses, hierarchies of use), thereby facilitating their formalisation in information systems. In the field of heritage, these semantic dimensions are essential for relating built forms to cultural logics and to the processes of production of space (Doerr, 2003; Naifer et al., 2023; Abidi et al., 2024).

All this information constitutes the input phase of the system. In an AI-assisted analysis context, the performance of the device depends closely on the quality, reliability, and level of structuring of these data (Naifer et al., 2023). Multi-source data fusion is therefore not merely a technical improvement of geometric precision, but takes part in a paradigm shift, allowing a move from a mere reproduction of the real to a systemic and evolving understanding of architectural logics (Hervy et al., 2015).

Processing, Analysis, and Structuring of Data

The processing, analysis, and structuring of data constitute a central step aimed at integrating the morphological and semantic dimensions within a unified operational framework. The morphological data are organised according to hierarchical and relational structures allowing the spatial units, their properties, and their interactions to be characterised (Hillier & Hanson, 1984; Murphy et al., 2013). In parallel, the semantic data are interpreted, categorised, and formalised through ontologies and conceptual relations, to make explicit the cultural and functional logics that underlie the organisation of space (Doerr, 2003; Naifer et al., 2023; Abidi & Bouaita, 2026).

The main challenge lies in the matching of these two heterogeneous registers. This entails an operation of translating qualitative information into structured, comparable, and interoperable descriptors, capable of being associated with the morphological entities. This formalisation makes it possible to establish explicit links between spatial forms and meanings, by aligning the semantic variables with the spatial units and relations. The processing of data is not limited to their organisation; it engages a process of bringing into coherence aimed at building a common language between geometry and meaning. This articulation makes possible an integrated reading of the architectural system, in which the different layers of information are no longer dissociated but interconnected. It therefore constitutes the methodological foundation for the construction of a multilayer model, allowing a joint, progressive, and systemic analysis of the architectural object (Simeone et al., 2021; Abidi & Bouaita, 2026). It thereby opens the way to AI-assisted analysis tools, capable of identifying regularities between the different layers of the model and of inferring the architectural logics that structure the heritage systems under study (Tzitzikas et al., 2022).

Multilayer Modelling

Data management is not reduced to a mere operation of storage or classification but constitutes a process of transformation aimed at structuring heterogeneous observations into a coherent architectural information system. This process makes it possible to organise, analyse, and relate the data to reveal the spatial structures and the design logics of the built fabric. In this perspective, the integration of the different categories of information requires a coherent framework capable of articulating the spatial structures and the design logics. To this end, the data are organised according to a multilayer modelling resting on three complementary analytical dimensions.

Morphological Layer

The morphological layer constitutes the descriptive dimension of the proposed methodological framework. It aims to characterise the physical, geometric, and configurational properties of the building by describing its forms, dimensions, and spatial organisation. It includes the dimensions of the spaces, the volumes, the proportions, as well as the presence of specific architectural elements, thus constituting the material basis of the architectural envelope. This approach is in continuity with the work on geometric modelling and the digital documentation of heritage (Naifer et al., 2023; Naifer, 2025).

However, the understanding of morphology cannot be limited to a strictly geometric approach, hence the integration of *space syntax*, developed by Bill Hillier and Hanson (2004; 1984). Founded on a topological modelling and on graph theory, it makes it possible to translate the spatial organisation into quantitative indicators such as connectivity, depth, or integration (Barouni & Claeys, 2024), thereby revealing the structural and social logic of the spatial system. These approaches have been widely mobilised to analyse the relations between spatial morphology and uses, notably in the work of Bafna (2003) and Van Nes & Yamu (2021) who emphasise the importance of the configurational dimension in the understanding of architectural systems.

Within this framework, the morphological process rests on the structuring of data into architectural entities organised according to a multi-scale hierarchy. This hierarchy distinguishes the building as a global entity, subdivided into storeys, then into spaces (rooms, corridors, courtyards), themselves composed of architectural elements such as walls or openings. This decomposition is part of a systemic analysis logic that makes it possible to transform a continuous architectural object into a set of comparable analytical units.

From this structuring, a set of morphological attributes is extracted for each entity. These attributes include quantitative measures such as surface area, volume, geometric ratios, proportions, as well as formal characteristics describing the configuration of the spaces and elements. In parallel, configurational indicators derived from syntactic analysis can be integrated to enrich the morphological description with a spatial reading of the system. Recent developments highlight the value of coupling the metrics of *space syntax* with computational approaches, notably through the integration of deep learning and semantic segmentation methods, thereby making it possible to analyse, simulate, and predict complex spatial configurations (Zhou et al., 2025).

The data thus produced are then subjected to a normalisation phase aimed at ensuring their homogeneity and comparability. This step includes the conversion of measurements into standardised metric units, the use of ratios to neutralise scale effects, and the classification of forms according to geometric and typological criteria. The data are then structured in tabular form, facilitating their organisation and exploitation within an information system.

The result of this process corresponds to the constitution of a structured morphological *dataset*, in which each architectural entity is described by a set of geometric, formal, and configurational attributes. This *dataset* constitutes an essential analytical basis for the subsequent modelling stages, for the articulation with the semantic layer and the analysis of inter-layer interactions.

Semantic Layer

The semantic layer constitutes the interpretive dimension of the proposed methodological framework. In the field of built heritage, several studies have shown that digital models often remain limited to geometric representation, while the knowledge relating to the historical context, social uses, or construction practices remains external to the model. Approaches founded on ontologies and knowledge systems make it possible to overcome this limit by structuring heritage data in the form of networks of entities and relations (Acierno et al., 2017; Sanfilippo Emilio Maria, 2020). Likewise, research on the semantic enrichment of HBIM models has underlined the importance of integrating non-geometric information, such as historical transformations or cultural meanings, to support the analysis and management of heritage (Simeone et al., 2019).

In this context, the semantic layer aims to transform the heterogeneous data collected during the various phases of analysis into a structured knowledge system, coherently integrating several categories of sources: historical sources (archives, texts, old documents), cultural knowledge relating to the social rules and uses of the spaces, as well as the architectural analysis bearing on the observation of the built fabric and the identification of spatial typologies.

From these data, the semantic process unfolds in several successive steps: (1) the identification of the architectural concepts that structure the spatial organisation of the system under study. These concepts correspond to spatial or functional categories such as the courtyard, the private space, the reception space, or the transition zones; (2) the annotation of the architectural entities, consisting in associating with each identified architectural element information relating to its function, its use, and its cultural meaning. This phase makes it possible to enrich the morphological and spatial data with an interpretive dimension; (3) the structuring of the relations between the entities. The spaces and architectural elements are then linked through semantic relations such as connection, belonging, or functional dependency relations. This relational structuring makes it possible to represent architecture as an organised system rather than as a mere collection of objects; (4) the formalisation of the architectural rules, which describe the relations between morphology, spatial organisation, and social uses. These rules make it possible to express explicitly the architectural logics observed in the system under study; (5) the integration of all the information into a heritage information system, structured in the form of a *dataset* semantic and an architectural relations graph. This structuring of the data makes it possible to constitute a heritage knowledge base in which the architectural entities are linked to their functions, their cultural meanings, and their spatial organisation (Abidi & Bouaita, 2026).

The result of this process comprises a structured semantic *dataset* composed of an architectural relations graph and a set of explicit architectural rules describing the organisation of the system under study. This knowledge base constitutes a resource exploitable for advanced analyses, within the framework of the use of artificial intelligence methods such as knowledge graphs, which make it possible to identify regularities and complex relations between the different dimensions of the architectural model (Buglisi et al., 2026; Rao & Wang, 2025).

Relational Layer (AI)

In the general economy of the device, the relational layer does not constitute a mere intermediate stratum, but the genuine operator of systemic circularity. It ensures the junction between the physical world (morphology) and the world of representations (semantics), transforming an accumulation of heterogeneous data into an intelligible knowledge system (Le Moigne, 1990). The passage from the "real" to the "model" takes place through a process of analytical decomposition. This step is not a mere reductionist simplification, but a heuristic strategy aimed at isolating the components of the architectural phenomenon: (1) the morphological *dataset* (geometry, wall, structure) captures materiality; (2) the semantic dataset (uses, traditions, cultural systems) integrates intentionality. It is within the relational layer that these sets are matched, transforming the building from an assemblage of objects into a network of meaningful relations. This functioning is part of an iterative dynamic. At a given moment, the AI processes the available data, produces results, then reintegrates the new information arising from the evolution of the building, the transformations of the environment, or documentary contributions. This looped process ensures a continuous updating of the system: the data enrich the analysis, guide the decision, and the decisions may in turn transform the state of the building. At each iteration, the morphological and semantic data are mobilised jointly in a morpho-semantic articulation space to produce an updated reading of the architectural system. The analysis then rests on a set of variables describing the operating conditions of the system, formulated in terms of "fit" and "misfit," expressing the adjustments between technical, functional, and cultural requirements (Alexander, 1964, p. 27).

Sub-model	Inputs	Tasks	Learning Model	Recommended Algorithms
Morphological Layer	2D and 3D surveys, point cloud, configuration graphs, observation, etc.	extract, structure, and complete the geometric characteristics	supervised or unsupervised	*Random Forest, Clustering…*
Semantic Layer	observation, experience, practices, surveys, texts, etc.	extract, structure, and complete the semantic characteristics	supervised or semi-supervised	Classification…
Relational Layer	morphological dataset, semantic dataset	learn and model the morpho-semantic relations	Deep Learning (DL)	*Knowledge Graph, Graph Neural Network…*

Tab.1. Distribution of the learning sub-models by layer.

From an operational standpoint, AI can be understood as a multilayer device of algorithms: a first layer processes the morphological data, a second the semantic data, while a third ensures their articulation. This relational layer does not correspond to an autonomous database, but to a dynamic mechanism of matching between entities arising from distinct structures. It makes it possible to render the data comparable, associable, and jointly interpretable, without directly modifying the initial bases. Thus, AI does not constitute an additional layer, but a transversal operator that generates an emergent relational layer, at the heart of the process of analysis and decision.

Integrated Informational Model

The final step consists in bringing together the three layers within an integrated informational model, conceived as a graph structure in which each architectural element is formalised as an entity, each relation as a link, and each piece of information as an attribute. The model articulates three complementary operations. An encoding first transforms the morphological and semantic datasets into comparable representations within a common latent space. A matching, performed by the relational layer, then projects these representations into a morpho-semantic articulation space in which the inter-layer regularities are learned. Finally, a decoding produces a generated multilayer table, exploitable as a decision support. This model is distinguished from a classic database by its dynamic and inferential character: it does not merely store attributes, it makes relations explicit and produces hypotheses. Its output feeds directly into the heritage project in the form of design scenarios (restoration, transformation, extension), evaluation metrics (compatibility, coherence, conformity), spatial recommendations (organisation, adjacency, dimensions), constraints and alerts (conflicts, inconsistencies), as well as elements of decision guidance (ranking, selection, justification). The system thus constitutes an evolving informational device, whose value grows as new data enrich it.

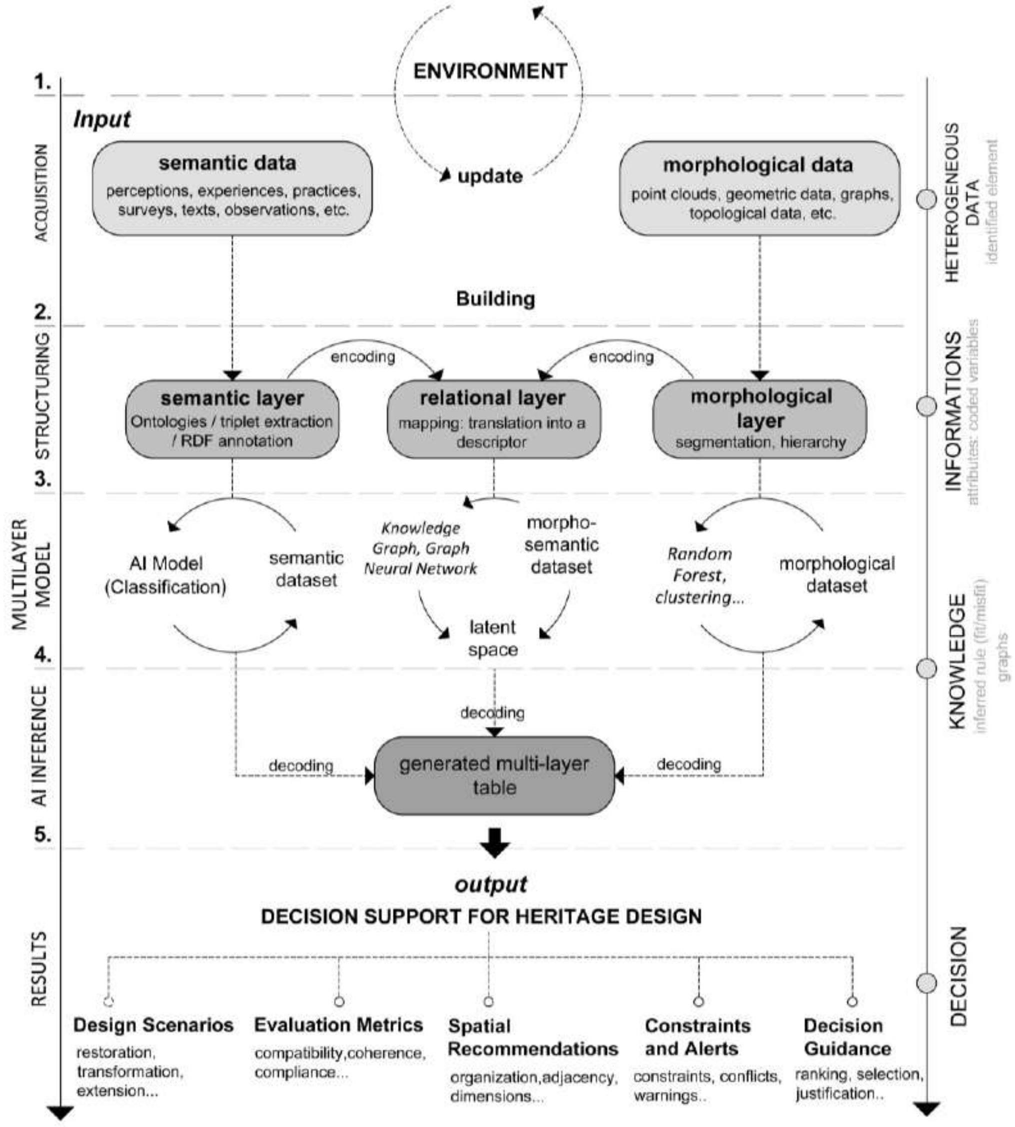

Fig. 2. Representation of the integrated informational model

Results and Discussion

AI-assisted multilayer modelling aims to advance the understanding of architectural heritage from a collection of heterogeneous observations into a structured, traceable, and reproducible informational system. Decomposing the heritage asset into morphological, semantic, and relational layers enables heterogeneous information to be organized into coherent datasets, leading to a reconfiguration of the architectural entity as an integrated system of forms, spaces, and meanings rather than as an isolated geometric object (Buglisi et al., 2026).

This layered decomposition also ensures the internal consistency of the proposed framework, as each processing stage relies on explicitly defined inputs and produces structured outputs that are systematically propagated to subsequent stages. The sequential organization of the workflow preserves the logical interconnection between morphological, semantic, and relational information throughout the modelling process, thereby reducing inconsistencies across data representations in accordance with the principles of modular system decomposition (Parnas, 1972).

Nevertheless, the proposed approach does not eliminate the epistemological tension between standardization and semantic richness. Translating cultural values into encoded variables inevitably entails a degree of information loss, which requires expert human validation to ensure the reliability and interpretability of the generated knowledge (Bos et al., 2025). Furthermore, the applicability of the framework remains contingent upon comprehensive validation combining quantitative and qualitative assessment methods, together with expert evaluation on sufficiently large and well-documented heritage datasets.

Within this framework, the relational layer operates through a morpho-semantic articulation space that establishes explicit correspondences between heterogeneous datasets, thereby generating the knowledge structure underpinning the entire system. Artificial intelligence is conceived as a transversal reasoning operator rather than as an autonomous modelling layer. Because AI functions exclusively as a relational mechanism connecting explicitly defined datasets, every inference can be traced back to identifiable morphological and semantic descriptors. This traceability establishes a transparent reasoning chain linking heritage observations to the decision-support outputs generated by the framework, while preserving the interpretability of the inference process (Rao & Wang, 2025).

The direct outcome of this multilayer articulation process is a generated knowledge table derived from the decoding mechanism previously described. Rather than constituting a static database, this knowledge structure explicitly captures recurrent patterns, correlations, and inferred architectural rules emerging from the interaction between the morphological, semantic, and relational layers. It provides the operational foundation from which the framework generates decision-support outputs, including design scenarios, evaluation metrics, spatial recommendations, constraints and alerts, as well as transparent decision justifications that remain traceable to their underlying morphological and semantic descriptors. Consequently, the proposed framework constitutes a dynamic informational system capable of generating interpretative hypotheses while supporting both decision-making and the prediction of transformations affecting the built heritage.

Evaluation Perspectives and Assessment Methods

The supervised sub-models operating on the morphological and semantic layers can be evaluated using standard classification metrics, including accuracy, precision, recall, and the score, computed through cross-validation in accordance with the evaluation and optimization protocols recently adopted for supervised machine-learning classification of built heritage (Cera et al., 2025). The relational layer requires graph-specific evaluation metrics, including graph coverage, internal consistency, and link prediction accuracy achieved by the Graph Neural Network (GNN). These quantitative indicators should be complemented by ontology validation against the CIDOC-CRM reference model to assess the semantic interoperability and structural reliability of the proposed knowledge representation (Tzitzikas et al., 2022; Wang & Zhang, 2025).

Ontology consistency would be assessed by verifying the logical coherence of classes, properties, and semantic relationships, together with their compliance with the CIDOC-CRM ontology. Such validation ensures that the resulting knowledge representation remains interoperable, semantically coherent, and free from contradictory relationships. In parallel, graph completeness would evaluate the extent to which the generated knowledge graph adequately represents morphological entities, semantic concepts, and the relationships linking them.

Beyond quantitative performance metrics, the interpretative nature of architectural heritage knowledge calls for an expert-in-the-loop validation strategy. This process would include the assessment of inter-annotator agreement for semantic annotations, the systematic review of inferred architectural rules by domain experts to establish their face validity, and a comparison with a geometry-based baseline represented by a conventional HBIM model that excludes both semantic and relational layers. Such a comparison would enable the interpretative contribution of the proposed multilayer framework to be quantitatively and qualitatively assessed.

Expert validation would therefore evaluate not only the plausibility of the inferred architectural relationships but also the transparency, interpretability, and practical relevance of the decision-support outputs generated by the framework. These quantitative and qualitative evaluation procedures constitute a comprehensive validation protocol intended for future experimental implementation rather than evidence of current model performance. Their primary objective is to establish a rigorous methodological foundation for the empirical assessment of the proposed framework once implemented and evaluated on sufficiently large, well-documented, and semantically annotated heritage datasets. Accordingly, the present research provides the conceptual and methodological basis for future experimental validation, benchmarking, and reproducibility studies.

Limitations and Research Perspectives

The proposed approach contributes to the field of digital heritage modelling by introducing a systemic framework designed to structure heterogeneous morphological and semantic data within an integrated analytical environment, while facilitating the integration of artificial intelligence into analytical workflows and decision-support processes. Nevertheless, the performance of the proposed framework remains highly dependent on the quality of the available data and on the algorithmic strategies employed. The inherent complexity of the interactions among morphological, spatial, and semantic dimensions makes comprehensive modelling contingent upon further methodological refinements, technological advancements, and long-term research efforts.

From this perspective, the present study should be regarded as a conceptual and methodological contribution that establishes a generic operational framework for the multilayer modelling of architectural heritage. The framework is grounded in a reproducible and systematically structured processing pipeline encompassing the entire workflow, from data acquisition to knowledge generation for decision support. Although the proposed framework still requires validation using real-world heritage datasets, its systemic architecture provides a robust foundation for future developments by ensuring reproducibility, scalability, and adaptability across diverse architectural heritage contexts.

Conclusion

This study proposes a conceptual and methodological framework that rethinks the modelling of architectural heritage by integrating multi-source data into a structured, traceable, and evolving knowledge system based on transparent and explainable relationships across multiple information layers. Beyond introducing a multilayer representation of heritage knowledge, the proposed framework formalizes a reproducible methodological pipeline that combines data structuring, semantic enrichment, relational modelling, and explainable AI-driven reasoning within a unified analytical architecture. As such, it provides a generic reference framework for future research seeking to integrate artificial intelligence into heritage documentation, analysis, and decision-support processes (Acierno et al., 2017).

The present contribution is intentionally positioned upstream of empirical validation. The proposed framework has not yet been implemented or evaluated on real-world heritage datasets, and its operational performance therefore remains to be demonstrated through future applications involving sufficiently documented and representative heritage corpora.

At the same time, the framework acknowledges the persistent epistemological tension between the standardization required for computational modelling and the preservation of the semantic richness inherent to heritage knowledge. While computational methods can formalize and infer relationships, the interpretation and validation of cultural meaning ultimately remain dependent on domain expertise (Bos et al., 2025). Consequently, this study should be regarded as the establishment of a rigorous conceptual and methodological foundation rather than as an experimental demonstration.

Future research should therefore focus on three complementary directions: (i) the development of large-scale, representative, and semantically enriched annotated heritage datasets; (ii) the design of robust data integration and interoperability protocols; and (iii) the systematic evaluation of the framework with respect to predictive performance, reliability, explainability, and reproducibility across diverse heritage contexts. The methodological workflow introduced in this study provides the basis for such investigations by integrating predictive performance metrics, ontology consistency assessment, knowledge graph quality indicators, expert validation, and benchmarking against geometry-based reference models (Tzitzikas et al., 2022; Wang & Zhang, 2025). In this respect, the proposed framework establishes the methodological foundations for the future development, implementation, and scientific validation of AI-assisted decision-support systems for architectural heritage.

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