Urban Artificial Intelligence as a Meta-Modelling Framework: Repositioning AI in Urban Analysis and Planning

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Abstract. The rapid increase of Artificial Intelligence (AI) in the urban studies has substantially broadened the analytical capability of the urban modelling, spatial analysis, as well as planning practice. Although this has increased adoption, the conceptual place of AI in the urban planning knowledge is still not well established, tied to a solitary application of technology as opposed to an analytical system. This paper takes a conceptual and review-based approach and contends that Urban Artificial Intelligence needs to be re-valuated as a meta-modelling framework that complements and restructures existing analytical traditions and not replacing them. Drawing on a critical synthesis of recent literature, the paper examines the integration of AI with Geographic Information Systems (GIS), configurational approaches such as space syntax, and urban morphology. The review identifies the predominance of predictive accuracy, automation and computational efficiency at the expense of interpretability, spatially reasoning and planning relevance. To fill this gap, the paper suggests a conceptual framework, which considers AI as an enabling analytical stratum, which will aid data integration, pattern recognition, and exploration of scenarios, yet retain human interpretation and normative judgment as the central components to planning processes. By introducing AI to a broader urban modelling ecology, the presented framework defines the role of the former in the generation of spatial knowledge and decision support, but not the autonomous decision-making. Implications of transparency, methodological coherence and people-centered planning with a focus on explainable and situation-dependent applications of AI are also provided in the paper. The study

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contributes to ongoing debates on the epistemological and methodological foundations of Urban Artificial Intelligence and offers a planning-oriented perspective for its responsible integration into urban modelling and analysis workflows.

Keywords: Artificial Intelligence · GIS · Spatial Analysis · Urban Modelling · Urban Planning

1 Introduction

Incorporation of Artificial Intelligence (AI) into urban studies has been greatly accelerated in the last ten years due to the spread of huge volumes of spatial data, the development of computational power, and the growing need to use data to inform planning. The use of AI methods, and especially machine learning and deep learning, has become common in various areas of urban research, such as land-use classification, mobility prediction, environmental monitoring, and infrastructure optimisation. Such a fast growth has clearly amplified the analytical abilities of urban modelling, allowed the handling of multifaceted, high-dimensional data and allowed predictive information to be produced at never previously experienced spatial and temporal levels [1].

Although these developments occur, the theoretical role of AI in urban planning and analysis has not been adequately described. In a great part of the available literature, AI is still largely presented as a separate technological solution, commonly optimised in predictive quality, automation features, and computational efficiency. Although such a framing is methodologically beneficial, it runs the risk of making urban analysis a more technical procedure, rather than one that relates to the interpretative, contextual and normative aspects that define the practice of planning. As a result, AI-based solutions are often used side by side, not in combination with, existing traditions of analysis, including Geographic Information System (GIS), configurational analysis (e.g. space syntax), and urban morphology studies. Such fragmentation is obvious in which AI is applied to augment some of the analytical processes such as classification, clustering, or prediction without a due interaction with the broader epistemological foundations of urban knowledge production [2]. AI models are convenient tools when it comes to identifying spatial patterns or forecasting city dynamics. However, they lack the human-understandability and interpretability, restricting their application in decision-making scenarios.

In this framework, a gap is identified, namely, the lack of a consistent conceptual framework where AI is not considered as a tool of analysis, but rather as a component of integration in the overall ecology of urban modelling. To fill this gap, it is necessary to consider a change of perspective, that is, to stop seeing AI as an alternative to the current methodology and as having the potential to restructure and improve the old methods of analysis. This repositioning can allow AI to serve as an enabling layer that enables the integration of data, pattern recognition, and the exploration of situations, and maintains the central position of human interpretation and planning judgement.

The paper will support this purview by conducting a systematic survey of the recent literature on the use of AI in urban analysis. It also highlights its combined usage with GIS, space syntax, and urban morphology. It assumes a critical approach to determine

the current trend of methodology, limitations of the conceptual nature, and areas of overlap in these fields. Therefore, the study suggests a conceptual framework which redefines Urban Artificial Intelligence as a meta-modelling system being integrated within a multi-layered analytical framework that includes data, methods and decision-making processes.

This paper has two contributions to make. First, it offers a conceptualised epistemological positioning of AI in urban planning to address endemic uncertainties about the role of AI in knowledge generation and analytic practice. Second, it presents a conceptual framework of planning that will be able to support the responsible and contextualisation of the application of AI in the process of urban modelling. Through this, the study will add to the growing discussions on the methodological coherence, transparency, and human orientation of AI in urban studies, and it is important to note that the value of AI is not found to lie in the process of autonomous decision-making, but rather in its ability to supplement and enhance the processes of analysis that inform planning interventions.

2 Positioning AI within Urban Analytical Traditions

The integration of AI in urban studies has been both fast and unequal, with an innovative approach and conceptual vagueness. Instead of providing a coherent analytical paradigm, AI has been integrated into the existing urban traditions of analysis in a fragmented and application-focused form. In this section, a thematic synthesis of existing paths is developed based on the intersection between AI and existing methods, especially GIS, configurational analysis and urban morphology, and the shortcomings of AI as largely instrumentally applied.

2.1 AI in Urban Studies: Current Trajectories

The development of AI in the urban studies has been informed by the intersection of greater processing power, the spread of high-resolution spatial data, and the rising need to use predictive and more data-driven planning methods. In the last ten years, AI has stopped being a marginalised analysis instrument and has become the core of the research processes in cities, especially in the areas that can be described as multi-dimensional and complex datasets. This change is indicative of a wider change in urban analytics, where models-based approaches have been increasingly complemented, and in certain directions even replaced, by data-driven approaches [3].

The main aspect of this change is the massive implementation of machine learning (ML) and deep learning (DL) methods. Supervised learning algorithms are useful in classification and 0 regression problems. This includes land-use mapping, population density prediction and urban growth prediction. On the other hand, unsupervised learning methods including clustering methods and dimensionality reduction methods, are more useful. They can analyse latent spatial patterns and functional areas in cities. However, deep learning systems have also shown substantial abilities to process spatial and spatio-temporal data.

One of the major factors that inspire is the presence of geospatial big data obtained through satellite images, sensor networks, mobile phone data, social media sites and

administrative documents. The detailed information on urban dynamics is what enables the modelling of the previously inaccessible phenomena using AI techniques. They acquire the capability to capture nonlinear relationships, model complex interactions, and scale to large scale data. AI has already found application in the creation of the smart city analytics, real-time city monitoring, and optimisation of infrastructures. However, the trend in AI pursued in the urban research is very skewed towards predictive accuracy and computational efficiency. Models are commonly measured by the performance metrics of accuracy, precision, recall, or error minimisation and little thought given to their understandability or theoretical basis [4, 5]. This focus has had the effect of increasing dependence on black-box models where the inner workings of the algorithm cannot be easily accessed. Though these models can be very predictive, they lack transparency, and it is difficult to incorporate them in planning processes.

The other exciting fact behind the AI trends today is that it is inclined towards domain specific applications. AI models are trained to solve highly specific tasks, like traffic prediction or land-use classification, producing highly specialised solutions that cannot be easily generalised to new settings [6]. Although this specialisation has the benefit of improving performance in the context of tasks, it is limited to disciplinary or methodological frames.

2.2 Integration with Established Urban Methods

Although it develops very fast, AI in the field of urban studies has not been developed as an independent analytical paradigm but a complement to existing methodological traditions. It is most integrative in three prevailing areas of urban analysis that are, GIS, configurational approaches, which include space syntax, and urban morphology. Although these integrations have improved analytical capacities, they are mostly instrumental and they aim at augmentation of performance, as opposed to concept synthesis [7].

In the context of GIS urban analysis, AI has been broadly used to further the spatial data processing, classification and modelling capability. Machine learning and deep learning are among the techniques used on a regular basis to classify remote sensing data with land-use and land-cover, object detection, and change detection. These applications are very helpful to the speed and accuracy of spatial analysis, especially when dealing with large and heterogeneous datasets [8]. AI is also useful in spatial interpolation, anomaly detection, and predictive modelling in GIS environments, thus making it possible to have more dynamic and scalable analytical processes. In most instances, however, AI is used as an improvement layer on top of GIS and does not substantially change its underlying logic as a spatial data representation and analysis system. The epistemological principles of GIS based on spatial relations and cartographic reasoning have not changed much, and AI has been used to improve automation and efficiency [9].

AI has been used to reinforce the predictive and empirical validation of spatial network models in the framework of configurational analysis, especially space syntax. Space syntax has traditionally been based upon the graph-based representations of the urban form to study the patterns of movement, accessibility as well as the integration of space. With the integration of machine learning, it is possible to calibrate syntactic

measures to observed behavioural data, e.g. pedestrian or vehicular flows. This combination strengthens the explanatory capacity of configurational measures, which allows making stronger predictions regarding movement dynamics in various urban settings [10]. However, AI is not usually used in this area beyond the optimisation and validation of models. It does not radically redefine the theoretical constructs of configurational analysis, including spatial cognition, visibility, or network centrality, but rather puts them into better empirical service. Another area where AI has been popularised is urban morphology, especially in-built form analysis, spatial patterns, and urban development. Morphological features of large-scale datasets, e.g. satellite imagery, street-level images, and cadastral maps, are extracted by AI methods, e.g. image segmentation, clustering, and pattern recognition. The approaches enable the classification of the urban forms, the definition of typologies, and the examination of the temporal changes in the built environment. The scalability of AI allows morphological research to be carried out in more than one city and region, which allows comparative and longitudinal research [11]. AI applications to urban morphology are more inclined to focus on descriptive and predictive results, notwithstanding limited participation in the interpretative and theoretical facets.

AI is applied as a task-specific addition that enhances the efficiency, scalability and predictive power of the current techniques. They are implemented in each field as a consonant with the specific methodological priorities and data forms in each field. This leads to parallel developments and not convergent integration. Therefore, traditional methods remain within their respective limits of epistemology, and AI is merely an aide to the process rather than a unifying process [12].

The given form of integration indicates a larger shortcoming of the current trend of urban AI. The use of AI along with already existing approaches has delivered the quantifiable technical dividends. But it has not resulted into the logical recalibration of how various analytical tactics can be linked together. There are no well-developed possibilities of cross-domain synthesis. This includes the correlation between morphological patterns and movement dynamics or the integration of environmental performance in spatial configuration. Therefore, AI is not applied to its maximum potential as the bridging element between these areas but rather, it is an independent enhancement of both [13]. Collectively, these curves suggest that AI is mostly utilized as a performance-enhancing addition to the preexisting analytical traditions, rather than a unifying epistemological structure. Although, considerable progress has been made in the efficiency, scalability, and predictive ability, integration has continued to be largely instrumental and domain specific. Consequentially, the current working conditions of urban analytical practices remain in parallel siloing with slight conceptual overlaps, which supports the necessity of a reframing of AI as an integrative meta-modelling layer.

2.3 Key Limitations in Current Approaches

The present implementation of AI in urban research demonstrates a set of structural constraints, which are due to the overwhelming instrumental and application-oriented framing. The constraints are not just technical, but also epistemological and methodological contradictions. Therefore, they contradict the introduction of AI into the urban analytical practice. With the further introduction of AI into various fields, the issues of

interpretability, the relevance of planning, coherence in concepts and methodological fragmentation are even more acute [6].

The major weakness is the problem of interpretability. Most AI models, especially the deep learning models, are opaque systems. Such models may be highly predictive, but due to their lack of transparency it is difficult to implement using such models with the planning context where decisions must be justified. The absence of an explanation of the production of certain outputs negatively affects trust and reduces the practicality. This is a critical concern especially in the field of urban planning with long-term socio-spatial consequences of decisions [14]. Also, the poor translation of AI outputs into practical planning contexts is closely associated. AI models are very effective in producing predictions, classifications, or pattern detections. However, the results usually do not have the interpretation frameworks essential to decision-making. An example is that a model can be accurate in forecasting regions of urban development or traffic congestion, but lack contextualisation in the form of socio-economic situations, governance systems or spatial orders. Such separation indicates a larger disparity between computational analysis and planning practice where AI are not adequately congruent with the normative and strategic aspects of urban decision-making.

Besides, the current situation in AI usage in urban studies is linked to the significant degree of the methodological fragmentation. It is mostly incorporated into analytical fields including GIS, configurational analysis, or urban morphology with little interaction between the domains. This develops disconnected analytical pipes where knowledge is produced in isolation and not in a cumulative and integrated knowledge of urban systems. The lack of an overriding framework limits the possibility of AI being able to promote cross-domain synthesis [15]. This discontinuity is also supported by the fact that most AI applications are task oriented. Models are merely designed to solve small-focused problems, and this results in specialised solutions. Although this improves the performance in the context of single tasks, it restricts the wider applicability of AI.

Additionally, novel challenges relate to bias, data quality, and representational disadvantages. Bias in AI models is also based on the data that they are trained on, and any bias in these data can be multiplied by the operation of an algorithm. In urban areas, it can lead to the strengthening of existing inequalities or false representation of the underrepresented groups. These difficulties are further complicated by the uneven access to high-quality data in the different regions especially in those areas that have less established data infrastructure. These challenges bring out the importance of critical interaction between the ethical and socio-political aspects of AI in urban planning [16].

These restrictions suggest that the present-day use of AI in the context of urban studies, is technologically advanced but lack coherent and planning-oriented relevance. The issues of interpretability reduced the relevance of decision-making, the epistemological inconsistency, and methodological fragmentation demonstrate the necessity of the redefinition of the role of AI (Fig. 1).

3 Conceptual Gap: from Tool to Meta-Modelling

The fast integration of AI into the urban studies has caused its common belief as an effective analytical tool. Yet, such attitude is frequently supplemented by a conceptual mismatch, as AI is either regarded as an independent method of analysis, or perceived

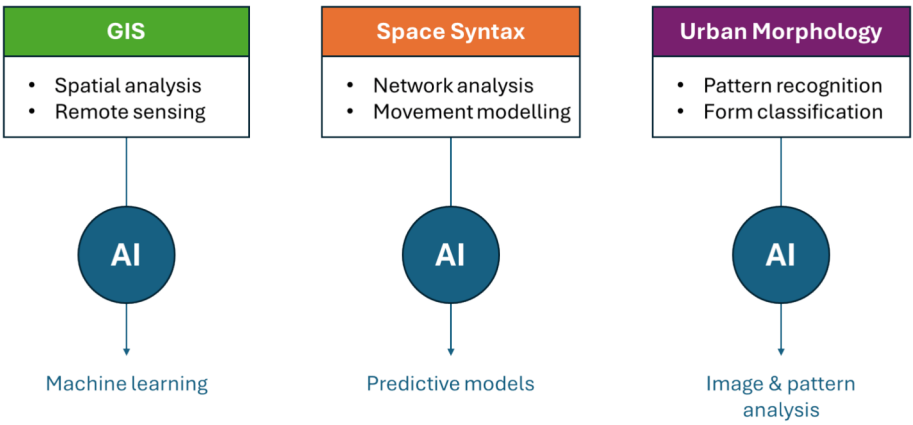

Fig. 1. Fragmented integration of Artificial Intelligence within urban analytical traditions [elaborated by the authors].

as a possible replacement of human thinking in the process of planning. To begin with, AI models are fundamentally reliant on input data, feature selection and problem framing which are informed by existing traditions of analysis including GIS, configurational analysis, and urban morphology. AI is not used to create knowledge, but to process information based on such structures and rearrange it. In the absence of the contextualisation of the outputs of AI offered by domain-specific knowledge, the products of AI will become decontextualised abstractions, which have no relevance in the actual conditions of urban life. Second, the concept of AI as a self-reliant analytical procedure ignores the interpretative aspect of urban analytical process. Urban systems are not simply purely computational systems but rather influenced by the complex socio-spatial, cultural and political processes [17]. Thus, by making it a standalone technique, it is possible to disregard the interpretative and critical elements of the planning practice.

No less problematic is the conceptualisation of AI as a substitute of human reasoning. Although AI can be used to process a significant amount of data and find patterns with great efficiency, it lacks the ability to make judgements, act morally, or understand the situation in the context of human planners. Making decisions and planning them frequently encompasses having competing interests, negotiating the views of the different stakeholders and considering the long-term implications of the society. Such processes demand reasoning that goes beyond computational optimisation, and excessive reliance on AI in the area will result in technocratic decision-making, in which algorithmic outputs are given priority without adequate critical analysis. The lack of transparency in the functioning of the algorithmic systems becomes a major issue when the authority to make decisions is implicitly passed on to them [18].

The paper highlights that AI needs to be re-defined as a meta-modelling framework in urban analysis. Under this role, AI does not act as an individual process, but as a mediating analytical level that is applied in various fields. The main contribution that it makes is that it can integrate heterogeneous datasets, improving pattern recognition, and scenario exploration, which complements existing analytical methods without replacing

them. Having been developed as a meta-layer, AI allows consolidating various data sources, which tend to be disconnected between various analytical systems. The city data are usually across different formats and scales, spatial, temporal, socio-economic, and environmental. The synthesis of such datasets is made possible by AI techniques, which can be used to come up with more comprehensive representations of urban systems. Such integrative ability is especially useful in solving multi-dimensional problems in cities that are complex.

Besides the integration of data, AI improves the ability to recognise patterns in the urban data. AI can also uncover the insights that might not be easily traced by using standard analysis techniques by establishing non-linear associations and latent structures. Notably, these understandings are to be interpreted as supplementary to but not substitutes of the current modes of spatial thinking. Pattern recognition based on AI could be used to add to the interpretative process, when incorporated into a larger analytical framework, which would be used to arrive at more nuanced interpretations of urban processes. It is also very important in assisting in scenario exploration. The process of urban planning usually requires predicting the future situation and assessing other interventions. Under various conditions, AI models can simulate possible results, which may be considered as useful contributions to the strategic decision-making. These simulations are however not to be understood as deterministic predictions. Rather, they are to be adopted as exploratory aids that inform deliberation and planning decisions in a human-centred context.

In epistemological terms, the switch of AI to a meta-modelling framework is compatible with a more integrative conceptualisation of the production of urban knowledge. Instead of giving precedence to data-driven insights above theory, this approach considers the interdependence of computational approaches and domain-specific knowledge. The AI is integrated into a wider ecology of analytics, in which alternative ways of understanding urban systems are added to an accumulative and context-specific one. In the context of the theory of planning, this view makes the role of human judgement and normative reasoning central [19]. The proposed meta-modelling framework should be differentiated with the current hybrid or AI-supported urban modelling methods. Although hybrid models are normally the integration of method at the application or workflow integration level, they are task specific and do not have an overriding epistemological framework. Conversely, the conceptualisation of AI as a higher-order integrative layer that functions across domains of analysis, interpreting data, domain-specific models, and planning, is proposed herein. This reverses the aim of AI as methodological boost, to epistemological supplement.

4 Proposed Framework: Urban AI as Meta-Modelling System

This paper presents an idea framework which redesigns AI as a meta-modelling platform in urban analysis. Instead of being a specific analytical instrument or a substitute of the currently existing approaches, AI is viewed as a middle ground that incorporates, improves, and rearranges various elements of analysis within a single framework. This framework reacts to the requirement of methodological coherence, interpretability and planning relevance by placing AI in a wider analytic ecology, which preserves the primacy of human judgement.

4.1 Framework Structure

The suggested framework is structured in the form of a multi-layered system that has four interconnected elements, such as the data layer, the analytical layer, the AI layer, and the interpretation layer. Each layer has a specific task to complete as it is dynamically connected with the rest.

The data layer is the bottom part of the framework and is the composition of various spatial and non-spatial data. These are GIS-based data, remote sensing data, socio-economic data, mobility data, environmental data and administrative data. Notably, the heterogeneity of these sources of data also indicates the multi-dimensional character of urban systems, with spatial, temporal, and socio-economic variables interacting at different scales. More to the point, this layer is not neutral, but it is influenced by the process of data collection, availability and representation, which subsequently affect reliability and inclusiveness of the future analysis.

Most importantly, the analytical layer entails developed urban analytical approaches, such as configurational approaches, such as space syntax, urban morphological analysis, and statistical modelling techniques. This layer gives the theoretical and methodological basis of the interpretation of urban phenomena. It is in this field where spatial relationship, network structures and form-function interactions are studied. Such approaches are more structured in the way they understand urban systems, in contrast to purely data-driven approaches, as they incorporate domain knowledge and conceptual reasoning, providing a way of understanding the urban system beyond pattern appearances on the surface.

The AI layer, which is above the analytical layer, is the heart of the framework meta-modelling. It does not take the place of the analytical techniques below it but traverses over it, thus making it integrate and augment. Through the processing of the results of several analytical streams, AI enables the generation of heterogeneous information, the discovery of latent patterns, and the discovery of complex relationships that might not be evident when using a single approach. This framing is important, as it re-identifies AI as a mediating process that bridges and enriches the already existing strategies as opposed to it being a self-sufficient destination.

The interpretation layer is at the top of the framework, and it focuses on the planners, decision-makers and the stakeholders. This layer involves the conversion of analytical product into actionable knowledge based on contextual understanding, normative considerations and policy goals. It supports the fact that urban planning is a human-centric process by nature, and decisions should consider social, cultural, and ethical aspects, which are not limited to computational results. The interpretation layer as well provides a feedback loop, in which planning choices and results are used in future data gathering and analysis, such that the structure is adaptive and sensitive to context.

4.2 Functional Role of AI

It is in this hierarchical system where AI undertakes some of its most important functions that in combination characterise its functionality as a meta-modelling system. Such functions are not limited to individual analytical activities and help to create and develop the overall structure. One of the main purposes of AI is data fusion, which is a combination of various datasets of various formats, scales, and fields. Urban data are naturally

discrete, stored in a range of different systems and characterised by a different degree of granularity and quality. It allows consolidating data sets which is crucial in the solution of complex urban issues facilitating multi-dimensional analysis.

The use of AI models is especially useful when it comes to the recognition of non-linear relationships and latent structures in large data sets. It reveals patterns that cannot be perceived using traditional tools directly and improves domain-specific analysis. Pattern extraction helps to develop a more detailed image of the urban processes. It allows exploring other (alternative) urban futures in different conditions. It can also be used to guide planners to examine the consequences of policy or design interventions, or environmental changes. These simulations are a good foundation in strategic planning, and it is possible to evaluate risks, trade-offs, and uncertainties. However, it is necessary to note that this type of simulation is not a deterministic forecast but a discovery tool that can guide deliberative procedures.

4.3 Conceptual Diagram

The conceptual diagram (Fig. 2) is arranged in a vertical manner to show how the raw data is transformed into a decision-making. The data layer is the bottommost layer that reflects the heterogeneous character of urban data. This is preceded by the analytical layer, which exemplifies methodological traditions configurational analysis, morphological studies, and statistical modelling. The two layers are together the pillars of the foundational elements of urban knowledge production, based on domain-specific reasoning.

The AI component is conceptualized as an analytical layer that is intermediate and not a destination. The argument of the paper revolves around this positioning. AI works on the results of the analytical layer, making it easier to integrate, better pattern recognition, and allowing scenario-driven exploration. Its operations, such as data fusion, pattern extraction, and simulation, are represented in this layer to highlight its functionality in augmenting, but not eliminating, the existing methods. The interpretation layer is the layer where planners, decision-makers and stakeholders interact with the outputs produced by the other layers. This layer emphasises the importance of human judgement in the processes of urban planning whereby the analytical insights must be put in a context of socio-political, cultural and ethical considerations. The information flow of data to interpretation upwards is an indication of how the raw inputs would be transformed into feasible decision-making. It also includes a feedback mechanism between the interpretation layer and the data and analytical components. This feedback loop denotes the iterative character of urban planning in which decisions inform the further data collection, model refinement and analysis. It strengthens the dynamic and flexible nature of the framework, so that it is responsive to evolving urban circumstances and priorities in planning.

5 Implications for Urban Planning and Research

The metamodelling of AI as a framework has important implications on the practice of urban research and planning. The shift towards positioning AI as an integrative layer, rather than an independent analysis instrument, in a larger analytical ecosystem is associated with the need to reconsider methodological and governance frameworks as well

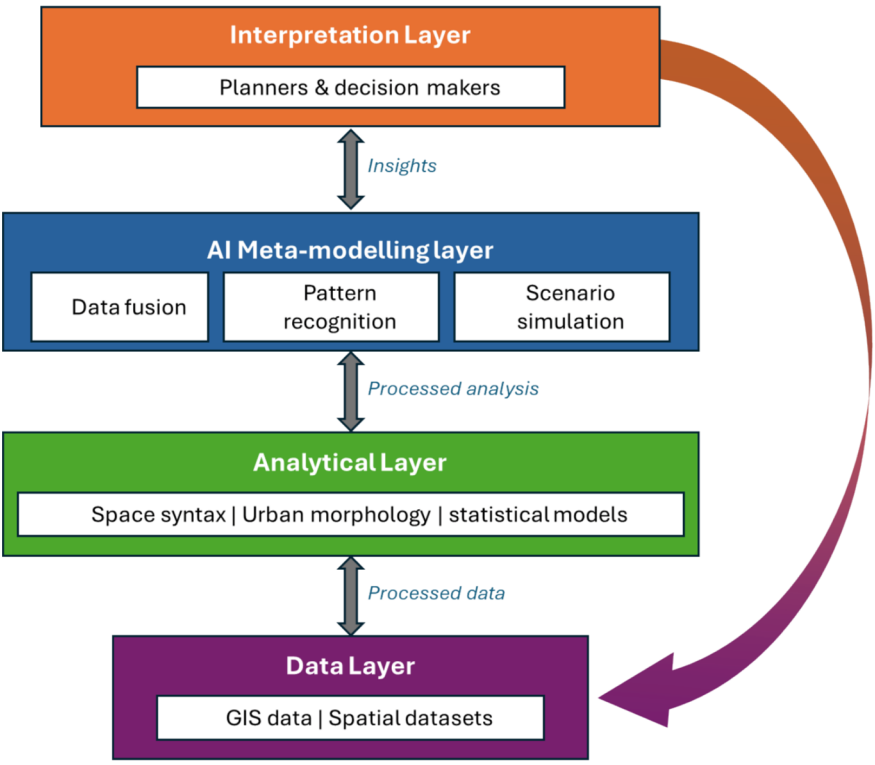

Fig. 2. Urban Artificial Intelligence as a meta-modelling framework. Source: authors' elaboration.

as the practices of various professionals, which is not merely a technical matter, but a question of epistemology and normativity in urban planning.

5.1 Methodological Implications

The key implication of the framework is that there is a necessity to transition to hybrid modelling methods. The recent trend of AI in urban studies can be largely described in terms of parallel innovations, where machine learning models are developed without the involvement of configurational methods, or morphological studies. Such a division constrains the possibility of the comprehensive analysis of urban systems [20]. The meta-modelling perspective highlights integration over substitution. Rather than replacing traditional analytical methods with AI, the framework emphasises their coordinated use within a unified structure. This involves leveraging the strengths of each approach. By enabling interaction between different configurational methods, hybrid models can produce more robust and context-sensitive insights [21].

This transition requires the development of interoperable analytical workflows and frameworks that allow for the seamless exchange of data and outputs across different modelling domains. It also requires a re-evaluation of standards of evaluation. More

emphasis should be put on interpretability, transferability and planning relevance instead of just focusing on the predictive accuracy. This also means that the performance of the model should not be measured in terms of technical performance alone but also in terms of the ability to facilitate the decision-making process and lead to the production of urban knowledge. Moreover, the implementation of hybrid methods promotes a more iterative and reflexive modelling process. The introduction of AI into a stratified structure of analysis allows one to provide a continuous feedback mechanism between data, methods, and interpretation, which helps to develop adaptive modelling practices to the changing urban environment. This is consistent with new trends in urban science that focus on complexity, uncertainty, and flexibility in the analysis.

5.2 Governance and Ethics

The application of AI in urban planning poses very important questions regarding governance, ethics, and accountability. With the growing levels of AI systems integration in the analytical and decision-support processes, the transparency and explainability is a core requirement. Making decisions with a far reaching social and spatial impact, planning decisions may also require justifications. Black-box AI models are uninterpretable and create serious challenges due to obscure conclusions [22].

The framework proposed addresses these concerns by placing AI within a broader analytical context. This layered approach enhances transparency by allowing AI-derived insights to be cross-referenced with domain-specific analyses. Another critical issue is the risk of algorithmic bias as they are inherently shaped by the data on which they are trained. These biases can be perpetuated or amplified through computational processes. In urban contexts, this may lead to the reinforcement of existing inequalities. Addressing this challenge requires careful consideration of data sources, model design, and validation processes, and incorporation of ethical safeguards within analytical workflows. Therefore, to integrate AI, it is essential to maintain clear lines of responsibility for decisions and their outcomes. The meta-modelling framework reinforces accountability by explicitly positioning AI as a decision-support tool rather than a decision-maker. This ensures that responsibility remains with human actors, who can exercise judgement, consider contextual factors, and address ethical implications. In this sense, the framework aligns with governance principles [23].

5.3 Planning Practice

Although AI may offer useful insights due to the ability to integrate data, recognize patterns, and simulate scenarios, the results need to be evaluated in the context of the overall goal of planning. This view affirms the role of planners as important decoders of analytical products. Planners will need to work more with data and models, and build the ability to interpret, analyze, and contextualize AI-generated outputs. This change has implications on professional practice, such as the requirement of interdisciplinary skills that integrate technical skills with spatial thinking and policy knowledge. The model also emphasizes that urban systems are influenced by the local conditions, cultural practices, governance structures, and socio-economic dynamics that cannot be entirely represented by data only. AI models work within the confines of input data and assumptions.

Incorporating AI into the planning practice helps to make more informed and proactive decisions. AI will be able to help planners predict upcoming challenges and see strategic opportunities. But this power must be construed as enhancing and not determining. Scenario simulations are a foundation of discussion and deliberation, not a point of prediction. Thus, the consequences of redefining AI as a meta-modelling framework go beyond methodological, governance and practical levels. The suggested strategy encourages integration, transparency and human-centred decision-making. An example is that, in a workflow of metropolitan planning, spatial data that is stored in GIS and configurational measurements such as accessibility can first be analysed using well-known methods, after which such outputs should be combined with socio-economic and environmental data using AI models to identify latent trends or simulate future scenarios. The planners then contrast these results with policy objectives and local conditions and demonstrate how AI can be an integrative layer to facilitate, but not supplant, planning judgement.

6 Discussion and Conclusions

This work can be added to existing discussions on the crossroads of urban planning and AI. The proposed perspective pre-empts integration, interpretability, and planning relevance, in opposition to the dominative approaches that focus on predictive performance and automation. The article fills an essential gap of Missing a coherent epistemological stance of AI in urban knowledge production. Practical implications of this framework can be seen in emerging applications, such as AI-assisted urban digital twins, combined GIS-AI workflows to analyse land-use and mobility, and mixed models combining configurational metrics with predictive analytics. These examples demonstrate that the meta-modelling approach can be applicable to real planning situations and retain interpretability and methodological consistency.

The contribution is topical in the context of growing dependence on data-driven methods of urban studies. Although AI has been able to enlarge the analytical powers, its implementation has been fragmented and lacked enough integration with the theoretical and normative basis of planning. The framework suggested in this paper provides a direction towards more methodological coherence. It moves the emphasis in the solitary technical optimisation to interpretive reasoning, which supports the claim that AI is an enabling, but not a determining aspect of urban analysis. Simultaneously, the research is limited to several weaknesses. To begin with, being a conceptual and review-based contribution, it lacks empirical confirmation of the suggested framework [24]. The arguments are based on a critical review of current literature, which might fail to reflect the fast-changing nature of AI applications in cities in a holistic manner. Second, the review is necessarily selective, concentrating on major traditions of analysis and representative use AIs, as opposed to an exhaustive overview of all current AI-related urban studies, which may further change the role of AI in other ways that are not fully covered in this paper.

Such limitations indicate significant avenues to future research. The next step required is empirical validation of the proposed meta-modelling framework by use of case studies. They may also investigate the impact of AI-mediated integration on decision-making, enhance interpretability, or optimize the results of planning. It further explains the significance of maintaining interpretability and logic of planning in the implementation of AI in urban analysis. Although computational models are strong instruments of complexity processing, its usefulness ultimately lies in its ability to elicit meaningful understanding and decision-making. The threat of excessive dependence on data-driven models points to the necessity of the methods that would strike a balance between computational efficiency and transparency and contextual sensitivity [25].

Finally, this paper suggests that AI can be reconceptualized as a meta-modelling infrastructure in the context of a larger urban analytical ecosystem. It helps AI serve as an integrative layer to improve data fusion, pattern recognition and scenario exploration. The proposed framework will enable more responsible and context-sensitive introduction of AI into urban research and practice due to its focus on augmentation over automation.

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