Review Article

From Functional Planning to Hybrid Approaches: Rethinking the Modelling of Complex Urban Dynamics

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Urban modelling has evolved since the 1950s, moving from classic, linear and deterministic models to systemic approaches capable of better understanding the complexity of territorial dynamics. While the first models helped to organise urban planning, they proved to be limited in the face of the unpredictability of social, economic and environmental interactions. The introduction of complexity theory paved the way for computational and multi-agent approaches, which are better suited to emerging phenomena.

In this context, structural equation modelling (PLS-SEM) has emerged as a key methodological tool, allowing latent variables to be integrated and complex causal relationships to be modelled. More recently, artificial intelligence, particularly Random Forest algorithms and their hybrid combinations with PLS-SEM, has enhanced the explanatory and predictive power of these models.

This review offers a chronological and critical overview of these developments, highlighting the contributions, limitations and prospects of current methods.

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I. Introduction

Urban modelling, as a set of methods and tools for creating digital, physical or conceptual representations of urban spaces by analysing their social, economic and environmental dynamics, has undergone a major transformation since the 1950s. The classical models, which predominated until the 1970s, conceptualised the city as a functional and hierarchical system, based on linear and deterministic approaches aimed at rationally organising urban space, infrastructure and mobility[1][2]. However, these

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models, such as those based on central place theory or concentric zone models, have shown their limitations in the face of the complexity of human behaviour and the unpredictability of urban dynamics.

From the 1980s onwards, complexity theory introduced a new perspective by defining the city as a dynamic, self-organising system characterised by non-linear interactions between multiple dimensions[3][4]. This evolution has fostered the development of systemic modelling, particularly through multi-agent approaches and computational simulation, which are better able to capture emerging phenomena such as residential segregation and differentiated mobility.

In this context, urban modelling now plays a strategic role in the analysis, understanding and management of urban systems, which are increasingly complex, dynamic and multifactorial. Traditional models, characterised by a deterministic approach, have certainly contributed to structuring urban planning and optimising infrastructure, but they remain insufficient to capture the multiplicity of social, economic, environmental and spatial interactions that characterise contemporary urban areas. Indeed, the diversity of human behaviour, emerging phenomena and the inherent unpredictability of urban systems require more flexible and integrative analytical tools.

The central issue is therefore twofold: how can urban modelling both accurately reflect the complexity of territorial phenomena and, through this exercise, stimulate methodological development to produce more refined knowledge and more robust predictive tools? More specifically, the aim is to examine the extent to which recent advances, such as the Partial Least Squares Structural Equation Modelling (PLS-SEM) approach and hybrid methods combining artificial intelligence and statistical modelling (notably Random Forest combined with PLS), offer a relevant response to these challenges, reconciling explanatory rigour, analytical flexibility and predictive power.

This issue is at the heart of current scientific debates in urban planning, land use planning and complex systems modelling, questioning the conditions for modelling that is theoretically sound, empirically robust and operationally useful to support decision-making processes in a rapidly changing urban context.

This methodological review is based on a narrative and chronological analysis of the specialised scientific literature, focusing on major developments in urban modelling from the 1950s to the present day. In order to identify the contributions, limitations and innovations of the different approaches, an exhaustive search was conducted in recognised French- and English-language databases (ScienceDirect, Web of Science, Scopus, HAL, Cairn).

The study was structured around three complementary areas. The first consisted of a critical analysis of classical and systemic models such as those of Forrester, Decazeville, Mobisim III and Signoret and Moine. This stage aimed to identify the theoretical foundations of these models, their contributions to urban planning and their limitations, in particular their inability to fully grasp the complexity and unpredictability of contemporary urban dynamics.

The second focus was on the positioning of the structural equation approach, particularly the PLS-SEM method, in the field of urban modelling. Through a careful examination of work applying this method to various urban themes (mobility, quality of life, health, logistics), this axis sought to demonstrate how PLS-SEM constitutes a pivotal methodological tool, capable of integrating latent variables that are difficult to observe directly and modelling multidimensional and complex phenomena.

Finally, the third area focused on recent contributions related to artificial intelligence, in particular Random Forest algorithms and their hybrid variants combining PLS-SEM and Random Forest (PLS-RF). This section analysed recent studies in urban planning and territorial management, as well as work from other disciplines such as forest ecology, in order to identify the opportunities and challenges associated with transposing these hybrid approaches to urban modelling. Taken together, these analyses have made it possible to place these methods within a coherent epistemological trajectory, ranging from traditional linear models to systemic approaches, including the innovative integration of machine learning techniques.

II. The city, an urban system

In the field of spatial planning, the systemic approach is defined by Houet et al.[5] as the set of spatio-temporal interactions between various constraints, including historical, economic, social, physical and material constraints. In addition, this approach encompasses all interactions that influence the functioning and configuration of the territory, as well as neighbouring territories, whether direct or indirect. The city is thus conceptualised as a complex spatial system that develops in a similar way to a living organism, according to the theory of urban metabolism. In the same vein, Signoret & Moine[6] propose a definition of territory as a complex system where interactions between actors and geographical space shape its dynamics. These territorial dynamics influence the planning process, which justifies the application of the systemic approach to the study of urban areas.

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1. From rational control to urban complexity

Between the 1950s and 1970s, modern urban planning was based on a conception of the city as a system that was generally controllable and predictable. This period corresponded to a phase of rapid urban expansion in the major industrial cities of North America and Europe, where urban planning became an essential tool for organising and rationalising land use, infrastructure and mobility.

The urban planning models developed at that time were largely based on deterministicand linear assumptions. The city was seen as a structured whole, where different urban functions (residential, industrial, commercial) could be spatially separated by functional zoning. This separation was intended to reduce conflicts of use and optimise transport networks and other infrastructure. Functional planning was hierarchical and based on rigid standards, translated into master plans aimed at organising urban growth in a predictable manner.

In terms of travel, cities such as Detroitand Chicagopioneered the development of quantitative models for predicting urban traffic flows. These models were based on mathematical and statistical principles, incorporating relationships between traffic volume, density and speed, such as the early formulations derived from Greenshields' law.

Greenshields' fundamental model (1934–1935) forms the historical basis for traffic modelling. It establishes a linear relationship between vehicle density and speed, making it possible to deduce traffic flow. The aim was to anticipate road infrastructure needs and manage traffic based on rational assumptions. This macroeconomic modelling of travel assumes that user behaviour can be represented by deterministic functions, reflecting a complete theoretical understanding of the urban system.

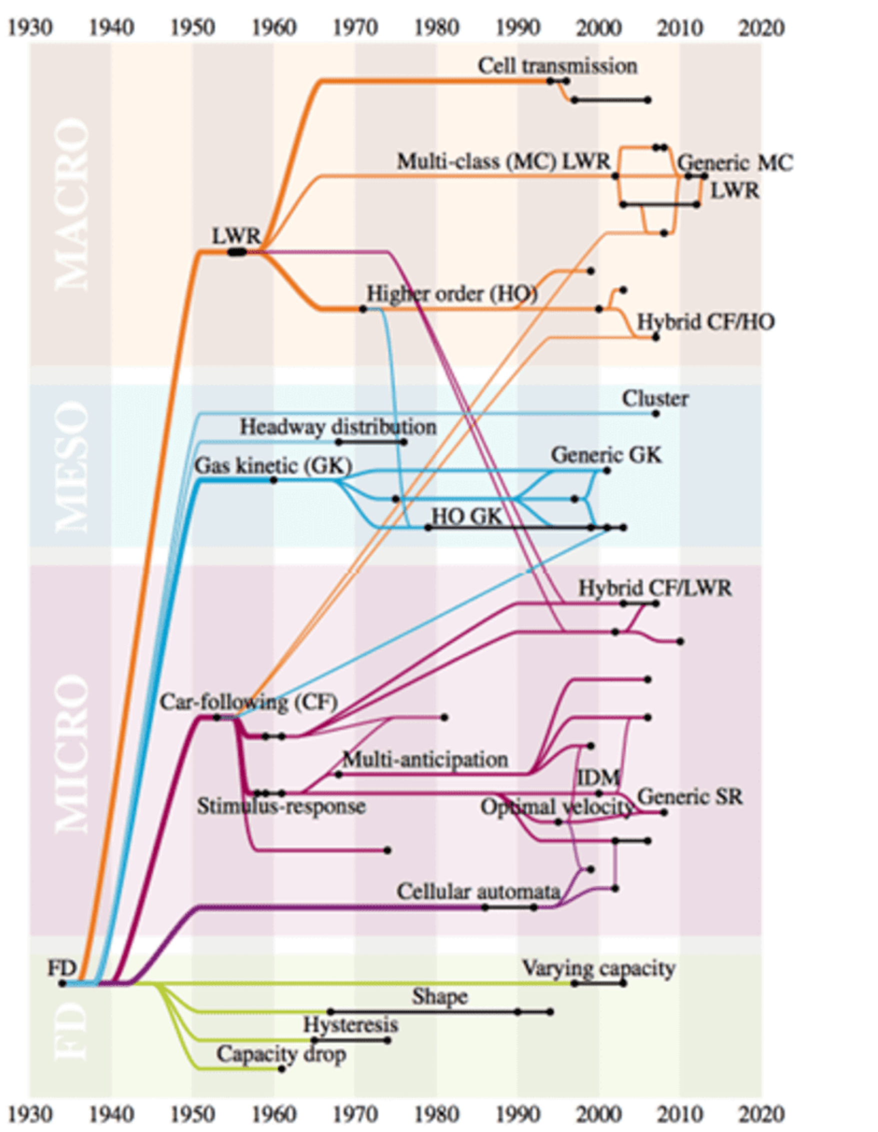

Figure 1. Genealogy of traffic flow models.

Source: Transportation Research Circular, 2015.

However, these approaches had significant limitations. The focus on functional planning and mechanical flows in the city masked the social complexity and dynamic interactions between residents, their choices and underlying economic changes. As Carriou & Ratouis[7] and Debizet[8] pointed out, these linear models did not take sufficient account of social interdependencies, cultural factors, or the uncertainties inherent in real urban systems. They therefore led to developments that were sometimes rigid and ill-suited to unforeseen changes and the diverse needs of urban populations.

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2. The emergence of systemic modelling in the 1960s-80s

Against this backdrop of questioning traditional approaches, the 1960s to 1980s marked a major turning point with the emergence of the systemic approachto urban modelling. This new perspective, inspired by advances in cybernetics, systems theory and social sciences, proposed viewing the city not as a fixed and isolated system, but as a dynamic and interactive set of interdependent elements. Systemic modelling thus integrates the complex interactions between the physical, social, economic and environmental components of the city, offering a more adaptable and realistic framework for understanding its intrinsic complexity.

The systemic approach to the city only really began to be discussed in the 1970s with the models developed by Forrester, Mobisin and, later, Signoret & Moine. We attempt to understand how these models work, as well as the evolution of methodological thinking about the city as a system.

2.1. Forrester'sdynamic model

Jay Forrester designed a dynamic behavioural model of an urban area, aimed at examining the long-term evolution of large cities and analysing the repercussions of political decisions[9]. This model, inspired by natural biodiversity, represents the feedback loops in urban development. It consists of three subsystems: industry, housing and population, each of which is subdivided into classes. The population subsystem is segmented into social classes, determined by the natural growth rate. The industry and housing subsystems are divided into separate units.

In reality, the relationships between these auxiliary variables are determined by linear flows. The urban area is formed by complex and evolving interactions between different population classes, the housing occupied by these populations, and the industries that provide jobs.

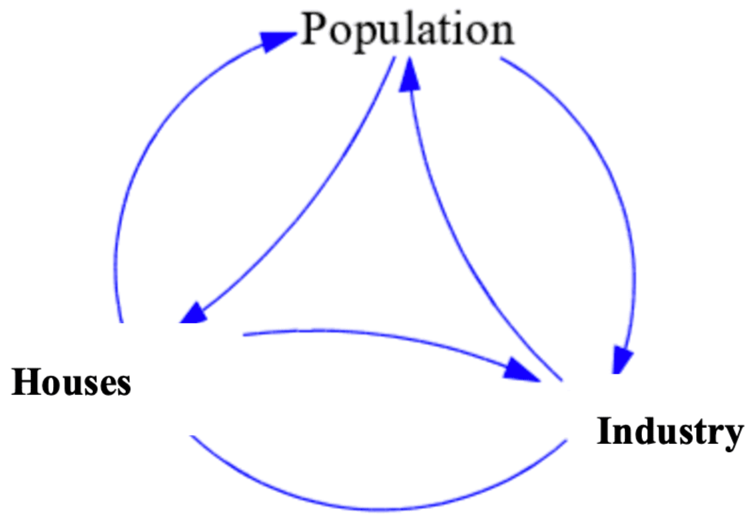

Figure 2. Forrester's dynamic model of the urban area.

Source: [10]

However, these urban interactions maintain linear relationships with their external environment, which do not significantly affect the urban area. Consequently, this model has been criticised because it assumes that the urban area is fixed and limited, failing to take urban expansion into account. This limitation makes the model unsuitable for American cities, leading other researchers to modify it to better adapt to different urban contexts.

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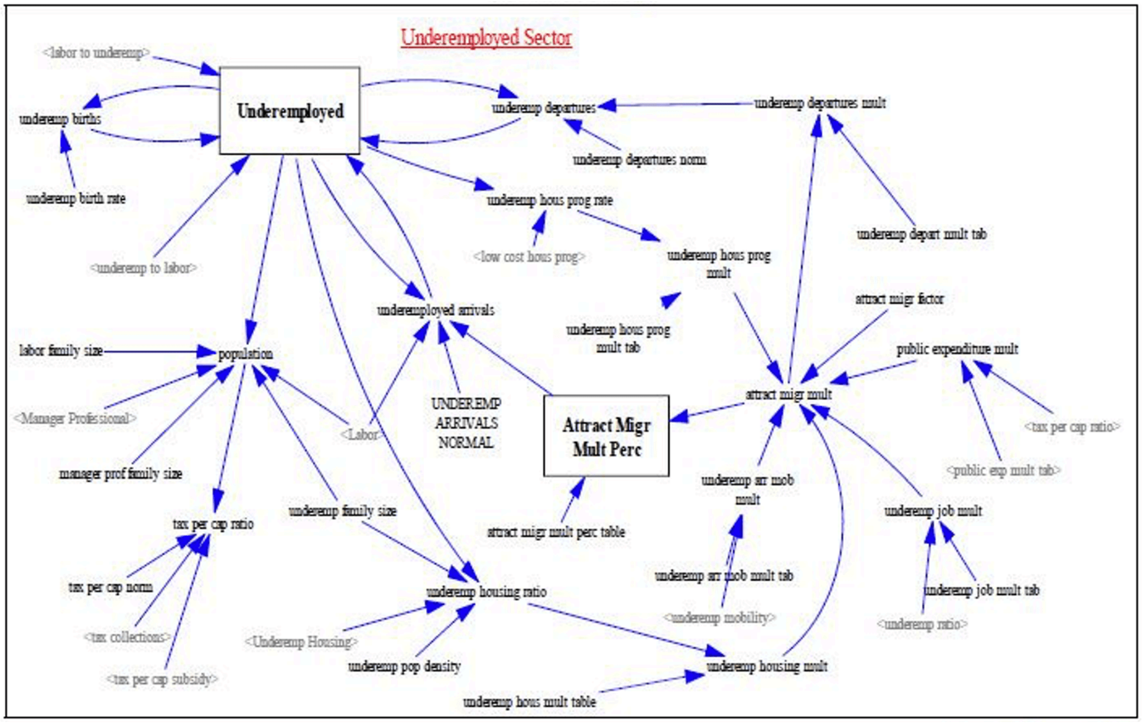

Figure 3. The unemployment sector in Forrester's model.

Source: [10]

2.2. The Decazeville model

The Forrester model needs to be adapted to the French context, as it assumes that urban growth is constrained by natural limits. However, this assumption does not correspond to the reality of French cities, which often develop by exploiting natural resources, as in the example of Decazeville, whose development is closely linked to coal mining[9]. Furthermore, this model considers the urban environment in a broader sense than the simple natural boundaries of American cities, including geographical and economic conditions conducive to urban expansion.

In this model, housing is essentially approached from an economic perspective, in contrast to Forrester's model, where housing is intrinsically linked to migratory movements. This difference highlights the focus of the Decazeville model on the economic and social aspects of the study, neglecting the importance of the spatial factor in urban growth.

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2.3. The Mobisim III model

In France, understanding urban areas as complex systems continues with the development of the Mobisim III model, designed by ATN (Application de Techniques Nouvelles). This model has emerged in response to the growing need to develop urban mobility.

The Mobisim III model aims to integrate the policies and developments that influence mobility, synthesised by urban, demographic and social factors. Its main advantage over other existing models is that it takes into account the interactions between the transport system and urbanisation[9]. It thusconsists of six subsystems:

- Travel.
- Transport.
- Employment/Business.
- Stakeholders.
- Environment.
- Population/Housing.

The complex phenomenon of urban mobility has been carefully taken into account, highlighting the relationships between the various actors that influence the transport system. Causal links have been established between the State, local authorities, public and private transport operators, and households. Despite the consistency and functionality of the Mobisin model, it has limitations, particularly with regard to the use of macroscopic relationships that limit the impact of the individual behaviour mechanisms of the actors.

2.4. The Signoret and Moine model

As urbanisation has evolved and needs have changed, adaptations have been made to the way urban environments are modelled. With this in mind, the model designed by Signoret and Moine considers the city as a dynamic and self-regulating system, which provides a more fluid view of the evolution of the territory and an understanding of its mechanisms. It is important to emphasise that territorialisation does not function as a closed circuit where the territory is simply made up of multi-agent entities. On the contrary, it shapes a collective territory where tensions and conflicts often arise, requiring the establishment of a system of governance. This system is based on detailed interactions between the various actors as well as a set of evaluation criteria, including

- The variety of elements considered, both in terms of their nature and their distribution in space and time.
- The distinction between approvals based on individuals or groups.
- The possibility of carrying out projects while taking into account their social impact and the compatibility between collective and individual interactions.
- The relevance of the measures taken and their compliance with development criteria

Despite their varied contexts and objectives, dynamic urban models such as those of Forrester, Decazeville, Mobisim III, and Signoret and Moine share a common conceptual basis: the representation of the city as a system made up of multiple interdependent subsystems that evolve in interaction with one another. These approaches integrate the complexity of urban dynamics by articulating feedback loops and social, economic and spatial processes, thus offering a holistic view of urban evolution. However, these models have certain limitations. Their spatial representation is sometimes too fixed and ill-suited to the realities of continuous urban expansion. Furthermore, many of them are based on linear or macroscopic relationships, underestimating individual mechanisms and the diversity of actors' behaviours. Finally, they often struggle to fully integrate the political, conflictual and governance dimensions that characterise the contemporary city. These limitations call for more flexible and integrative methodological approaches that can capture the multiple facets of urban complexity.

3. The revolution in complex systems and multi-agent modelling

Since the 1980s and 1990s, complexity theory has profoundly transformed urban modelling by introducing a new perspective on cities as complex, self-organising and inherently unpredictable systems[1][4]. This systemic approach recognises the chaotic dynamics and non-linear interactions between a multitude of urban agents — residents, businesses, institutions, services — whose individual and collective behaviours give rise to emerging phenomena such as gentrification, segregation and changing mobility patterns. The multi-agent models brought about by this evolution now make it possible to simulate these differentiated behaviours in detail, taking into account both local micro-dynamics and global macro-effects[11][12]. This epistemological change marks a clear break with traditional approaches, which are often linear and aggregated, paving the way for a better understanding of contemporary urban complexities and more flexible and realistic modelling tools, adapted to the current challenges of urban planning and governance[3].

This awareness has laid the foundations for innovative methods, in particular the adoption of analytical techniques capable of simultaneously processing multidimensional latent variables and complex causal relationships, such as the SEM-PLS approach, which fits perfectly into this renewed systemic paradigm[13][14].

3.1. Structural equation methods: a tool for the systemic approach

Conceptualising structural equation models

The representation of systems is the essential element of the systemic approach[15]. It aims to make complex phenomena easier to understand by examining their internal dynamics, as do the structural equation methods developed by Jôreskog[16] and Wiley et al[17] to synthesise a wide range of techniques for modelling complex theoretical models[18].

In other words, this modelling tool is based on interconnected complex systems, used to validate pre-established theories and to detect data patterns and relationships[14].

With this in mind, these models aim to examine the existence of causal links between different variables and to verify the relevance and consistency of a theoretical model[19]. These equations represent a system of interdependence that allows for the analysis of latent variables (concepts), which are not directly observable but can be understood indirectly through other variables, called manifest variables[20].

To represent these models, a standard diagram comprising various symbols is used:

- Ellipses symbolise latent variables, i.e. concepts that cannot be directly observed.
- Rectangles represent manifest variables, which contain raw data and can be measured directly.
- Arrows denote the relationships between latent and manifest variables.

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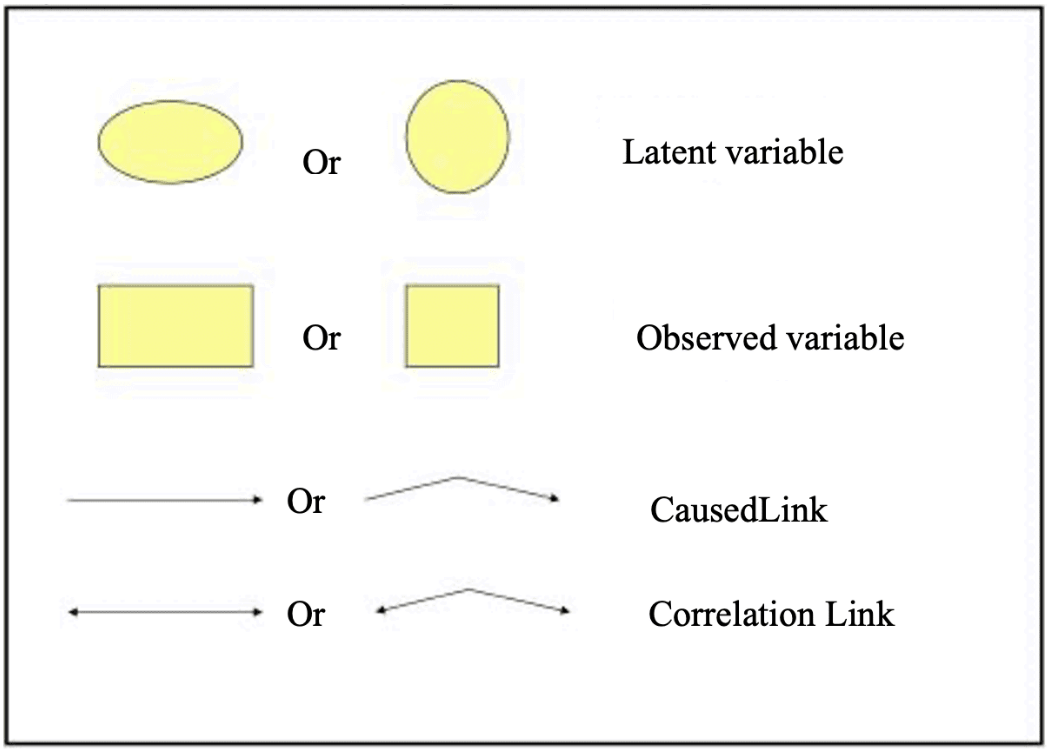

Figure 4. The conventional graph in structural equation models

Source: [21]

These models follow a deductive logical approach, comprising several stages:

- The theoretical design of the model, involving the conceptualisation of the relationships between variables.
- Estimation of the model parameters using a specific algorithm.
- Evaluation of the model using various indicators to verify its validity.
- Adjustment of the model based on the data collected and the performance indicators identified.

This method is composed of two main components: the measurement model and the structural model. According to Hair et al.[22], the measurement model (also called the outer model) specifies the relationships between the latent constructs and their observed indicators. It focuses on assessing the reliability and validity of the constructs, ensuring that the indicators accurately capture the theoretical concepts they are intended to measure[23].

. In contrast, the structural model (also called the inner model) represents the relationships among the latent constructs themselves. It tests the hypothesized causal links and allows researchers to evaluate the

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explanatory power and predictive relevance of the proposed theoretical framework. Together, the measurement and structural models form the basis of structural equation modeling (SEM), offering a comprehensive approach to both validating measurement instruments and testing theoretical relationship.

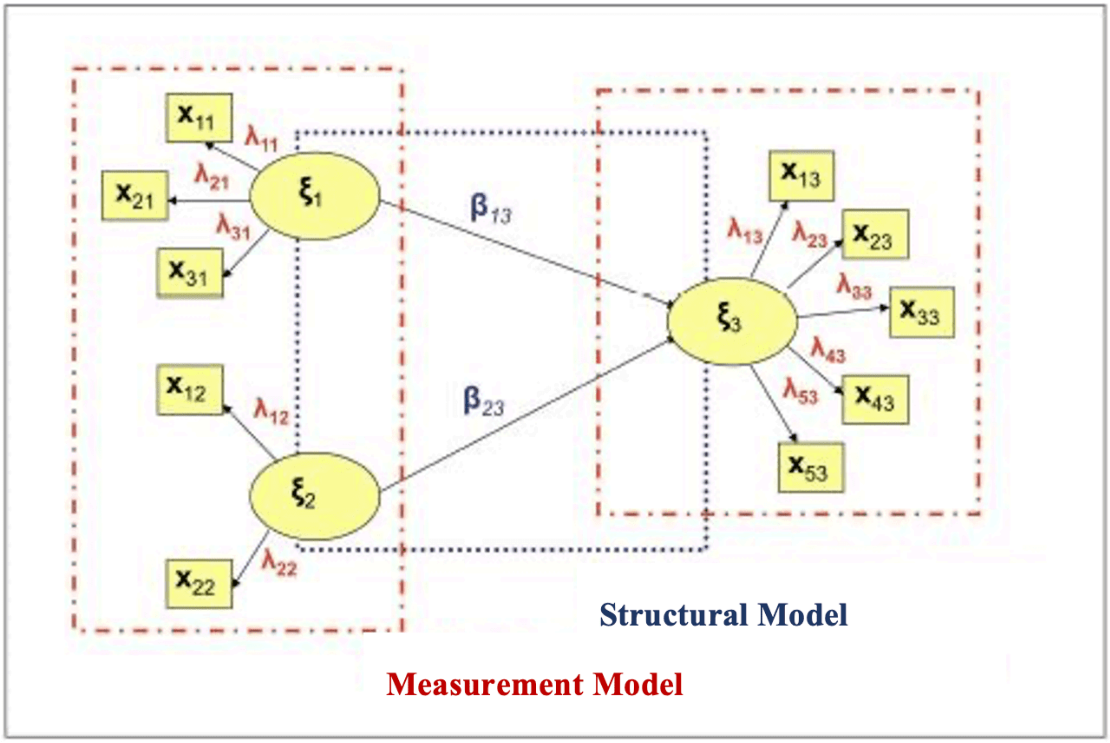

Figure 5. Representation of a structural equation model

Source: [21]

The measurement model or external model

The structural equation model provides a graphical representation of the links between observed and latent variables. It comprises three distinct types of models:

- The reflexive model: Each observed variable is considered a reflection of its corresponding latent variable. The arrows go from the latent variables to the observed variables, indicating that the constructs cause the measurements, thus leading to covariances between these variables.
- The formative model: In this case, the latent variable is determined by its observed variables. This is manifested by a linear function of the observed variables, accompanied by a residual error term.

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- The mixed model: Some observed variables follow the reflexive model, while others are related to the latent variable according to the formative model.

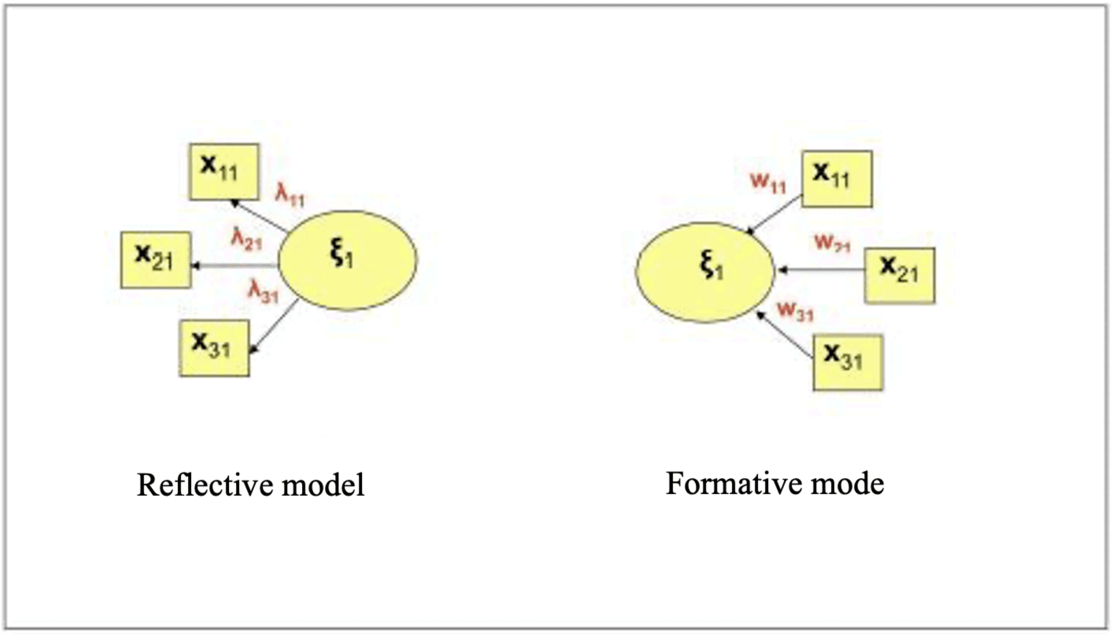

Figure 6. The different types of measurement models

Source: [21]

- **The structural model or internal model**

This analyses the relationship between latent variables. The parameters to be estimated are the regression coefficients that link the variables.

Approaches to estimating structural equation models

There are two types of structural equation methods:

- Covariance-based modelling (CB-SEM),
- Partial least squares modelling (PLS-SEM), also known as PLS path modelling

The CB-SEM (Covariance-Based Structural Equation Modelling) technique in the LISREL approach is based on covariance analysis. Its main objective is to empirically test the relationships between variables in order to verify the validity of the proposed theories. It seeks to reduce the differences between the covariances observed in a sample and those predicted by the theoretical model. This method is based on the assumption that the variables follow a multinormal distribution, which allows it to use maximisation algorithms to adjust the model. It is essential that all variables be continuous or interval and normally distributed to ensure the effectiveness of this approach[24].

The PLS method, or Partial Least Squares, is based on maximising the explanatory power of indicators by focusing on variance. It uses a specific algorithm, PLS, for this optimisation, which avoids problems of inadmissible solutions and indeterminacy[19]. This approach takes into account multi-normality conditions to ensure the effectiveness of optimisation algorithms, requiring all variables to be continuous or interval and normally distributed[24].

In all circumstances, the PLS approach remains the most widespread, distinguished by its essentially exploratory nature. This method does not presuppose any specific distribution of variables, which gives it great flexibility in handling large data sets. In any case, the PLS approach is the most widely used. It is a primarily exploratory method, as it makes no assumptions about the distribution of variables and develops a very flexible technique for handling huge data sets[21].

The PLS approach to structural equation modelling: between presentation and implementation

The Partial Least Squares Structural Equation Modelling (PLS-SEM) approach is a flexible and exploratory method, but can also be used in a confirmatory manner[14]. Unlike traditional methods, it does not presuppose a normal distribution of data, which makes it particularly suitable for modelling complex phenomena with latent variables[24]. Its objective is to maximise the explained variance of latent variables by estimating their scores through iterative regressions between latent and manifest variables[13].

The method is recommended for building evolutionary models, managing complex models with many variables, and large data sets[14].

Two key effects can be examined with PLS-SEM: mediation, which analyses the influence of an intermediate variable in the relationship between an explanatory variable and a dependent variable[25] [14], and moderation, which explores the effect of a third variable modulating the intensity or direction of a relationship[14].

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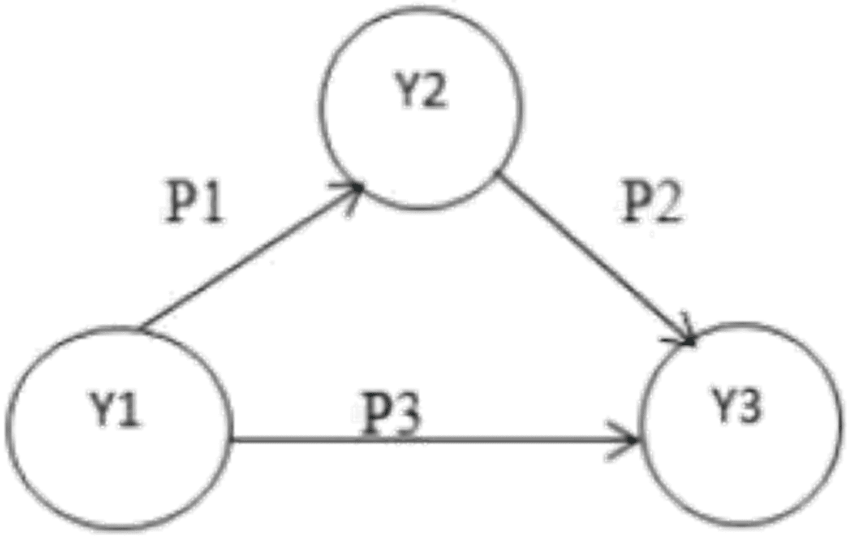

Figure 7. The general model of mediation

Source: [14]

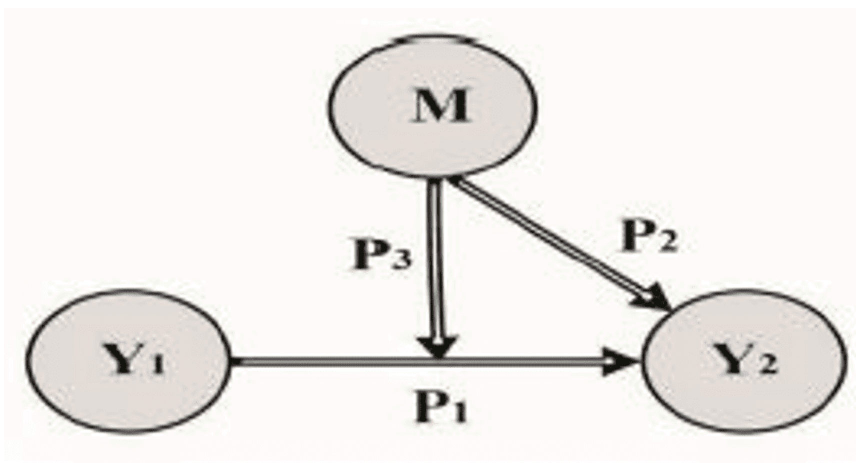

Figure 8. The general model of moderation

Source: [14]

Implementation follows an iterative procedure of estimating latent variables via the measurement model (convergent and discriminant validity) and then the structural model (regression coefficients, relevance indicators such as R^2 and f^2)[14][26]. Convergent validity ensures the consistency of the indicators measuring a construct, while discriminant validity verifies the uniqueness of the constructs in the overall model[14].

3.2. Urban systemic modelling: the contribution of PLS-SEM structural equations

Structural equation models, particularly the PLS-SEM method, are increasingly used to analyse the complexity of urban phenomena by integrating quantitative data from field surveys and latent variables that are not directly observable. For example, a recent study conducted in Babol, Iran, used SmartPLS to assess urban liveability from the perspective of older people[27]. This descriptive-analytical study identified urban health as the major driving factor influencing quality of life, highlighting the crucial role of infrastructure and services adapted to this vulnerable population. The integration of social, environmental and health dimensions provided a detailed model of the levers for improving quality of life in a complex urban context.

Complementarily, traffic noise modelling in Shah Alam, Malaysia, highlighted the complex interaction of environmental, climatic and traffic flow variables contributing to urban noise pollution[28]. PLS-SEM made it possible to disentangle the direct and indirect effects between these components, thus providing a precise analytical tool for urban planning focused on reducing noise pollution.

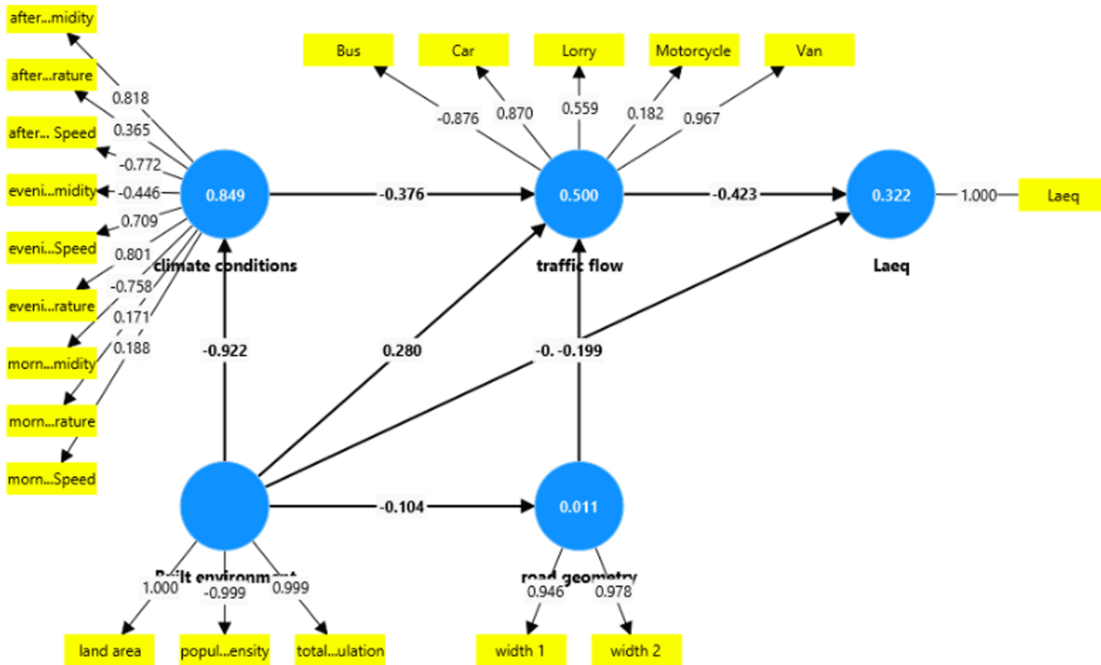

Figure 9. The final model of urban traffic noise estimated using the PLS approach

Source: [28].

Furthermore, Moufad's thesis[29] on urban freight transport logistics used PLS structural modelling to quantify the impact of delivery areas on traffic flow. The study demonstrated that optimising logistics flow management contributes significantly to reducing journey times and improving urban mobility, which are essential factors in high-density cities.

These examples illustrate the power of PLS-SEM in the field of urban planning, allowing for the simultaneous understanding of several dimensions social, economic, environmental and their complex interactions, while addressing challenges related to quality of life, public health, and urban management. They are thus part of a systemic approach, where modelling contributes to more informed decision-making that is adapted to contemporary urban realities.

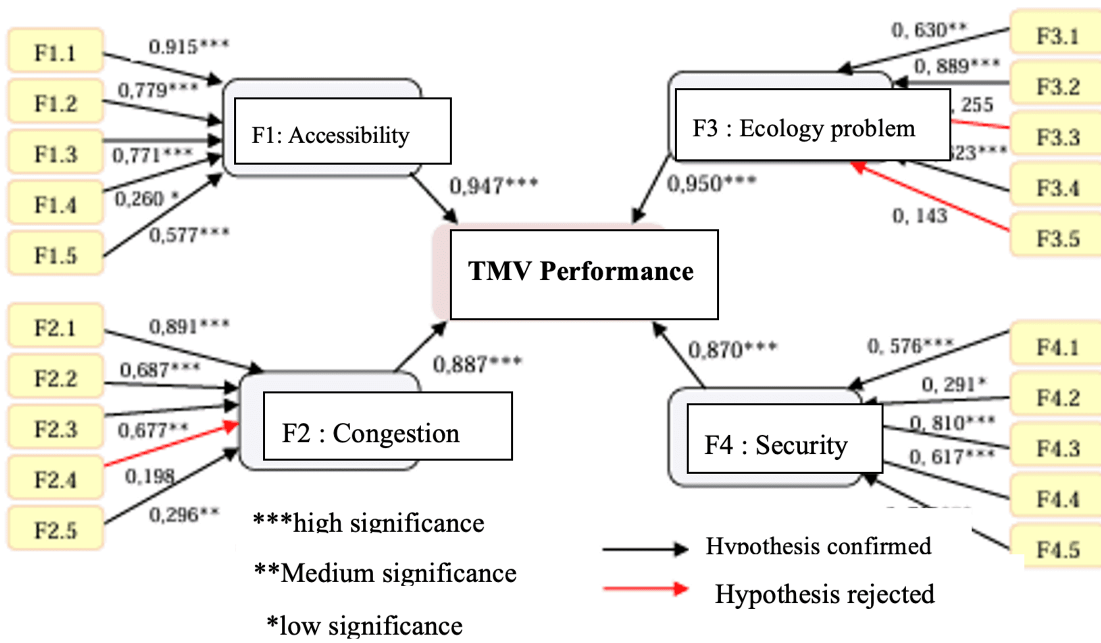

Figure 10. The final urban transport logistics model estimated using the PLS approach

Source: [29].

4. From linear modelling to machine learning: revolutionising our understanding of urban dynamics

Although PLS-SEM structural equation modelling is a powerful tool for analysing the complex relationships between latent variables in urban systems, it remains fundamentally a linear method. This characteristic limits its effectiveness in fully capturing the non-linear dynamics, complex interactions and heterogeneities specific to real urban environments[30][14]. Furthermore, PLS models require high data quality and can be sensitive to low factor loadings or poorly specified structures, which may limit their applicability in urban contexts with noisy or unstructured data[30].

Faced with these limitations, artificial intelligence (AI), with its capabilities for machine learning and unsupervised analysis, represents a major step forward in overcoming these constraints. AI techniques, such as random forests, neural networks, and ensemble methods, make it possible to directly model complex non-linear relationships, efficiently manage large and heterogeneous data sets, and identify patterns that are not explicit in traditional approaches[31][32]. These algorithms, combined with classical statistical methods such as PLS-SEM, offer a hybrid solution capable of combining the robust predictive power of AI with the interpretability and causal rigour of structural equations.

From this perspective, urban modelling is becoming more sophisticated, enabling a more detailed analysis of multifactorial urban phenomena while improving the quality of predictions and data-driven decision-making[33]. This methodological convergence opens up new avenues for a deeper understanding and innovative management of the complex contemporary challenges facing cities.

4.1. Urban modelling: towards a hybrid approach combining PLS and Random Forest

Recently, researchers have proposed hybrid approaches combining the robustness and interpretability of PLS with the non-linear and adaptive capacity of Random Forest. The method known as PLS-RFR (Partial Least Squares Random Forest Regression), developed in particular by Hao et al.[31], is a good illustration of this innovation. This method incorporates a concept known as "Partial Model Tree" (PMT), which combines local modelling using PLS regression in each leaf of a decision tree.

In concrete terms, rather than calculating an average of the values in a leaf as in the classic Random Forest, the PMT adjusts a local linear PLS model to the specific data in the leaf. The model is thus constructed based on a series of trees whose leaves contain local linear segments each derived from PLS modelling adapted to the restricted data set and the set aggregates these predictions. This approach retains the advantages of PLS (multicollinearity management, interpretative capabilities) while exploiting the adaptive power of trees to model non-linearity and spatial or structural complexity.

Experimental tests carried out on various data sets (traditional pharmacology, UCI Machine Learning Repository) show that PLS-RFR significantly improves predictive quality (higher R^2, reduced errors) compared to conventional PLS methods, multiple linear regression and Random Forest alone. This highlights the value of this method in fields where models must incorporate non-linear phenomena while maintaining a certain degree of interpretability.

4.1.1. Application in forest ecology: modelling tree decline

This methodological combination has been effective in complex environmental studies, such as modelling forest decline in the Zagros region of Iran[34]. The authors simultaneously used structural equation modelling (SEM), which shares certain affinities with PLS in terms of latent relationships, and a Random Forest method to analyse the combined influence of biotic (species richness) and abiotic (soil properties, topography, climate) factors on the intensity of decline.

SEM modelling made it possible to precisely quantify the direct and indirect relationships between these variables, with a very satisfactory statistical fit (model quality index > 0.94). On the other hand, Random

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Forest enabled accurate spatial mapping of the phenomenon[35]. Combining the two approaches makes it possible to take advantage of both structuralist modelling and non-linear predictive capabilities, paving the way for hybrid approaches in environmental and urban modelling.

However, it is important to note that this hybrid approach remains largely unexplored in the field of urban research. Existing work mainly concerns rural or forestry contexts, such as the modelling of forestry or agricultural attributes, and has not yet been applied to the prioritisation of urban infrastructure, spatial planning or smart city planning. This opens up unprecedented research potential for transposing this hybrid methodology to complex urban issues, where interactions between socio-economic, environmental and spatial variables are highly non-linear and multidimensional.

4.1.2. Random Forest in urban and territorial studies: applications and contributions

Although research applying a hybrid PLSR-RF approach in the urban field remains rare, it is important to note that urban studies using Random Forest alone are already numerous and successful, as shown by Maulindar and Guterres[36] for infrastructure prioritisation and Li et al.[37] for ecological, agricultural and urban assessment.

Infrastructure modelling

Maulindar and Guterres[36] applied RF to determine infrastructure priorities in smart cities. Their study, covering 50 regions, shows that the model achieves 90% accuracy on the test set and 88% on validation, despite a limited sample size. The most decisive variables for prioritising infrastructure are traffic, infrastructure availability and drinking water needs. This approach supports data-driven decisions and optimises urban infrastructure management. The authors suggest the future integration of real-time data from the IoT and comparisons with other algorithms to enhance planning capabilities.

Ecological, agricultural and urban analysis

Li et al.[37] used RF to assess ecological, agricultural and urban suitability in the Yulin region (China). The RF models achieved accuracies of 93% for ecology, 90% for agriculture and 92% for urban planning. The approach allows for automatic weighting of factors, avoiding subjective bias, and provides a solid scientific basis for sustainable land use planning. The study highlights the importance of water management, agricultural adaptation to local conditions, and social services in urban planning.

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III. Conclusion

Firstly, it should be remembered that urban modelling has long been based on linear and deterministic approaches, which have made it possible to structure urban planning and anticipate developments using simple, predictive models. Despite their fundamental importance, these linear models have proven insufficient for understanding the complexity and diversity of social, economic, and environmental interactions specific to contemporary urban systems.

Faced with these limitations, urban modelling has gradually evolved towards systemic approaches, notably thanks to PLS-SEM structural equation methods, which offer the ability to represent latent variables and complex causal relationships. More recently, the emergence of artificial intelligence techniques, in particular Random Forest algorithms and their hybrid combinations with PLS-SEM, has enhanced the explanatory and predictive power of modelling tools by integrating non-linear dynamics and massive, heterogeneous data.

This convergence between traditional statistical methods and artificial intelligence opens up promising new perspectives for research and practice in urban planning. It allows for the development of more robust, flexible models that are better suited to the complexity of today's urban systems, while supporting more informed and sustainable decision-making. However, the implementation and validation of these hybrid models remain largely unexplored in the urban context, calling for future work to fully exploit their potential.

Urban modelling is therefore part of a process of continuous innovation, which is essential for responding to the multidimensional challenges of contemporary territories and for effectively supporting urban development policies towards more inclusive, sustainable and resilient objectives.

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