DECIDE: An outcome-driven decision support system for urban-regional planning

Diego Altafini[1[0000-0002-6559-2372]*], Camilla Pezzica[1[0000-0002-0512-7591]], Clarice Bleil de Souza[1[0000-0001-7823-1202]], Andrei Gagarin[2[0000-0001-9749-9706]], Ges Rosenberg[3 [0000-0003-3527-9841]] Sam Gunner[4 [0000-0002-2467-6385]], Theo Tryfonas[4 [0000-0003-4024-8003]]

[1] Welsh School of Architecture - Cardiff University, Bute Building, King Edwrad VII Avenue, CF10 3NB, Wales, UK
[2] Cardiff University School of Mathematics – Cardiff University, Abacws, Room 4.56, Senghennydd Road, CF24 4AG, Wales, UK
[3] School of Electrical, Electronic and Mechanical Engineering – University of Bristol, Queen's Building, University Walk, BS8 1TR, Bristol, UK
[4] School of Civil, Aerospace and Design Engineering – University of Bristol, Faculty of Engineering, Queen‘s Building, University Walk, Bristol, UK
*correponding author: altafinid@cardiff.ac.uk

Abstract
This position paper argues that outcome-driven Decision Support Systems (DSS) are more appropriate than current data-driven approaches to integrate Multi-Domain Models (MDMs) in the context of sustainable urban-regional planning. This is because, for urban planning, DSS needs to provide fit-for-purpose answers to problems faced by practitioners when managing and designing city features. In fact, planners must cater for imagined scenarios, assessing viable solutions with regards to how they change in accordance with ever-changing constrains, to be able to improve cities towards becoming sustainable and resilient. The authors frame urban-regional planning as a design activity in which complex and interwoven requirements from multiple stakeholders need to be addressed by decisions involving multidomain knowledge. To this end, the paper highlights main characteristics of design activities, and then compares and contrasts data-driven strategies with outcome-driven strategies. This promotes the development of an outcome-driven DSS that better aligns with the needs of planners working with urban-regional development towards enhancing urban livability and addressing territorial inequalities. It then frames the role of data-driven strategies within outcome-driven DSS, showing how the DECIDE project embraces the creation of an outcome-driven DSS with punctual data-driven strategies.

Keywords: Decision Support Systems, Urban planning, Sustainable Cities, Digital twins.

1 Introduction

The demands for efficient Decision Support Systems (DSS) based on Multi-domain Models (MDMs) and tailored for urban planning and analysis have attracted significant attention from both academic and stakeholder communities, given the increasing complexity involved on the prospects provided by smart-cities and their frameworks [1]. Building-up those multi-domain systems have become important in the current, and to future-proof, urban planning as a discipline, since improving the efficiency of management and decision-making processes requires considering the many possible outcomes associated with urban phenomena.

However, due to limitations in computational processes and data retrieval methods, urban simulations and models tend to become restricted to closed Geographical information System (GIS) based environments, tailored to single aspects of analysis; or layering variables such as in the recent 15 minute and X-minute city approaches [2]. When open, GIS-based environments have a more collaborative "information atlas" nature [3]. In both cases, conceived DSS tend to be non-modular, and have data-driven approaches where infrastructural, environmental, and socio-economic data coexist, but without establishing proper relations that are useful for decision-makers.

Networking databases and models into actual instruments to operational research continues to be, as mentioned in [4, 5, 6], the historical issue in developing DSS for urban planning. Moreover, upgrading these systems so that they become effective instruments to aid decision-making in urban planning, means they need to provide fit-for-purpose answers to problems faced by practitioners when managing and designing city features. Thus, an efficient DSS must cater for imagined scenarios of different types, and enable decision-makers to assess solutions for these scenarios with regards to how they change, to improve cities towards becoming sustainable and resilient.

Scenario simulation and experimenting with imaginary futures are core activities in design [7]. This relates to the idea of conceiving DSS for urban planning as design tools. DSS tools that enable scenarios can thus be assessed with regards to their suitability to the different requirements imposed by different urban stakeholders, set together with parameters of livability, environmental sustainability, and disaster risk reduction.

This proposition is far more challenging than simply using existing DSS set within GIS, such as multi-criteria evaluation and multi-objective evaluation systems [8]. It implies understanding the needs and aspirations of different stakeholders involved in urban planning to develop fit-for-purpose models, analysis processes, and courses of actions, to better meet their needs. It also implies understanding that the implementation of solutions at the urban scale is slow and tends to happen in constantly changing environments. This means that these scenarios need to accommodate for change and uncertainty in terms of the outcomes they are expected to bring, as well as the risks on not fulfilling the requirements they were originally supposed to achieve.

The first set of implications suggests framing urban-regional planning as a design activity, in which complex and interwoven requirements and constraints from multiple stakeholders need to be addressed by decisions involving multidomain knowledge. It highlights that DSS should be outcome-driven. The second set of implications suggests constant change cannot be ignored, meaning feedback loops between proposals, implementation, and management, need to be established to ensure solutions are fit-for-purpose, resilient and sustainable.

This paper proposes the fundamentals for an outcome-driven DSS for sustainable urban-regional planning based on the integration of models from multiple domains. The premise behind developing an outcome-driven DSS for urban-regional planning is understanding planning as mainly a design activity. The paper also frames the role of data-driven strategies within outcome-driven DSS, showing how the DECIDE project embraces the creation of an outcome-driven DSS with punctual data-driven strategies.

Section 2 defines what are the main characteristics of design activities that call for an outcome-driven approach to DSS. Section 3 then contrasts and discusses the main characteristics of data-driven strategies in relation to the main characteristics of outcome-driven strategies, arguing that urban planning DSS should be mainly outcome-driven. Section 4 explores the issue of assessing design solutions or suitability of outcomes to fulfill stakeholders needs in a constantly changing environment, promoting the role of data-driven strategies within an outcome-driven DSS. Finally, section 5 introduces the DECIDE project and its research design, proposing it as an example of how to conceptualize an outcome-driven DSS with embedded data-driven strategies.

2 Main characteristics of design activities

Design assumes a pivotal role in the planning and making of built-environments, as practitioners must formulate cohesive spatial configurations and programmes that encompass considerations such as land-use, transportation networks, agents' behaviours, plus economic and environmental sustainability [9]. In this regard, urban-regional planning aligns with the essence of design choices, where a parallel can be drawn between the intentional organisation and coordination of diverse elements within a specific geographical area, and the strategic decisions inherent to design. This underscores urban-regional planning as an inherently design-oriented activity.

In *The Principles of Design* Suh [10] highlights that the key characteristic of design activities is that they are driven by design requirements and constraints. Therefore, decisions undertaken throughout the design process need to transform what a situation is into what a situation needs to be to fulfill them. To this end, design decisions are mainly outcome-driven; they are fit-for-purpose to fulfil a set of prescribed outcomes.

However, to propose design solutions, designers must understand the needs of all stakeholders as well as the constraints on what can be achieved [10], and the problem to be addressed. Since design problems tend to be complex and involve multi-domain knowledge, designers tend to better understand the problem while trying to solve it [7, 11], evaluating how well proposed solutions suit the problem at hand. Solutions designed to fulfill requirements and constraints need to be considered with regards to how well they respond to these requirements and constraints, in an iterative, evidence-based, and testable way [10].

To this end, solving design problems combines strategies used to make decisions towards achieving desired solutions with strategies used to test the quality of the solutions implemented. Particularly, "decisions are balanced to achieve overarching project targets, negotiated among project team members, propagated into the information flow of the design process, and subsequently revised as the project develops" [12]. Therefore, design problems: (i) have briefs, with information related to requirements and constraints; and (ii) use multi-domain decision support methods and information management systems, as well as project control methods, to ensure desired outcomes are achieved in a satisfactory manner [13]. In a changing environment, these characteristics call for the potential use of data-driven strategies to be punctually implemented in a fit-for-purpose way throughout the design process towards controlling, testing, and feeding back solutions.

3 The data-driven paradigm

In the past decade, data-driven strategies for decision-making became increasingly sought by both practitioners and researchers. This open pursuit for deeper problem understanding resulted in the creation of a myriad of 'predictive models' with questionable usefulness, and potentially issues related to biased samples, weak and flawed correlations, and pernicious feedback loops [14]. The data-driven approach can be interpreted as a close follow to economics' Game Theory, which proposed the alluring idea of searching for comprehensive information from widely available data to enable 'optimal' decisions to be made, towards fulfilling the most efficient business or policy outcome [15, 16]. This approach to decision-making adopts a rather *Marshallian* [17] paradigm, focused on an asymptote approach towards the optimal (considering all other things equal), which in the economic jargon is known as a *"point of equilibrium"* [18].

In urban analysis, such data-driven approaches have become the norm, especially after the development and popularization of smart cities [19] and, later, X-minute City [20] concepts, which require extensive datasets and right proxies to gauge how urban dynamics and city life occur. This approach can be seen as rather deterministic, reinforcing pre-existing beliefs and conditions with poor capacity to enable transformative change towards promoting new designs that ensure diversity and fairness [14]. Data-driven approaches can provide multiple outcomes. However, this does not mean that they are necessarily fit for purpose, as those are data-dependent (Table 1). This makes them suitable for grounded problem diagnosis and prediction, as they unfold patterns in events to define achievable outcomes based on available data. Still, since patterns are grounded on available data, they often provide knowledge, and recommendations that only work within the context of a specific problem [21]. This means that data-driven models are mostly not transferable, nor general. Therefore, they require domain expert knowledge to be validated and useful [22] and inform decision makers on achieving desirable outcomes.

Since data-driven models are not developed based on domain knowledge but by drawing patterns from available data, they depend on the data scientist to deploy sophisticated statistics, and potentially machine learning and AI algorithms, to extract knowledge and trends [21]. To this end, these models require large amounts of quantitative data and proxies to undertake predictions, and draw valid inferences on historical data (post-factum), displaying 'results' rather than concrete pathways to decision-making. What can lead to issues related to validity if proxies are not appropriately selected and if correlations are misinterpreted as cause [14]. In addition, since pattern recognition is grounded on data, data-driven strategies depend on the Internet of Things (IoT), secure data-sharing protocols, and storage, that heavily rely on data providers [23].

Nevertheless, one can see how seductive they are to decision-makers as they are prone to automation and ‘variabilise’ everything. Data-driven models reduce problems’ complexity by transforming them into computable entities. At the same time they enable feedback loops to be established so that ‘intelligent’ models can learn with constantly increasing amounts of available data from the IoT, towards improving their efficiency [23].

In this sense, data-driven models are information-focused, often rich in data, but poor in providing insights and/or pathways as to how decisions can be made to reach desirable outcomes [21]. Outcome-driven strategies and models challenge some of the paradigms set by data-driven strategies and models.

4 From data-driven towards an outcome-driven decision support systems

In outcome-driven strategies, the main objective is to reach results that are fit-for-purpose, i.e. tailored to the expectations of the user/decision-maker. This aligns with overarching design objectives that cater for different needs of the multiple stakeholders involved in the design process, and constrains on what is possible to be achieved [9]. It comprises a shift in efforts – and in the course of actions – from data collection and organisation to pattern discovery in a dataset that *fits a purpose*, towards what the decisions are made for, with a specific result – a *fit-for-purpose* outcome based on precise data – in mind [21]. These are fundamental characteristics of design problems [9, 25], and the main rationale for arguing in favor of outcome-driven DSS in urban-regional planning.

As the focus of these strategies is to recognise how desired outcomes can be achieved considering the requirements and existing constrains, identifying what are the key decisions and indispensable datasets – or the core elements – required for the attaining expected outcomes becomes essential. Therefore, models supporting the decision processes have only the necessary information to answer specific questions and data collection activities focus on sufficiency rather than quantity [21]. Models are built with a purpose on what is expected to emerge from the data gathered towards achieving a pre-established set of satisficing conditions [25] or solutions. These models are rule-based (normally science-based), or based on domain-knowledge heuristics. They are used simultaneously or sequentially, making the process of achieving desired solutions a sequence of events and arguments, with analyses tailored to achieving specific outcomes, and analytical methods and models chosen based on their relevance to the reach these outcomes [26].

Domain experts are the ones identifying the necessary data to be used. They build and/or use knowledge models or heuristics to reason with data towards achieving a specific outcome discussed with the stakeholders. Additionally, they create their own repertoire of pairs of data-to-be-collected/model-heuristics-to-be-used, re-using them again and again, every-time a new problem emerges. Meaning that sequences of events are custom-based to the activity at hand, and events or arguments are transferable [11]. This enables quantitative and qualitative data to be used and sequences of events and arguments to be built in multiple ways, including the "capturing of human agency in change and development" [24].

Table 1. Comparison between data-driven and outcome-driven strategies [based on 14, 24, 26]

	Data-driven strategies	**Outcome-driven strategies**
Type of outcome	Data-dependent (multiple) outcomes	Fit-for-purpose satisficing outcomes
Focus/ Purpose	Problem diagnosis, analysis, prediction – identifying *what*?	Solution development and decision-making – identifying *how?*
Analysis Process	Feedback loops. Unfold patterns in events to define achievable outcomes.	Rule-based and/or narrative-based. Use causal events and/or heuristics to meet desired outcomes.
Units of analysis	Variables	Events / arguments
Type of analysis	Statistics, machine learning, AI. require domain knowledge to be validated and useful	Causal models and/or heuristics. All domain-knowledge based
Type of data	Available data only	Meaningful and/or hypothetical data
Amount of data	Large amounts of data to draw valid inferences.	Sufficient data to make decisions
Uncertainty	Based on training datasets, large datasets, curated datasets.	Based on assumptions, risk assessment and uncertainty models.
Scope	Mainly based on quantitative data accepts continuous change in variable attributes, uses feedback models, enables models to learn with the data and improves their efficiencies.	Accepts quantitative & qualitative data and analysis processes, based on narrative/processes with dynamic models and sequence, ordering and context of events / arguments.
Strengths	Incorporates feedback, moderates flow of inferences *"Captures continuous variations in development and change with powerful mathematical models"* [26]	*"Captures the role of human agency in change and development"* [26]
Weaknesses	Correlations used as causation, use of proxies to assess results, work based on historical data, often limited fairness.	No feedback incorporated, linear flow of influence.
Model developer	Data-scientist & data providers	Domain experts (in collaboration with stakeholders)

Still, these characteristics are not as suitable for automation and the establishment of feedback loops. The role of uncertainty needs to be considered throughout the process as there is no feedback to enable adjustments to the solution after it is implemented. In limiting the data input to the essential, outcome-driven strategies must address uncertainty and complexity to a more refined degree. This calls for the use of sophisticated methods to deal with uncertainty as well as risk assessment methods, which go from probability and statistics up to agent-based models to gauge how well proposed solutions align with desired outcomes, and how well desired outcomes match the needs and aspirations of stakeholders as rationally assumed by decision-makers [26, 27]. Although outcome-driven strategies shift the paradigm towards a more guided approach to decision-making, and the construction of fit-for-purpose DSS, nothing prevents data-driven strategies from being used within outcome-driven sequences of action, as those can be powerful to support controlling and testing generated solutions.

5 Building and outcome-driven DSS: The DECIDE project

The DECIDE project (Decoding Cities for Informed Decision Making) aims to develop and test a framework for an outcome-driven DSS, based on the integration of Multi-Domain Models (MDMs) for sustainable urban-regional planning. The DSS addresses territorial inequalities through the interpretation and prediction of movement dynamics according to different modes of mobility, accessibility levels to services and road-network resilience, to promote livability. It applies state-of-the-art configurational models and spatial frameworks for representing urban-regional dynamics, supporting strategic and operational decision-making.

Urban livability interprets multiple key-factors related to agents' movement (e.g. urban form, natural environments, road-network configuration, and personal habits or characteristics that influence preferential routes' choice), and associates those to territorial resilience (e.g. identifying the fragility points in road-network, plus urban-regional exposures, imbalances, and disparities). These aspects make the DSS core. The MDMs that link to the DSS will integrate functional aspects of urban-regional areas (e.g., economic activities, public activities, and the distribution of living areas) with environmental and built-environment aspects (e.g., improvement of circulation, CO_2 reduction via pedestrianization, cycling, and fleet electrification) forecasting their relations with movement network spatial configurations.

MDMs will be applied to interpret general hierarchical relations between urban-regional spaces (e.g., X-minute cities, spatial inequalities, city-systems linkages), and to inform planning for disaster risk reduction. A Digital Twin (DT) approach will be used to organize the MDMs into a DSS. This involves creating a virtual representation of the territory in a GIS environment that can be updated with near Real-Time Data to simulate scenarios when urban systems are subjected to temporary or permanent change. The DT will provide stakeholders and planners with immediate access to spatial knowledge of different urban phenomena including movement dynamics, road-networks' redundancy and fragility, environmental risks, and the potential outcomes of events/interventions. The outcome-driven DSS will enable decision-makers to design cohesive spaces and be more efficient and effective in their decision-making processes.

The DECIDE project comprises three working packages (Figure 1). Its framework is mainly outcome-driven and developed through an iterative process with stakeholders. WP1 focuses on identifying MDMs outputs useful to decision-making together with case studies for testing the DSS. Useful outputs will be then categorised in terms of their complexity, and in accordance with the post-processing techniques needed for MDMs' data extraction (e,g. AHP, Optimization routines, Boolean operation overlays, etc.). Next, fit-for purpose post-processing techniques will be designed and implemented through Python scripts in GIS to produce useful MDMs outputs (WP1 and WP2). These scripts will be held in the project's Git-hub version-controlled library, to enable wider testing and dissemination to the academic community while still under development. A user manual and online tutorial to use the GIS scripts to streamline the extraction of, and produce, fit-for-purpose information for common applications of MDMs in decision-making will be developed for professional stakeholders. Finally, the framework for a WebGIS tool will be shared, together with a short online tutorial to facilitate the DSS' practical application and on-the-go data visualisation by all users.

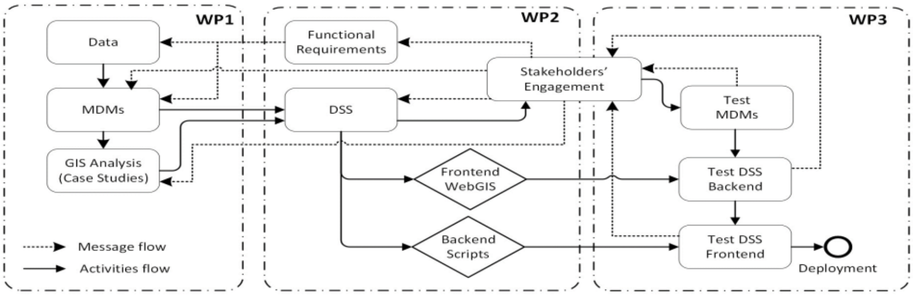

Figure 1. The DECIDE project working package structure.

A period of iterative participative evaluation and testing of the DSS will follow. During this period, requirements and experiences regarding stakeholders' interactions with GIS tools, MDMs, and the outcome-driven DSS, will be collected and assessed. Critical feedback will be collected also about the established user-guidelines and the data retrieval scripts operation, as well as the DSS effectiveness in aiding stakeholders' decision-making.

The fact that urban-regional processes are highly dynamic, constantly changing over time, calls for data-driven components to be incorporated into the DSS, justifying the adoption of a Digital Twin (DT) approach. Inserted on a DT, the MDMs will empower urban planners to visualise natural movement patters together with environmental and economic aspects, and digitally assess the effects of possible modifications and/or interruptions to different mobility networks as part of scenario-based assessments. The improved performance that a real-time system provides will enable gains in the efficiency and transparency of decision-making processes, reduction of costs – both financial and time-related – to implement planning and policy actions, plus provide routing-related advice in the event of temporary or permanent urban-regional circulation systems' interruptions linked to extreme events. Although both stakeholders and academic communities have strong interests in such DT tools, this is often obscured by a lack of in-depth knowledge regarding network analysis and models that can assist understanding of critical resilience factors related to the functioning of road network systems.

6 Concluding remarks

Data-driven strategies can be powerful in support controlling, testing, and feeding back solutions being generated, particularly after solutions' implementation and/or in constantly changing environments. However, we argue that outcome-driven strategies are imperative to handle the dynamic nature of urban-regional planning, as they incorporate design principles that are tailored to propose the required alternative/generative outcomes. In that aspect, adopting an outcome-oriented approach becomes important, as it allows to frame urban-regional planning as a design activity, in which complex and interwoven requirements and constraints from stakeholders can be properly addressed.

Additionally, it offers more flexibility with respect to pure data-driven strategies. As we move forward with the DECIDE project, further endeavors will warrant to establish the operational framework for the proposed outcome-driven DSS, outlining the core principles that ascertain the broader applicability of this instrument in real decision-making contexts.

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