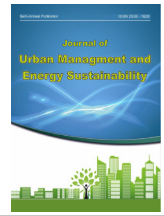
Int. J. Urban Manage. Energy Sustainability, 7(3):1-13, 2026

International Journal of Urban Management and Energy Sustainability (IJUMES)

Homepage: http://www.ijumes.com



ORIGINAL RESEARCH PAPER

Data-Driven Values in Data-Driven Architectural Design: Validation of the D2V Model**

Shahla Naderi Delpak, Azadeh Shahcheraghi*, Zahra Sadat Saeideh Zarabadi

Department of Architecture, SR.C, Islamic Azad University, Tehran, Iran

ARTICLE INFO

Article History:
Received 2026-05-11
Revised 2026-07-28
Accepted 2026-08-13

Keywords:
Big data; D2V model; Data-driven value; Ontology; Sspace syntax

ABSTRACT

The advent of big data in the architecture, engineering and construction industry has shifted the role of information from a purely representational instrument to a generative driver of the design process. Nevertheless, a deep operational gap persists between abstract data analytics and the physical realization of spatial relationships in architecture. This study introduces the notion of "data-driven value" as a mediating layer intended to bridge this gap, and proposes a conceptual model for translating structured physical and behavioral data into spatial qualities. The study introduces the D2V model, a framework for the conceptual integration of semantic-web technologies with space-syntax logic. To validate the model's components, a three-round Delphi panel of fifteen experts in architecture, urban design, spatial analysis, building information modelling and data science was convened. The Content Validity Ratio and Content Validity Index were computed for every component. The results indicate that "data-driven value" is realized when data act upon the spatial logic of the building and thereby enhance legibility, functional performance and prediction accuracy. The Delphi panel confirmed that all D2V components possess satisfactory content validity. The components "prediction accuracy" and "spatial legibility" attracted the greatest expert consensus, and Kendall's coefficient of concordance reached 0.85 by the third round, indicating strong agreement among the experts. The proposed D2V model redefines the architect's role from "author of form" to "designer of semantic systems." By realizing data-driven value, architects can reduce ambiguity in design and ensure that data-driven methodologies produce function-oriented, human-centered environments rather than mere geometric complexity.

DOI: 10.22034/ijumes.2026.2096172.1386

Running Title: Data-Driven Values in Data-Driven Architectural Design

NUMBER OF REFERENCES	NUMBER OF FIGURES	NUMBER OF TABLES
36	02	06

*Corresponding Author:
Email: *shahcheraghi@iau.ac.ir*
Phone: 00989123290241
ORCID: https://orcid.org/0000-0003-1947-2772

**This article is taken from Shahla Naderi Delpak's doctoral dissertation, entitled "Explanation of a Model of Architectural Design Method Based on Big Data (Case Study: Experiences of Selected Architectural Laboratories)," which was extracted under the guidance of Dr. Azadeh Shahcheraghi and the consultation of Dr. Zahra Sadat Saeideh Zarabadi.

INTRODUCTION

In traditional architectural paradigms, "value" was defined largely through the tension between aesthetic qualities and physical functions. Vitruvius, with his triad of "function, firmness and beauty," and Ruskin, with his "Seven Lamps of Architecture," articulated value systems that invariably reflected the technology and worldview of their time (Ruskin, 2009) (Vitruvius, 1914). The emergence of big data over the past two decades, however, has transformed the nature of information from a mere instrument of representation into a "generative driver" of the design method (Carpo, 2017) (Olanrewaju & Bruno, 2024). The vast datasets produced by sensors, computational simulations, building-management systems and social networks offer unprecedented potential to redefine the design process (Loyola, 2018) (Deutsch, 2015). Despite remarkable advances in computational tools and building information modelling (BIM), a framework capable of connecting the descriptive language of BIM to the topological language of space syntax is still missing (Lu & Zhang, 2021). The greatest challenge on the path to data-driven design is the absence of an operational approach for engaging with big data. In the course of their translation into the "spatial relationships of the building," data encounter a rupture: they often remain at the level of abstract quantitative analysis and are never converted into a "design instruction." In other words, what is missing in architectural design practice is not awareness of the importance of data, but rather the "how" and the "method" of using data within the design process. Data from sensors, building-management systems and social networks, after semantic processing in the ontology layer of the D2V model, are translated into spatial metrics compatible with space-syntax analysis. This translation ensures that such data contribute primarily to the behavioral and configurational understanding of space, rather than to purely technical or energy-related parameters. Accordingly, the present research seeks to answer the question of how, by articulating the concept of data-driven value, a bridge can be established between the data layer and the physical layer. The main objective of this study is to propose a conceptual model capable of transforming structured physical and behavioral data into tangible spatial qualities through a semantic and logical process, and to subject this model to content validation using the Delphi method. The paper stresses the necessity of a transition toward a "digital and continuous framework" in which value is not a final product but a dynamic flow throughout the entire design process (Demirdöğen et al., 2021) (Olanrewaju & Bruno, 2024). The remainder of the paper is organized as follows: after this introduction, the theoretical foundations are presented in two parts, "redefining value in architecture" and "the D2V model." The research methodology, comprising the Delphi panel and the content-validity indices, is then described. Subsequently, the findings including the extracted model and the Delphi validation results are reported. In the discussion, the findings are interpreted in relation to the literature, and finally conclusions and suggestions for future research are offered.

MATERIALS AND METHODS

Redefining value in architecture: from historical definitions to a conceptual synthesis

Value, as a foundational concept in philosophy, economics and architecture, admits multiple definitions. In dictionaries, value denotes "intrinsic worth" or "price" and is explained through the relationship between benefits received and costs incurred. Saxon (2005) defined value as "the balance of the benefits and sacrifices involved in a value judgement" and characterized values, in the plural, as "criteria for judging worth that are subjective and grounded in culture, transactional role and personal experience." From a philosophical standpoint, Pirsig (1999), in his "Metaphysics of Quality," defined value as "pure experience" that precedes rational thought, a notion consonant with the concept of knowledge (Volker, 2010). In architecture, value systems have always mirrored the technology and social conditions of their time. Vitruvius introduced the triad of “function, firmness and beauty” as the pillars of architectural value, while Ruskin, in “The Seven Lamps of Architecture,” described values such as sacrifice, truth, power, beauty, life, memory and obedience that characterized the Gothic Revival (Ruskin, 2009). Contemporary research in computational design has shown that ontology-based approaches can assist the integration of multi-domain data in the design process and lay the ground for the creation of novel spatial values (Tyc et al., 2025). Ove Arup, likewise, distinguished between measurable value (the physical commodity) and immeasurable value (artistic quality and social worth) (Emmitt et al., 2009). Despite the diversity of these definitions, a common thread is discernible: value in architecture has always been bound up with “judgement” and “choice” in the design process. Yet what was performed in the pre-digital era as an intuitive judgement rooted in the designer’s personal experience requires fundamental redefinition in the age of big data. Samuel (2014) identified four types of architectural skill-set commercial, cultural, technological and social which show that the architect’s role is shifting from “master designer” to “data-driven specialist” across different contexts (Samuel, 2014). On this basis, it can be argued that, in the present paradigm, the value of data lies in its capacity to generate “evidence” that converts the architect’s subjective judgements into reliable knowledge (Golchehr, 2019). Value in the architecture of the digital age is no longer a merely subjective quality; it is the outcome of the intelligent conversion of “design intuition” into “data-driven structures” (Deutsch, 2015). In other words, if value is sought along the continuum between objective and subjective attributes, big data enable the transition from purely qualitative judgements toward measurable performance criteria (Olanrewaju & Bruno, 2024). This redefinition constitutes the theoretical basis of the D2V model introduced below. It is important to emphasize that in this framework, data do not replace the architect’s intuition; rather, they transform intuition into a spatially evaluable structure by providing evidence-based parameters for configurational decisions.

The D2V (Data-to-Value) model

The D2V model introduced in this research rests on the premise that “data-driven value” is neither an accidental product nor an intuitive outcome, but the result of a “systematic process of semantic translation.” The model is inspired by comparable frameworks in data science (Castellanos et al., 2020) and draws on the concepts of architectural ontology (Barekati et al., 2015) and space syntax (Hillier & Hanson, 1984). It comprises three principal layers that convert the flow of data into spatial value:

•Layer 1- Data ontology: In this layer, structured physical and behavioral data of a non-architectural nature (such as numerical codes, descriptive statistics or raw movement data) are transformed, through semantic processing, into “value-bearing information.” Here the architect, by defining an “architectural ontology,” specifies for the system which data affect which spatial quality. To this end, the semantic-web approach and tools such as ifcOWL are used to link heterogeneous environmental and human data to the layers of building information modelling (BIM). The output of this layer is a coherent data graph that turns scattered data into structured, meaningful information.

•Layer 2 - Semantic translation and configuration engine: This layer is the core of the model and covers the gap between data and physical form. Here, the processed information from the first layer enters the algorithms of space syntax and computational design. The principal mechanism of this layer is the conversion of data into “spatial-configuration rules.” For example, data on movement patterns are translated into space-syntax measures such as integration and the choice index (Hillier & Hanson, 1984). In this layer, the concept of “configurational ontology” is employed, linking topological measures such as degree centrality, closeness centrality and betweenness centrality to spatial elements (Cataldo et al., 2014). The output of this layer is the generation of multiple design alternatives shaped by digital evidence and adopted on the basis of predictive analysis rather than guesswork.

•Layer 3 - Value realisation and evaluation: In the final layer, the model evaluates the outputs generated in the second layer to ensure that "data-driven value" has been converted into "tangible value." Using a 'Value Balancer' mechanism, this layer measures the success of the design in improving three sets of indicators: (1) spatial legibility and perceptual quality (human value), (2) functional optimisation and spatial efficiency (technological value), and (3) spatial configurational quality (configurational value). With the aid of multi-objective optimisation algorithms, the best alternative for implementation is then fixed. This layer also possesses a feedback mechanism that returns the evaluation results to the second layer so that the design process is continuously improved. Figure 1 depicts the data-flow diagram of the model across the three layers, together with the operational components and the corresponding measurement indicators.

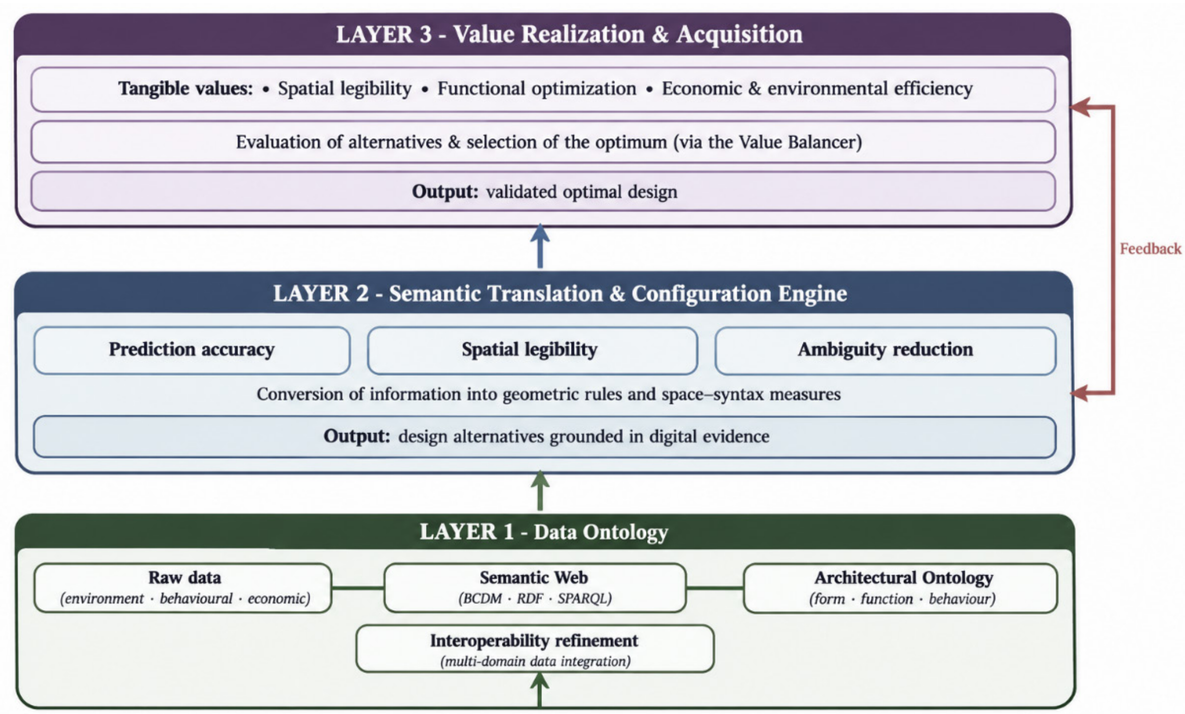


Figure 1: The D2V conceptual model, comprising three layers (data ontology, value-generation engine, and value realization and acquisition), four operational components and the corresponding measurement indicators.

The D2V model traces the flow of data from the ontology layer to the realization of value. Solid arrows denote the main data path and dashed arrows denote the feedback loops that enable continuous optimization. Previous research has demonstrated that the logic of spatial organization based on behavioral and environmental data applies across various scales, from urban open spaces to interior architectural configurations (Jeddi Farzane, 2021); The proposed D2V model adopts this principle while focusing specifically on architectural spatial configuration at the building scale. Data-driven value is operationalized in the model at three levels: (1) disambiguation, by converting behavioral uncertainties into stable performance models; (2) automation, by optimizing the process with computational and artificial-intelligence algorithms; and (3) decision support, by presenting optimal alternatives on the basis of digital evidence (Deutsch, 2015) (Castellanos et al., 2020). Data-driven value is an infrastructural, enabling value: its deployment makes possible the emergence and acquisition of other values (physical, human, and configurational). Articulating this value gives rise to a new specialism, the "designer of semantic systems," whose role is to design the semantic structure governing the relationship between data and space and to guarantee the conversion of structured data into architectural values (Olanrewaju & Bruno, 2024) (Tyc et al., 2025).

Relationship between the layers and the operational components of data-driven value

One of the ambiguities in previous research is the lack of a clear account of the relationship between the operational components of value and the layers of the model. In the D2V model, four principal operational components "prediction accuracy," "spatial legibility," "ambiguity reduction" and "data integration and interoperability" are distributed across the different layers of the model. Table 1 sets out this distribution. (Tab. 1)

Table 1: Correspondence between the operational components of data-driven value and the layers of the D2V model

Operational component	Principal layer	Role within the layer	Related measurement indicators
Prediction accuracy	Semantic translation & configuration engine (Layer 2)	Converts behavioral and environmental data into predictive rules for movement patterns, density rates and spatial performance	Integration, spatial depth, choice index, isovist (visibility) analysis
Spatial legibility	Semantic translation & configuration engine (Layer 2)	Optimizes spatial configuration on the basis of visual and perceptual indices to improve discoverability and wayfinding	Intelligibility coefficient, visual-richness index, access hierarchy
Ambiguity reduction	All three layers (transversal)	In the ontology layer through appropriate data selection, in the engine layer through predictive analysis, and in the realization layer through evaluation of alternatives	Key performance indicators (KPIs), key risk indicators (KRIs), sensitivity analysis
Data integration & interoperability	Data ontology (Layer 1)	Integrates multi-domain data (environmental, behavioral, physical) using the semantic web and the ifcOWL ontology	Structured data, knowledge graph, data-matching rate

As Table 1 shows, the "ambiguity reduction" component is present as a transversal component across all three layers, playing a different role in each evidence of the importance of managing uncertainty at every stage of the data-to-design conversion. The 'data integration and interoperability' component is primarily embedded within the data-ontology layer, because the prerequisite for any interaction among different data is the creation of a shared semantic language. The "prediction accuracy" and "spatial legibility" components sit in the semantic-translation and configuration engine, since this layer is responsible for the direct conversion of data into spatial rules.

Methodology

In terms of purpose, the present study is developmental–applied, and in terms of nature it is a mixed (qualitative–quantitative) study with a sequential exploratory design (Creswell & Clark, 2017). In the qualitative phase, using qualitative content analysis and a systematic literature review, the initial components of data-driven value and the D2V model were formulated. In the quantitative phase, the Delphi method was used for the content validation of the model. The Delphi method is recognized as a systematic technique for reaching group consensus in complex, interdisciplinary domains where because the frameworks for integrating the semantic web and space syntax are still emerging sufficient empirical data are not available (Häder, 2014) (von der Gracht, 2012).

Delphi panel

Composition of the expert panel. The statistical population comprised specialists in architecture, urban design, spatial analysis, building information modelling (BIM) and data mining. Purposive sampling was carried out with explicit inclusion criteria: (1) at least ten years of professional or research experience; (2) a doctoral degree in a relevant discipline; (3) a record of at least three scholarly publications in architectural design, BIM or data mining; and (4) familiarity with the concepts of big data, space syntax, the semantic web and computational design methods. After initial screening, the final panel consisted of four architects specializing in the design of commercial centers and large-scale complexes (mean experience 14 years), three specialists in spatial analysis and space syntax (mean 12 years), three specialists in data mining and information systems for the built environment (mean 11 years), three specialists in building information modelling and ontology (mean 10 years), and two urban-design specialists (mean 14 years). All participants held doctoral degrees in relevant fields. The initial sample size was set at fifteen; however, after attrition, thirteen experts participated in all three rounds. Accordingly, the critical CVR value was determined based on N=13, which according to Lawshe's (1975) table is 0.54 (Lawshe, 1975).

Delphi process. The Delphi panel was conducted in three rounds. Round 1 (open questionnaire): a questionnaire with open questions was distributed to the experts to elicit their views on the components of the D2V model, the relationships among them and the model's practical feasibility; the responses were collected and coded using qualitative content analysis, and on this basis the second-round questionnaire was designed. Round 2 (closed questionnaire): a structured questionnaire with closed questions was designed. To measure the CVR, a three-point scale (essential; useful but not essential; not necessary) was used in accordance with Lawshe's method; to measure the CVI, a four-point scale (1 = little relevance, 4 = very high relevance) was used in accordance with the method of Polit and Beck (Polit & Beck, 2006). The mean, standard deviation and CVR were computed for each item. Round 3 (consensus-building): the second-round results, together with the experts' dissenting or corrective comments, were returned to them as controlled feedback (with anonymity preserved), and the experts were asked to reconsider their views if necessary. The stopping criterion for the panel was a Kendall's coefficient of concordance above 0.70 together with the absence of a significant change in the mean responses between two consecutive rounds (von der Gracht, 2012). Attrition and participation. Of the fifteen initial experts, thirteen participated fully in all three rounds (participation rate 86.7%) and the attrition rate was 13.3%. To maintain participation, telephone follow-ups and regular reminders were carried out.

Content-validity indices

Two standard coefficients were used to assess the content validity of the proposed model. The Content Validity Ratio (CVR) was computed for each item from the number of experts who rated the item as "essential," using the following formula:

$CVR = (n_e - N/2) / (N/2)$

where n_e is the number of experts who rated the item as "essential" and N is the total number of experts. According to Lawshe's (1975) table, for N = 13 the critical CVR value is 0.54; items with a CVR below this value are removed or revised. The Content Validity Index (CVI) measured the experts' agreement on the "relevance," "clarity" and "comprehensiveness" of each component on a four-point Likert scale, and was computed as the proportion of experts rating the item 3 or 4 (Polit & Beck, 2006). The acceptable threshold for the CVI was set at 0.78. To compute the content-validity index at the level of the whole model, the simple average of the item-level CVIs of the four components was used, known as S-CVI/Ave (Polit & Beck, 2006). Worked example for the prediction-accuracy component: of the thirteen experts, eleven rated this item as "essential" ($n_e = 11$), giving CVR = (11 − 6.5)/6.5 = 0.69. Likewise, eleven of the thirteen experts assigned this item a score of 3 or 4 on the CVI scale, yielding CVI = 0.85.

FINDINGS AND DISCUSSION

The extracted D2V model

On the basis of the systematic literature review and qualitative content analysis, the D2V model was articulated as comprising three layers (data ontology; semantic translation and configuration engine; value realization and evaluation) and four operational components (prediction accuracy, spatial legibility, ambiguity reduction, and data integration and interoperability), as shown in Figure 1. The relationship between the components and the layers is depicted in (Tab. 1).

Delphi panel results

To present the consensus-building process in full, the results are reported in several tables. Table 2 shows the change in the validity coefficients of each component across the three rounds. (Tab. 2)

Table 2: Delphi panel results across the three rounds (CVR and CVI coefficients)

Component	Round 1	Round 2	Round 3
Prediction accuracy	CVR = 0.54, CVI = 0.72	CVR = 0.62, CVI = 0.78	CVR = 0.69, CVI = 0.85
Spatial legibility	CVR = 0.49, CVI = 0.68	CVR = 0.58, CVI = 0.75	CVR = 0.65, CVI = 0.83
Ambiguity reduction	CVR = 0.46, CVI = 0.65	CVR = 0.54, CVI = 0.72	CVR = 0.62, CVI = 0.80
Data integration & interoperability	CVR = 0.38, CVI = 0.58	CVR = 0.46, CVI = 0.68	CVR = 0.54, CVI = 0.79

The rising trend of the CVR and CVI coefficients across all components indicates the convergence of expert opinion toward consensus over the three rounds. Table 3 presents the overall consensus and concordance indices for each round. (Tab. 3)

Table 3: Consensus and concordance indices across the three rounds

Index	Round 1	Round 2	Round 3	Acceptance criterion
Interquartile range (IQR)	2.0 – 2.5	1.5 – 2.0	1.0 – 1.5	IQR < 2
Agreement (≥ 3), %	65 – 70	75 – 80	85 – 90	≥ 75%
Kendall's W	0.58	0.72	0.85	W ≥ 0.70
Significance (P-value)	P < 0.05	P < 0.05	P < 0.05	P < 0.05

As Table 3 shows, the interquartile range (IQR) fell below 2 in the third round and Kendall's coefficient of concordance exceeded the 0.70 threshold, indicating the formation of strong consensus among the experts. Table 4 shows the trajectory of each component separately. (Tab. 4)

Table 4: Trajectory of the components across the three rounds (the consensus-building path)

Component	Round 1 → Round 2 → Round 3	Final status
Prediction accuracy	CVR: 0.54 → 0.62 → 0.69 ↑	Strong consensus
Spatial legibility	CVR: 0.49 → 0.58 → 0.65 ↑	Strong consensus
Ambiguity reduction	CVR: 0.46 → 0.54 → 0.62 ↑	Good consensus
Data integration & interoperability	CVR: 0.38 → 0.46 → 0.54 ↑	Acceptable consensus

To visualise the consensus-building process, Figure 2 shows the change in Kendall's coefficient of concordance (W) and in the components' CVR coefficients across the three rounds. (Fig. 2)

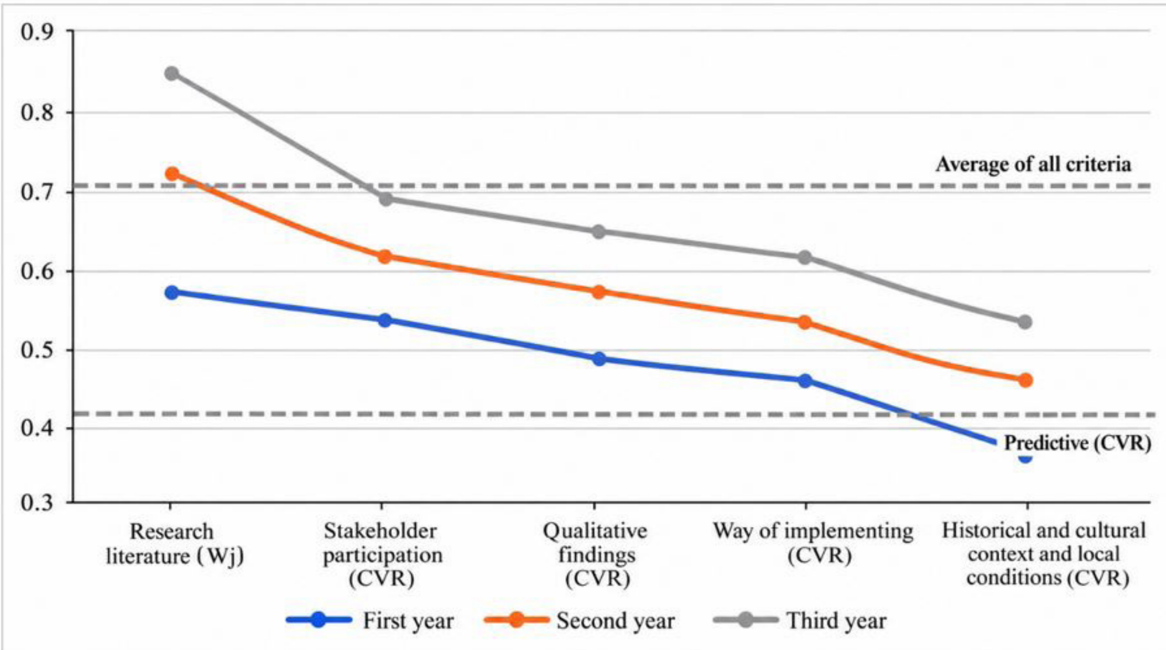


Figure 2: Convergence of expert consensus over the three-round Delphi panel: (a) Kendall's W against the 0.70 consensus threshold; (b) component CVR values against the 0.54 critical value

After completion of the three-round Delphi process, the final content-validity coefficients for each component are presented in Table 5. As can be seen, all components exceed the specified thresholds (CVR ≥ 0.42 and CVI ≥ 0.78). (Tab. 5)

Table 5: Final Delphi panel results (CVR and CVI coefficients)

Component	CVR	CVI	IQR	Status
Prediction accuracy	0.69	0.85	1.0	Satisfactory
Spatial legibility	0.65	0.83	1.0	Satisfactory
Ambiguity reduction	0.62	0.80	1.0	Satisfactory
Data integration & interoperability	0.54	0.79	1.5	Satisfactory
Overall model index (S-CVI/Ave)	–	0.82	–	Satisfactory

The greatest expert agreement was for the "prediction accuracy" component (CVI = 0.85) and the "spatial legibility" component (CVI = 0.83). The "data integration and interoperability" component, with CVI = 0.79, lies at the margin of the acceptable threshold, indicating the need for closer examination of this component in future research. Kendall's coefficient of concordance was 0.72 at the end of the second round and 0.85 at the end of the third round; with three degrees of freedom ($df = 4 - 1 = 3$) and $P < 0.05$, this indicates strong consensus among the experts and exceeds the 0.70 threshold adopted as the criterion of acceptable consensus. The rise from 0.72 in the second round to 0.85 in the third confirms the convergence of opinion toward consensus during the Delphi process.

CONCLUSION AND RESULTS

The findings indicate that the D2V model, by introducing a mediating layer of "semantic translation and configuration," fills the gap between abstract data and spatial form. This finding corroborates previous research on the necessity of integrating multi-domain data in the design process. The model's emphasis on "prediction accuracy" and "spatial legibility" as key components of data-driven value is consistent with the concepts advanced in space-syntax theory (Hillier & Hanson, 1984) and evidence-based design (Medhat Assem et al., 2023). Recent approaches in architectural and urban design have shown that combining spatial analysis with big data can lead to a better understanding of users' behavioral patterns and to the optimization of spatial configuration (Scheutz & Mayer, 2016) (Ding, 2023). Recent work on data-driven architecture has likewise stressed the need to develop adaptive reference architectures for big-data systems, which can improve the efficiency and flexibility of design processes (Ataei & Atemkeng, 2025). The Delphi results showed that the greatest expert agreement concerned the "prediction accuracy" and "spatial legibility" components. This may be because these two components are most closely related to well-established analytical tools (such as DepthmapX for space syntax) and are therefore more tangible for experts. By contrast, the "data integration and interoperability" component, with CVI = 0.79, attracted the least agreement, indicating that aspects concerning the integration of multi-domain data through the semantic web and ontologies still require further research and conceptual clarification (Xu & He, 2022). Recent research in building-space modelling has shown that big-data-based approaches can improve the efficiency of traditional methods by up to around 65% (Xu & He, 2022). Designing on the basis of spatial data and using interactive maps enable designers to analyses different information layers simultaneously (Peng et al., 2024). A comparison of the D2V model with prior approaches shows that it possesses three distinguishing features, summarized in Table 6. (Tab. 6)

Table 6: Comparison of the D2V model with related approaches

Approach	Main focus	Strengths	Weaknesses	Advantage of D2V
Space syntax	Analysis of spatial configuration and movement prediction	High accuracy in analyzing spatial relationships; strong theoretical basis	Lacks a value-generation layer and qualitative–behavioral indices	Adds a value-realization and evaluation layer to spatial analysis
BIM-based frameworks	Management of building information and integration of technical data	Integration of technical data across the project life cycle	Neglects qualitative, behavioral and human data	Adds behavioral and semantic data to the design cycle via ontology
Evidence-based design (EBD)	Decision-making grounded in scientific evidence	Reduces design errors; transparency of decisions	Static approach based on past data; lacks dynamism	Dynamism and connection to real-time data flows through feedback loops
Proposed D2V model	Converting data into value through semantic translation	Combines spatial analysis, value generation and dynamism	Requires an appropriate data infrastructure	–

As Table 6 shows, relative to traditional space-syntax approaches the D2V model adds a value-realization and evaluation layer; relative to BIM-based frameworks it integrates behavioral and semantic data; and relative to evidence-based design it adds dynamism and continuity to the value-generation process through feedback loops. These features render the D2V model a more comprehensive framework for data-driven design. Recent approaches in the teaching and practice of architectural design have likewise shown that the use of big data and emerging technologies can markedly improve the quality of education and design outcomes (Lv, 2024), and that AI-assisted, data-driven spatial-layout methods are increasingly able to generate and evaluate configurations at building scale (Ko et al., 2023) (Yan et al., 2025).

5.1. Redefining the architect's role as a designer of semantic systems

The findings of this research show that the D2V model transforms the architect's role from "author of form" to "designer of semantic systems." In this new paradigm, the realization of "data-driven value" lies neither in the accumulation of big data nor in mere reliance on hardware tools, but in the architect's ability to establish a logical link between "structured data" and "spatial form" (Carpo, 2017) (Peng et al., 2024). This theoretical articulation and Delphi validation reveal that the operational gap in buildings' spatial relationships can be repaired only through the establishment of a semantic framework one that converts data from an abstract statistical report into the "raw material for producing space syntax." This redefinition is consistent with Samuel's (2014) argument that the architect's role is shifting from "master designer" to "data-driven specialist," yet it goes further, elevating the architect to a "system designer" who not only uses data but designs the semantic structure governing the relationship between data and space. This shift allows the architect, in the age of big data, to retain creative control over the design process while harnessing the power of computational analysis to reduce ambiguity and increase the accuracy of decisions. Contemporary research on AI- and big-data-driven architectural design has shown that such approaches can serve as instruments for critical thinking and ideation in the design process, and not merely for optimization (Saldaña Ochoa et al., 2023) (Zhuang et al., 2025); adaptive reference architectures in the field of big-data systems likewise emphasize the importance of flexibility and continuous learning in design processes (Ataei & Atemkeng, 2025). Despite achieving theoretical consensus in the Delphi panel, the present research has focused chiefly on theoretical aspects, and a full operational test of the model in a real architectural project has not been carried out. The validation performed is of the "content validity" type, which examines the conceptual adequacy of the components, rather than "criterion validity," which examines correlation with practical outcomes. Moreover, although the composition of the expert panel (thirteen members in the final round) is statistically sufficient for computing the CVR, it may not fully reflect the diversity of viewpoints within the scholarly community. Future research should implement the D2V model in a sample project and test its operational efficacy through quantitative simulations (such as space-syntax analysis with DepthmapX) and the measurement of performance indicators (such as footfall and user satisfaction). The development of native plug-ins to automate data retrieval on BIM platforms could also open new horizons for operationalizing the model in architectural practice. Emerging approaches in architecture and urbanism have shown that combining computational methods with spatial analysis can yield a deeper understanding of behavioral patterns and the performance of spaces (Ay & Akçayol, 2017). By articulating the concept of "data-driven value" and proposing the D2V model, the present research has taken a step toward repairing the rupture between data-driven analysis and the physical realization of spatial relationships in architecture. The findings showed that data-driven value is an infrastructural, enabling value realized through a process of semantic translation across three layers (data ontology; semantic translation and configuration engine; value realization and evaluation) and manifested in four operational components (prediction accuracy, spatial legibility, ambiguity reduction, and data integration and interoperability). The Delphi panel confirmed that all model components possess satisfactory content validity ($CVR \geq 0.42$ and $CVI \geq 0.78$). The greatest expert agreement concerned "prediction accuracy" (CVI = 0.85) and "spatial legibility" (CVI = 0.83). Kendall's coefficient of concordance at the end of the third round ($W = 0.85, P < 0.05$) indicates strong consensus among the experts, and the rising trend of the coefficients across the three rounds confirms the gradual formation of consensus and the content validity of the model. These findings indicate that the scholarly community holds considerable consensus on the necessity of a semantic framework for converting data into design. By introducing a mediating layer of "semantic translation and configuration" and drawing on architectural ontologies (such as ifcOWL) and space-syntax logic, the D2V model makes it possible to convert structured data into spatial rules. The model redefines the architect's role from "author of form" to "designer of semantic systems" a role in which the architect, by designing the semantic structure governing the relationship between data and space, can reduce ambiguity and improve the accuracy of performance prediction. In this paradigm, technology is not an end but a means for returning to the essence of architecture: "creating value-bearing space for human beings" within the most complex data-driven contexts.

REFERENCES

Ataei, P., & Atemkeng, M. (2025). Terramycelium: A reference architecture for adaptive big data systems. Journal of Big Data, 12(1), 260. https://doi.org/10.1186/s40537-025-01311-6

Ay, S., & Akçayol, M. A. (2017). A comprehensive analysis of architectures and methods of real-time big data analytics. Journal of Internet Technology, 18(4), 809–818.

Barekati, E., Kensek, K., & Noble, D. (2015). A BIM-compatible schema for architectural programming information. In Computer-Aided Architectural Design Futures (pp. 245–260). Springer.

Carpo, M. (2017). The second digital turn: Design beyond intelligence. MIT Press.

Castellanos, C., Pérez, B., Correal, D., & Varela, C. A. (2020). A model-driven architectural design method for big data analytics applications. In 2020 IEEE International Conference on Software Architecture Companion (ICSA-C) (pp. 89–94). IEEE. https://doi.org/10.1109/ICSA-C50368.2020.00025

Cataldo, A., Cutini, V., Di Pinto, V., & Rinaldi, A. M. (2014). Subjectivity and objectivity in urban knowledge representation. In ICCSA 2014 (Lecture Notes in Computer Science, Vol. 8580). Springer. https://doi.org/10.5220/0005152404110417

Creswell, J. W., & Plano Clark, V. L. (2017). Designing and conducting mixed methods research (3rd ed.). Sage.

Demirdöğen, G., Işık, Z., Aladağ, H., & Diren, N. S. (2021). Lean based maturity framework integrating value, BIM and big data analytics: Evidence from AEC industry. Sustainability, 13(18), 10029. https://doi.org/10.3390/su131810029

Deutsch, R. (2015). Data-driven design and construction: 25 strategies for capturing, analyzing and applying building data. John Wiley & Sons.

Ding, J. (2023). Intelligent design and modeling of landscape architecture image based on big data. In 2023 International Conference on Data Science and Network Security. IEEE. https://doi.org/10.1109/ICDSNS58469.2023.10245283

Emmitt, S., Prins, M., & den Otter, A. (2009). Architectural management: International research and practice. Wiley-Blackwell.

Golchehr, S. (2019). Data for design: Adopting data-driven approaches for long-term citizen participation and social sustainability in design for the public realm [Doctoral dissertation, Royal College of Art].

Häder, M. (2014). Delphi-Befragungen: Ein Arbeitsbuch (3rd ed.). Springer VS.

Hillier, B., & Hanson, J. (1984). The social logic of space. Cambridge University Press. https://doi.org/10.1017/CBO9780511597237

Jeddi Farzane,O and Khayami,F . (2020). Investigation of Urban Open-Spaces Organization Effects in Urban Management. International Journal of Urban Management and Energy Sustainability, 1(4), 67-76. doi: 10.22034/ijumes.2019.4.10.0349

Ko, J., Ennemoser, B., Yoo, W., Yan, W., & Clayton, M. J. (2023). Architectural spatial layout planning using artificial intelligence. Automation in Construction, 154, 105019. https://doi.

org/10.1016/j.autcon.2023.105019

Lawshe, C. H. (1975). A quantitative approach to content validity. Personnel Psychology, 28(4), 563–575. https://doi.org/10.1111/j.1744-6570.1975.tb01393.x

Loyola, M. (2018). Big data in building design: A review. Journal of Information Technology in Construction, 23, 259–284.

Lu, Y., & Zhang, J. (2021). Bibliometric analysis and critical review of the research on big data in the construction industry. Engineering, Construction and Architectural Management, 29(9), 3574–3592. https://doi.org/10.1108/ECAM-01-2021-0005

Lv, D. (2024). Research on teaching reform and practice of architectural design courses in colleges and universities based on big data analysis. Applied Mathematics and Nonlinear Sciences, 9(1), 1–15.

Medhat Assem, H., Mohamed Khodeir, L., & Fathy, F. (2023). Designing for human wellbeing: The integration of neuroarchitecture in design, A systematic review. Ain Shams Engineering Journal, 14(6), 102102. https://doi.org/10.1016/j.asej.2022.102102

Olanrewaju, A., & Bruno, S. (Eds.). (2024). Advancements in architectural, engineering, and construction research and practice. Springer. https://doi.org/10.1007/978-3-031-59329-1

Peng, Z., Zhang, Y., Lu, W., & Li, X. (2024). Data-driven generative contextual design model for building morphology in dense metropolitan areas. Automation in Construction, 168, 105820. https://doi.org/10.1016/j.autcon.2024.105820

Pirsig, R. (1999). Subjects, objects, data and values. In Proceedings of the Einstein Meets Magritte Conference.

Polit, D. F., & Beck, C. T. (2006). The content validity index: Are you sure you know what's being reported? Critique and recommendations. Research in Nursing & Health, 29(5), 489–497. https://doi.org/10.1002/nur.20147

Ruskin, J. (2009). The seven lamps of architecture. General Books LLC. (Original work published 1849)

Saldaña Ochoa, K., Huang, L.-S., Guo, Z., & Bokhari, S. M. A. (2023). Playing dimensions: Images/models/maps, Conceptualizing architecture with big data and artificial intelligence. In Proceedings of ACADIA 2023 (pp. 558–567).

Samuel, F. (2014). The cultural value of architecture in homes and neighbourhoods. University of Reading / Transvaluation Symposium, Göteborg.

Scheutz, M., & Mayer, T. (2016). Combining agent-based modeling with big data methods to support architectural and urban design. In Understanding complex urban systems (pp. 15–31). Springer. https://doi.org/10.1007/978-3-319-30178-5_2

Tyc, J., Ahmeti, A., Sunguroğlu Hensel, D., & Hensel, M. (2025). The ECOLOPES voxel model: multi-domain data integration for ontology-aided generative computational design of ecological building envelopes. Journal of Building Performance Simulation, 1–20. https://doi.org/10.1080/17508975.2025.2508896

Vitruvius. (1914). The ten books on architecture (M. H. Morgan, Trans.). Harvard University Press. (Original work ca. 15 BCE)

Volker, L. (2010). Deciding about design quality: Value judgements and decision making in the selection of architects by public clients under European tendering regulations. Sidestone Press.

von der Gracht, H. A. (2012). Consensus measurement in Delphi studies: Review and implications for future quality assurance. Technological Forecasting and Social Change, 79(8), 1525–1536. https://doi.org/10.1016/j.techfore.2012.04.013

Xu, Q., & He, L. (2022). Research on building space model method based on big data map visual design. Computational Intelligence and Neuroscience, 2022, 3384948. https://doi.org/10.1155/2022/3384948

Yan, S., Li, Y., & Cheng, X. (2025). Generative design for architectural spatial layouts: A review. Journal of Asian Architecture and Building Engineering. Advance online publication. https://doi.org/10.1080/13467581.2025.2512235

Zhuang, X., Zhu, P., Yang, A., & Caldas, L. (2025). Machine learning for generative architectural design: Advancements, opportunities and challenges. Automation in Construction, 174, 106129. https://doi.org/10.1016/j.autcon.2025.106129

COPYRIGHTS
©2023 The author(s). This is an open access article distributed under the terms of the Creative Commons Attribution (CC BY 4.0), which permits unrestricted use, distribution, and reproduction in any medium, as long as the original authors and source are cited. No permission is required from the authors or the publishers.

HOW TO CITE THIS ARTICLE
Naderi Delpak,Sh , Shahcheraghi,A and Sadat Saeideh Zarabadi,Z . (2026). Data-Driven Values in Data-Driven Architectural Design: Validation of the D2V Model. International Journal of Urban Management and Energy Sustainability, (), e738806
DOI: 10.22034/ijumes.2026.2096172.1386