Urban Planning
2024 • Volume 9 • Article 7165
https://doi.org/10.17645/up.7165

ARTICLE

Open Access Journal

# Digital Participatory Model as Part of a Data-Driven Decision Support System for Urban Vibrancy

Gülce Kırdar [1] and Gülen Çağdaş [2]

[1] Department of Informatics, Istanbul Technical University, Turkey
[2] Department of Architecture, Istanbul Technical University, Turkey

**Correspondence:** Gülce Kırdar (kirdarg@itu.edu.tr)

**Submitted:** 10 May 2023 **Accepted:** 17 August 2023 **Published:** 16 January 2024

**Issue:** This article is part of the issue "Citizen Participation, Digital Agency, and Urban Development" edited by Simone Tappert (University of Applied Sciences Northwestern Switzerland), Asma Mehan (Texas Tech University), Pekka Tuominen (University of Helsinki), and Zsuzsanna Varga (University of Glasgow), fully open access at https://doi.org/10.17645/up.i327

## Abstract

Digital participation relies on computational systems as the instruments for expert engagement, data-driven insight, and informed decision-making. This study aims to increase expert engagement with the Bayesian-based decision support model in evaluating urban vibrancy decisions. In this study, urban vibrancy parameters are defined using "economic, use, and image value" measures. This article focuses on the visual aspect of vibrancy, defined as the image value of place. The image value is evaluated through likability and likability features. The case study area is the Eminönü Central Business District in the Istanbul Historic Peninsula due to its distinctive urban dynamics derived from the duality of being a cultural and cosmopolitan city center. This research presents a method as a decision support system (DSS) model based on the Bayesian belief network (BBN) and spatial BBN for supporting urban vibrancy decisions. The spatial BBNs monitor spatial outcomes of variables' dependencies that form through the BBN relationship network. Spatial BBN tools monitors the spatial impact of decisions for informed urban interventions. The results demonstrate that urban greening, pedestrianization, and human-scaled streetscapes should be prioritized to make streets more likable. The most significant intervention areas are Tahtakale for signboard regulation, Sultanahmet and Vefa for cultural landscape improvement, and Vefa and Mahmutpaşa for planning building enclosures. The participation is achieved by evaluating urban vibrancy with what-if scenarios using BBN. The developed DSS model addresses which parameters should be prioritized, and what are their spatial consequences. The use of spatial BBN tools presents certain limitations in terms of interoperability and user interaction. Overall, this research contributes to participatory urban planning by incorporating both conditional and spatial dependencies. This unique approach not only promotes a more holistic understanding of urban vibrancy but also contributes to the advancement of digital participation in urban planning decisions.

**Keywords**
decision support; digital participation; expert participation; place value; spatial Bayesian belief network; spatial dynamics; urban vibrancy

## 1. Introduction

Participation plays a critical role as an effective decision support mechanism, fostering transparency, inclusivity, and responsiveness in the decision-making process (Skogheim & Atkinson, 2013). Empowering citizens with access to information and the ability to influence the urban environment (Sanoff, 1992; Skogheim & Atkinson, 2013) leads to dialogue, collaboration, and improved justice and democracy. Digital participation further amplifies these advantages by increasing community engagement and acceptability while promoting the democratization and dissemination of information (Kingston, 1998; Rinner & Bird, 2009). Integrating computational tools and online systems significantly enhances digital participation (Moura & Campagna, 2018). From an expert perspective, digital participation tools enhance expert engagement, collaboration, and co-design, ultimately improving decision-making in design practices (Moura & Campagna, 2018).

While participation has been recognized as a valuable element in decision-making, it is often poorly integrated into data-driven methods. Developments in smart cities and big data augment data-driven analysis and decision-making methods. Incorporating them into digital participation practices is seen as a future trajectory for informed decision-making (Hollands, 2008; Kitchin, 2013). Recognizing this, the presented study seeks to bridge this gap. This study will focus on developing a data-driven decision support model that incorporates expert participation for more informed decision-making. It utilizes Bayesian belief networks (BBNs) to evaluate urban vibrancy decisions, specifically visual attractiveness. Participation is achieved through surveys to calibrate the BBNs and utilizing scenarios via a spatial BBN platform to prioritize actions. This research explores the use of spatial BBN tools to support informed decision-making in urban vibrancy scenarios, addressing key research questions: (a) How can urban vibrancy be evaluated using BBN? (b) Which parameters should be prioritized? and (c) What will the spatial consequences be? By assessing the role of spatial BBN tools in expert participation, frequently used in environmental modeling and landscape planning decisions (Landuyt et al., 2015; Langemeyer et al., 2020; Stritih et al., 2020), this research contributes to the field of urban studies. Moreover, understanding the socio-spatial process in a city is crucial for achieving a participatory approach, as highlighted by Tekeli (2009). To address this gap, this research offers a user-interactive and spatially related BBN model to evaluate urban vibrancy decisions.

The research methodology quantifies place value measures, reveals direct and indirect relationships between them, and supports site decisions based on this relationship network using spatial BBN tools. This study aims to assist decision-makers in fostering vibrant neighborhoods through data-driven methodologies and a participatory approach, providing a useful tool to develop strategies and test actions for urban vibrancy.

The article's structure is as follows: Section 2 delves into urban vibrancy, specifically focusing on visual attractiveness defined as image value. Section 3 presents a systematic review, examining the role of BBNs and spatial BBNs in decision-making and participatory processes. Section 4 elaborates on the methodology, followed by Section 5, which applies the spatial BBN model to site decisions and presents the results.

The article concludes with a discussion of the outcomes and limitations in Section 6, followed by concluding remarks and potential avenues for further research in Section 7.

## 2. Urban Vibrancy and Place Value

Urban vibrancy, a vital aspect of urban life (A. Jacobs & Appleyard, 1987), has gained increasing significance in urban planning due to its positive impact on city livability (Montgomery, 1998). The concept of urban vibrancy was initially introduced by Jane Jacobs in her influential work *The Death and Life of Great American Cities*. J. Jacobs (1961) argued that urban vibrancy promotes active street activity and human interaction, thereby fostering a vibrant social life. Diversity in activities, people, and urban forms are necessary elements for vibrant neighborhoods (J. Jacobs, 1961; Talen, 2006).

Methods for evaluating urban vibrancy have been built upon J. Jacobs's (1961) six conditions for urban vitality, encompassing land use mix, density, block size, building age, accessibility, and street permeability. Montgomery (1998) further developed the principles of activity, image, and form as characteristics of urban vibrancy. The scope of quantitative measures for urban vibrancy has expanded to include urban form (Tang et al., 2018), urban functions, and user activities (Lin et al., 2017), along with quality (Zhang et al., 2019), using big data approaches, and leveraging geo-referenced datasets from locative media data (Wilken & Goggin, 2014). This diverse range of measurement approaches contributes to a comprehensive understanding of urban vibrancy and supports decision-making processes.

In this context, this study aims to gauge urban vibrancy by considering urban form, functional parameters, and user activities and perceptions, employing big urban data. Therefore, the study uses an extensive evaluation method to understand urban vibrancy from the perspectives of a place's economic, use, and image value. It benefits from the place value categorization by the Commission for Architecture and the Built Environment (CABE, 2006), which includes the economic, use, image, social, and environmental value of a place (Table 1). There is a circular relationship between place value and place quality: place quality enhances the urban environment, and place value describes place quality (Carmona, 2019). This research focuses on the economic, use, and image value of a place concerning economic prosperity, attractiveness, and visual likability. The study defines economic value through Carmona's (2019) compiled evidence. It defines use value by applying J. Jacobs' (1961) diversity generators and Montgomery's (1998) activity principles for attractiveness. Lastly, it defines image value through Nasar's (1998) likability features. Although urban vibrancy is measured through different place value concepts, this study primarily focuses on image value to evaluate urban vibrancy from aspects of visual quality and attractiveness.

This study concentrates on the image value measures based on the evaluation of the visual quality of urban scenes by the public, known as evaluative image or likability (Nasar, 1998). Image value is measured using the likability concept and likable features developed by Nasar (1998). Likability is a key indicator of the public's positive evaluative response toward an urban scene, primarily determined by the presence of likable features (Nasar, 1998). The five evaluative criteria for likability include naturalness (reflected in elements such as countryside, urban greening, and water landscapes), upkeep (related to cleanliness, maintenance, and the condition of the built environment), openness (associated with views, panoramas, and scenery), order (pertaining to the organization and clarity of the built environment), and historical significance (denoted by vernacular architecture or historical buildings; Nasar, 1998).

**Table 1.** Place value measures.

| Place value | Description |
|---|---|
| Economic value of place (economic viability) | The focus is on the economic viability and economic productivity (Carmona, 2019), the trade value of urban environment as mentioned in CABE (2006) |
| Image value of place (design quality of streetscapes) | The focus is on the visual quality and attractivity of the place |
| Use value of place (activity) | The focus is on activities and active user density. The dimension has termed as use value (CABE, 2006), handled under social value (Carmona, 2019), or activity dimensions (Montgomery, 1998) |
| Cultural value of place (attractiveness of heritage) | The focus is on the cultural significant of the place within the conservation, revitalization of cultural attributes (CABE, 2006) |
| Social value of place (wellbeing) | The focus is on social relations of people and the psychological connection with place (CABE, 2006; Carmona, 2019) |
| Environmental value of place (sustainability and public health) | The focus is on environmentally aware design with minimum consumption and contribution to sustainability (CABE, 2006). Carmona (2019) includes health value that concentrates on public health such as walkability |

Source: Adapted from CABE (2006).

This study employs likability attributes as evaluation criteria for assessing the image value of a place. Specific indicators within each criterion are identified, such as urban greening for naturalness, traffic density, building condition and signboards for upkeep; building enclosure rate for order; and cultural landscape for historical significance.

The study examines urban vibrancy in Eminönü Central Business District (CBD) of Istanbul's Historical Peninsula as the case study area. Eminönü CBD is characterized by having both historical importance and a cosmopolitan city atmosphere (Site Management Directorate of Istanbul Historic Peninsula, 2018). The juxtaposition of historical and cosmopolitan aspects in Eminönü CBD presents challenges and opportunities that influence urban dynamism. Therefore, this area was selected as a testbed for this study. In this study, BBN is used as a decision support tool to reveal complex relationships for knowledge discovery about relationship patterns.

## 3. Bayesian Methods for Decision Support and Participation

Decision support systems (DSSs) are widely used to assist experts in making decisions in the field of urban design and planning. DSS is an information system that integrates other information systems and interactive models to facilitate decision-making activities (Sprague & Carlson, 1982). Erhan (2003) identified several research concerns in the use of DSSs, including understanding how computer systems can support designers and planners in various areas, how to formalize design problems, and how computers can generate alternative solutions based on these formalizations, and assess the proposed solutions.

As stated by Loo and Tang (2019, p. 139), "decision-making becomes a data-driven process" in the data-rich environment of smart cities. Data-driven DSS utilizes computational techniques and data analysis to support informed evaluations and generate alternative solutions. This study reviews reference studies adopting a data-driven approach in DSSs to support urban planning decisions. For instance, Sohtorik (2016) uses data mining techniques to extract knowledge and rules for decision-making in urban interventions, while Çalışır

Adem and Çağdaş (2022) integrate data mining techniques and cellular automata for interventions in historical sites.

Data-driven computational techniques also increase expert engagement by promoting informed decision-making processes. In the city induction model, Duarte et al. (2012) developed a computer model for the formulation, production, and evaluation of urban plans. The model seeks to facilitate expert collaboration, informed decision-making, and the generation of high-quality urban environments that meet community needs. It incorporates a GIS and utilizes a common urban space ontology, suggesting that data-driven approaches support urban planning decisions in terms of plan generation and evaluation. Lima et al. (2022) employ a data-driven process to evaluate different urban fabric layouts through shape grammars and multi-objective evaluation methods. Generating alternative designs enables urban planners to engage and make informed decisions about the optimum urban layout with increased pedestrian accessibility and decreased infrastructure cost.

Clearly, data-driven DSS plays a significant role in supporting informed evaluations and generating alternative solutions in the context of urban planning decisions. However, decision-making in complex urban environments demands a robust framework to handle the uncertainties and intricate relationships among various factors. In the field of DSSs, different inference mechanisms serve various decision problems: rule-based, data-based, purpose-based, and probabilistic inference (Luger & Chakrabarti, 2008). BBNs offer a powerful tool to incorporate probabilistic inference into the decision-making process to handle uncertainty and complex relationships (HUGIN Expert, 2013). BBNs encode human intuition and reasoning under uncertain conditions, enabling a natural and intuitive approach to decision-making (Pearl, 1986).

BBNs are useful tools for learning causal relationships, making predictions, and discovering knowledge by making inferences from data (Heckerman, 1997). BBNs' ability to handle incomplete datasets and learn causal relationships for predictions makes them advantageous as knowledge discovery tools (Heckerman, 1997). Fusco (2008) emphasizes that BBNs outperform other statistical methods in knowledge discovery, making them an optimal choice for this study to discover knowledge from the data that can support urban planning decisions.

In urban studies, BBNs have primarily been utilized to explore indirect and direct relationships between variables and evaluate decisions based on these relationship patterns. They have been utilized to evaluate sustainable mobility performance (Fusco, 2004), traveler satisfaction (Yanık et al., 2017), and changes in spatial dynamics (Fusco, 2008). BBNs support participatory modeling with their graphical structure and probabilistic nature, facilitating a participatory approach to decision-making by evaluating alternative scenarios while considering uncertainty (McCloskey et al., 2011). Yanık et al. (2017) incorporate experts in evaluating causality in BBNs through pairwise relationship comparison and causal Bayesian network construction to calibrate BBNs.

Spatial BBNs link Bayesian networks with spatial data through raster images. The application of spatial BBNs supports experts through uncertainty mapping. Langemeyer et al. (2020) used a spatial BBN tool in multi-criteria decision-making to build a screening tool for efficient green roof usage in Barcelona. They created a BBN with HUGIN software, developed spatially explicit BBNs with the HUGIN QGIS plugin, and used expert opinions for node weighting. Similarly, Landuyt et al. (2015) designed the Probabilistic Map

Algebra Tool plugin for pixel-based application of BBN models in probabilistic mapping, using Python to monitor BBN results in QGIS. This plugin supported stakeholder involvement, expert knowledge incorporation, and uncertainty consideration in landscape planning. Stritih et al. (2020) developed a spatial BBN platform (gBay) for ecosystem service modeling and mapping, using case studies to explore relationships and future scenarios with a participatory approach. These studies emphasize spatial BBNs' potential in decision support, stakeholder involvement, and uncertainty mapping through BBN and GIS integration.

## 4. Methodology

This study employed a quantitative methodology, incorporating an exploratory research approach to examine urban vibrancy, considering spatial, functional, and perceptual attributes. In this exploratory research, knowledge discovery was achieved through the application of BBN to reveal complex relationships between place value measures. The exploratory analysis results were also validated through expert consultation. Expert participants evaluated the correlation and causality of the relationships between place value attributes through a survey facilitated by BBN. BBN was utilized in this study to explore the intricate relationships between vibrancy measures and understand the causality of these relationships. The BBN in this study was constructed using automated learning algorithms. Specifically, the Necessary Path Condition (NPC) learning algorithm, among constraint-based learning algorithms that measure the conditional independencies of nodes through statistical tests, was utilized (Steck & Tresp, 1999).

This study implemented a data-driven DSS through BBN and supported it with expert participation through a survey. In this study, the relationship network, calibrated with expert participation, was evaluated using a spatial BBN platform to make decisions regarding vibrancy indicators. The study methodology encompassed phases such as data collection, information retrieval, data analysis with BBN, and the use of spatial BBNs, as shown in the flowchart (Figure 1).

### *4.1. Data Collection and Information Retrieval Phase*

For data collection, this research utilized data from both physical and online localities to address the multidimensionality of vibrancy. Web-scraping methods were applied to collect data from location-based social network (LBSN) platforms. This research employed locative media data from various sources, including Flickr, Foursquare, Google Places, and Google Street View (GSV). This study used Flickr photo-sharing to estimate heritage visitation, Foursquare check-ins to estimate user density, Google Places to obtain information about activity places, and GSV to audit streetscape elements. This research chose to apply big data analysis of locative media data obtained from LBSN platforms instead of conducting a survey for user data collection. Big data provides a rich source of information about people's activities, movements, and behaviors. There is consensus on the high level of representativeness of LBSN data in capturing the common user patterns of citizens (Martí et al., 2019). Additionally, master plans were digitized and transformed into vector attributes to collect data about urban function and urban form attributes. The research employed various quantitative methods, such as entropy-based indices, clustering algorithms, image segmentation, and surveys, to gauge measures in information retrieval. Table 2 presents the variables within the data collection and information retrieval methods for each value of place.

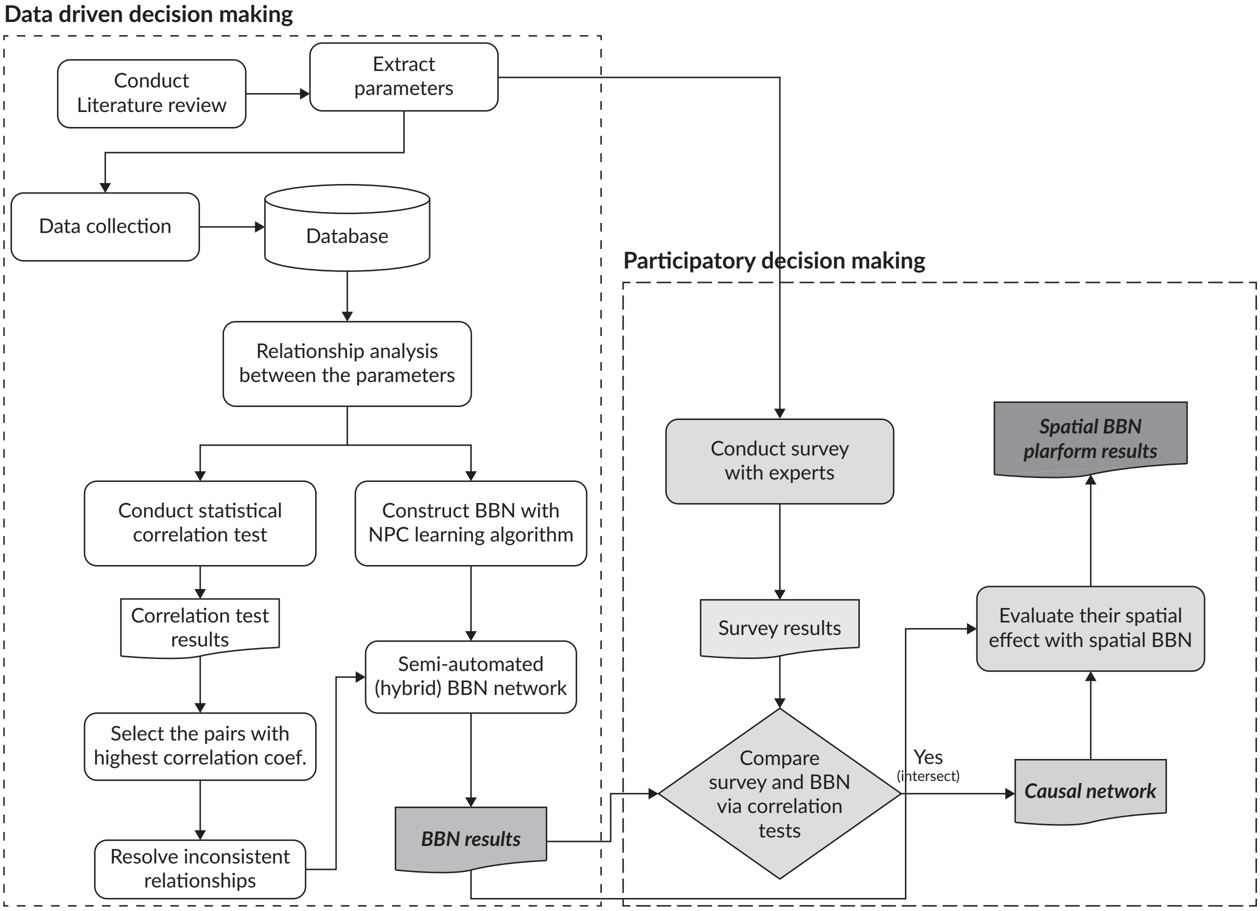


**Figure 1.** The flowchart of the methodology.

This study focuses on image value, measured through likability, and its dependence on factors such as urban greening, public open space, building conditions, traffic density, and cultural landscapes (Nasar, 1998). GSV images were scraped to extract streetscape attributes. A visual survey for likability was conducted with 60 participants, in which respondents evaluated the images using a Likert scale. Likability scores were obtained by calculating the mean of respondents' scores. To gauge likability features, GSV images were analyzed using image segmentation methods. The image features were extracted using the TensorFlow extension developed by Abadi et al. (2016). Semantic labels were assigned to pixels in the image, and the ratio of the labeled features was calculated.

These multiple datasets were organized and combined into a SQL database for data organization, enabling CRUD (create, read, update, delete) operations to manage the data effectively. A spatial database was created using PostgreSQL and PostGIS extensions to monitor and manipulate spatial data in a GIS environment. The NPC learning algorithm was utilized as a learning algorithm to construct the BBN. Ambiguities were resolved through the correlation test results. The BBN analysis uncovers the probabilistic relationship between place value measures based on their conditional dependence.

**Table 2.** The variables and methods for data collection and processing.

| Aspect of urban vibrancy | Dependent variable | Independent variables | Data collection methods | Applied methods for information retrieval | Data source |
|---|---|---|---|---|---|
| Economic value of place | Land price change per square meter | Urban function features<br>Urban form features<br>Accessibility<br>Socio-demographic features | Municipality databases for land price, Istanbul Metropolitan Municipality (IMM) Master Urban Maps (2011)<br>Open Street Map | Entropy-based indices<br>Coefficient of variation<br>Cumulative opportunities-based accessibility | Fatih Municipality Database |
| Use value of place | Active people density | Activity features<br>Time diversity<br>Heritage attractiveness (visitation rate of heritage)<br>Attractiveness of activities (place rating)<br>Accessibility, public open spaces | LBSNs<br>IMM Master Urban Maps (2011)<br>Open Street Map | Getis-Ord Gi*<br>Entropy-based diversity indices<br>Cumulative opportunities-based accessibility photo-user-day | Foursquare<br>Google Places API<br>Flickr API |
| Image value of place | Likability | Urban greening<br>Vista<br>Building enclosure rate<br>Signboards (physical incivilities)<br>Traffic density<br>Cultural landscape | GSV images<br>Visual survey | Image segmentation methods | GSV images<br>Visual survey data |

The directed acyclic graph (DAG) is shown in Figure 2, and conditional probability table (CPT) of the image value relationship network is displayed in Table 3. Based on the DAG results, the physical elements of the built environment (including building enclosure rate, traffic, and signboards on the facade), natural elements (urban greening), and vista, directly affect the likability of the streetscapes. The DAG graphic monitors the direct and indirect relationship between likable features, while the CPT gives information about the conditional probability rate of likability based on changes in the other attributes. According to the CPT results, urban greening, vistas, and cultural landscapes contribute positively to the likability of an area, with urban greening accounting for 8.37% of the effect, vista for 5.68%, and cultural landscape for 2.06%. The CPT illustrates that 25% of places with high levels of urban greening are associated with high level likability. Similarly, 24% of places with vistas and 20% with cultural landscapes exhibit high levels of likability. On the other hand, the building enclosure rate has a significant negative impact on likability, accounting for 12.98% of the effect, while the presence of facade signboards contributes negatively, at 10.67%. Among the places with lower building enclosure rates, 44% are highly likable, as are 26% of places without signboards on facades, and 20% of places with low traffic density. The results demonstrate that an increase in urban greening, heritage, and vista improves likability, while a rise in building enclosures and facade signboards decreases likability. Lastly, participants evaluated the causality and correlation of the relationships found in the BBN network through a survey.

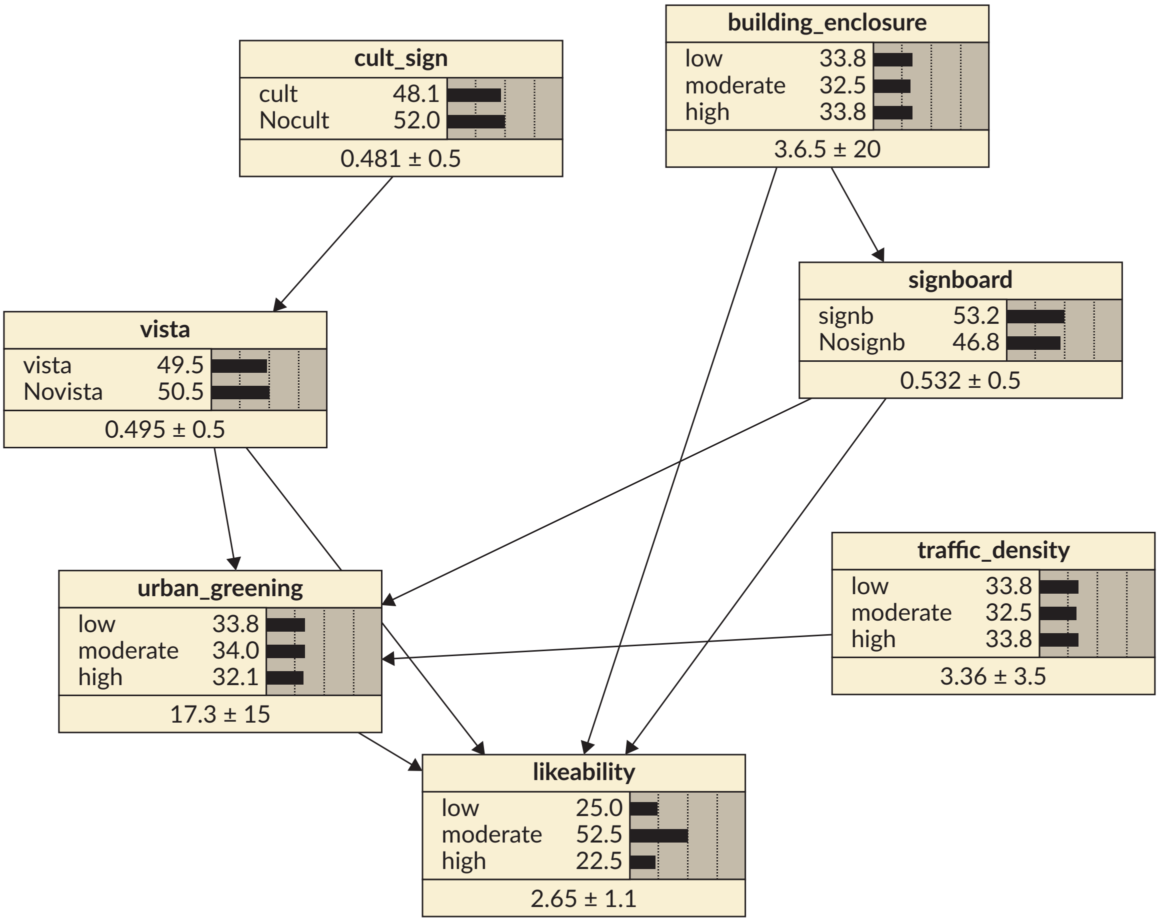


**Figure 2.** BBN network of image value shown with DAG.

Lastly, the data-driven decision-making process was complemented by participation in a survey. The survey involved 15 researchers, all of whom had been engaged in urban studies at the graduate or postgraduate level. In the survey, participants identified the correlation and causality of the relationships using a pairwise relationship matrix. The relationship between expert responses and BBN results was also assessed using a correlation test as a method of statistical analysis. Chi-square test results reveal significant associations for all measures, with Cramér V values indicating moderate associations for economic ($V = 0.460$) and use ($V = 0.475$) values and a high association for image value ($V = 0.522$). Overall, the analysis demonstrates a significant correlation between BBN and survey results, supporting the use of the survey to assess BBN results. The image value relationship network was selected as a case due to its high association level. A causal map was generated based on the participants' evaluations, as shown in Figure 4a.

**Table 3.** BBN network of image value shown with CPT table.

| | | | Likeability | | | |
|---|---|---|---|---|---|---|
| Rank | Variables | Updating condition | Low | Moderate | High | Change |
| 1 | Urban greening | Low | 35.64 | 53.49 | 10.88 | 12.74 |
| | | Moderate | 16.86 | 61.39 | 21.75 | 6.04 |
| | | High | 16.58 | 59.17 | 24.25 | 6.32 |
| 2 | Signboard density | Signboard | 34.25 | 54.61 | 11.13 | 11.35 |
| | | No signboard | 12.92 | 61.12 | 25.96 | 9.98 |
| 3 | Traffic density | Low | 23.07 | 56.72 | 20.21 | 1.35 |
| | | Moderate | 20.87 | 60.13 | 19 | 2.06 |
| | | High | 24.66 | 57.46 | 17.88 | 1.76 |
| 4 | Vista | Vista | 17.14 | 58.99 | 23.87 | 5.76 |
| | | No vista | 28.50 | 57.18 | 14.32 | 5.60 |
| 5 | Building enclosure rate | Low | 2.42 | 52.62 | 44.96 | 25.93 |
| | | Moderate | 29.45 | 63.2 | 7.25 | 11.78 |
| | | High | 37.07 | 58.51 | 4.42 | 14.17 |
| 6 | Cultural sign | Cult | 21.4 | 58.31 | 20.29 | 1.50 |
| | Cultural landscape | No Cult | 24.51 | 57.82 | 17.67 | 2.61 |

### *4.2. The Use of Spatial BBN Platforms*

Among BBN programs, HUGIN and Netica have spatial BBN tools that integrate Bayesian networks with spatial data. GeoNetica and Probabilistic Map Algebra Tool are the GIS extensions of Netica that facilitate the linkage of BBNs to spatial data (Norsys Software Corporation, n.d.). GeoNetica allows Bayes nets to interact with GIS for probabilistic processing of raster data, while the Probabilistic Map Algebra Tool provides user-friendly model development and result analysis, coupling BBNs with spatial input data through Python and QGIS (Norsys Software Corporation, n.d.). As another plugin, Stritih et al. (2020) developed the gBay platform that considers spatial interactions and feedback loops, unlike other spatial BBN tools. This online platform connects BBNs with spatial data (raster or vector) and enables iterative BBN execution considering spatial interactions (Stritih et al., 2020). Lastly, the HUGIN QGIS plugin applies Bayesian network methodology to analyze raster data layers and generate a new raster layer that contains the results (Karlsen & Madsen, 2018). The Bayesian network is employed within node values, linked to the raster layers, to calculate and propagate the probabilities for each point in the raster layer (Karlsen & Madsen, 2018).

In this study, the use of spatial BBN platforms involved two phases: (a) the generation of raster layers and (b) the incorporation of BBN into spatial BBN platforms. In the first phase, variable attributes in the spatial database were divided into separate vector data layers (in the form of shapefiles). These vector data layers were then converted into raster data and standardized by resolution (100 × 100 cm), extent (Istanbul Historical Peninsula Eminönü CBD boundaries), and EPSG (European Petroleum Survey Group) projection (4326, the same as vector layer) in Geotif format, including raw data. The band ranges of the raster layers were organized in accordance with the same interval in variables in the BBN. This procedure is essential for utilizing the spatial BBN tools as they operate with raster data. The raster images of the likability and urban greening variables are illustrated in Figure 3. Converting vector data to raster may result in information loss due to image resolution. In QGIS, the raster layer is visualized using the singleband pseudocolor settings, whose color range represents the intervals of the variables.

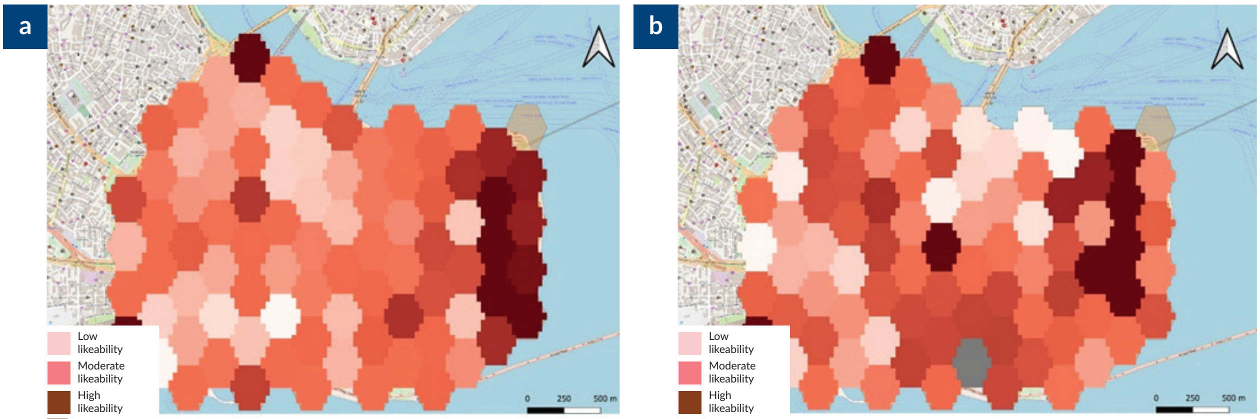


**Figure 3.** Raster layers of the likable features: (a) likability raster layer and (b) urban greening raster layer.

The gBay platform was employed as a spatially interactive BBN, and its interface is displayed in Figure 4. The process begins by uploading the BBN in Netica DNE format to the gBay platform. Once uploaded, the user can proceed by indicating the target node of this BBN (Figure 4a). The output will monitor the posterior probability distribution for this target node. Non-spatial evidence is set by clicking on the state of a node, and spatial inputs are uploaded into raster file format. After these configuration steps, the user can initiate the analysis by running the network. gBay utilizes spatial data to conduct inference in the BBN for each pixel or feature, producing posterior probability distribution results for the target node. Users have different options to access the results, which can be downloaded or received via email. The results are given as a command summary of BBN propagation and a raster layer, showing the posterior probability distribution of likability. The spatial statistics are calculated and represented with different raster bands for each state of the target node. The input values are hard evidence, which includes continuous nodes discretized as interval measures and discrete nodes represented as 0 and 1. In this study, Raster Band 1 signifies the entropy-based calculation (evenness index), Raster Band 2 indicates the mean-based calculation, and Raster Band 3 represents the median-based calculations for each state of likability, as seen in Figure 5.

The HUGIN QGIS plugin was also employed as another spatial BBN tool. HUGIN QGIS does not require user interaction, unlike gBay. The raster layer names are identical to the variable nodes in the HUGIN BBN. After generating the raster layers, the HUGIN Python document was reconfigured based on the model parameters. In the input section of the document, nodes were mapped to raster layers with the same node names as in the HUGIN BBN, and the raster identified a raster image file name. The output section lists the target node as max, Pmax, and avg, with the maximum probability, probability of the state with the maximum probability, and average change values of the target node calculated as an output raster layer (Figure 5b). The raster layers, HUGIN Python file, and HUGIN BBN are assigned as input layers in the HUGIN QGIS interface. The BBN is then propagated into spatial data using the raster images, with the target node being likability. Output options include maximum probability index states (Raster Band 1), the probability of the state with maximum probability (Raster Band 2), and maximum expected utility (Raster Band 3; Karlsen & Madsen, 2018). The HUGIN QGIS results are represented using a sequential color scheme ranging from green to yellow-orange and red. Sequential color schemes are often used to represent data with an ordered range of values. Green corresponds to low level likability, yellow to moderate level likability, and orange and red to high level likability areas, as shown in Figure 5b.

## 5. Results

This study delves into site planning decisions and strategies related to place value measures, specifically focusing on the Istanbul Historic Peninsula Management Plan (Site Management Directorate of Istanbul Historic Peninsula, 2011, 2018). The overarching goal of this management plan is to strike a balance between preservation and transformation while safeguarding the area's historical, socioeconomic, spatial, and cultural identity (Site Management Directorate of Istanbul Historic Peninsula, 2011, 2018). Table 4 lists site decisions pertaining to image value measures.

**Table 4.** The site decisions regarding the image value measures.

| Decisions | Parameters |
|---|---|
| Main goal: Improving the visual integrity of the site<br>The evaluative image of the site | Likability |
| Decision 1: Limiting car use on the site<br>Decreasing the vehicle density<br>Deautomobilization | Traffic density |
| Decision 2: Improving the landscape quality of the site<br>Improving the green pattern of the streetscapes | Urban greening |
| Decision 3: Evaluating the building silhouette<br>Controlling the facade extensions<br>Decreasing the building enclosure on the streets | Building enclosure rate |
| Decision 4: Controlling signboards and banners that affect the perception of cultural values of the site negatively<br>Developing an urban design guide for lighting, signboards,and building facade regulations | Physical incivilities (signboards) |
| Decision 5: Restoration of traditional street patterns as vernacular architecture examples | Cultural landscape |

Source: Site Management Directorate of Istanbul Historic Peninsula (2011, 2018).

In the existing conditions, areas with low level likability tend to cluster around the Tahtakale district, which is also a hub for commerce, particularly shopping. The low level likability in these areas can be attributed to the proliferation of dense signboards and other physical infrastructure, compounded by high traffic density. Another concentration of low level likability is observed in the Kumkapı district, known for its residential coastal setting. In this context, low level likability can be traced back to limited urban greening and high building enclosure resulting from the density of residential patterns. Moderate levels of likability are clustered in the Mahmutpaşa, Beyazıt, and Vefa districts. Notably, these districts boast a high number of cultural landmarks. High levels of likability are concentrated in the Beyazıt and Sultanahmet districts, characterized by abundant cultural landmarks, ample urban greening, and scenic vistas that seamlessly blend cultural and natural landscapes.

Adjustments were made to the variables' states to observe their impact on likability results, aligning with decisions made by the Site Management Directorate of Istanbul Historic Peninsula (2011, 2018). Notably, traffic and signboard density, reflecting physical incivilities, were reduced to their lowest states, set at 100%, while cultural landscapes and urban greening levels were heightened, backed by 100% evidence. The gBay platform interface, illustrated in Figure 4b, highlights selected variables (in bold) and the likability target node (indicated by a target icon). Causal relationships connect variables such as building enclosure, urban greening, vistas, and signboards with likability, while vistas are linked with urban greening, as shown in Figure 4a. Figure 5 presents the results for the likability target node, with raster bands representing entropy-based calculations (band 1), mean-based calculations (band 2), and median-based calculations (band 3) of the probability distribution for likability. The entropy index was not computed, and each grid displays two posterior probabilities based on mean and median evaluations. Notably, mean-based assessments (band 2) yield higher results for each likability state (Figure 5).

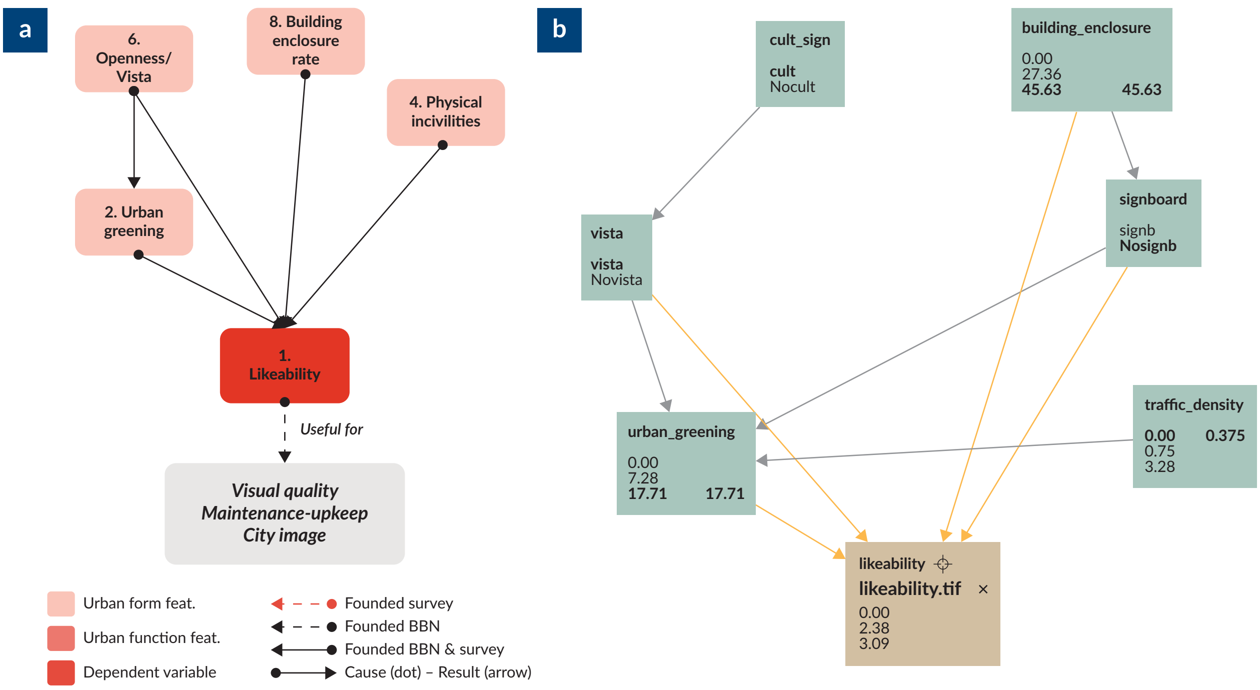


**Figure 4.** The Bayesian network: (a) the causal network diagram and (b) the BBN in gBay platform interface with causal linkages.

After BBN propagation, black represents low level likability, green indicates moderate level likability, and blue represents high level likability in Figure 5. Entropy based calculations are shown in raster band 1, mean-based calculations in band 2, and median-based calculations in band 3. When site decisions are applied, there is a slight change in low level likability results, with the number of grids displaying low level likability attributes shifting from 29.89% (26/87) to 27.59% (24/87), a 2.30% change. Notably, a limited part

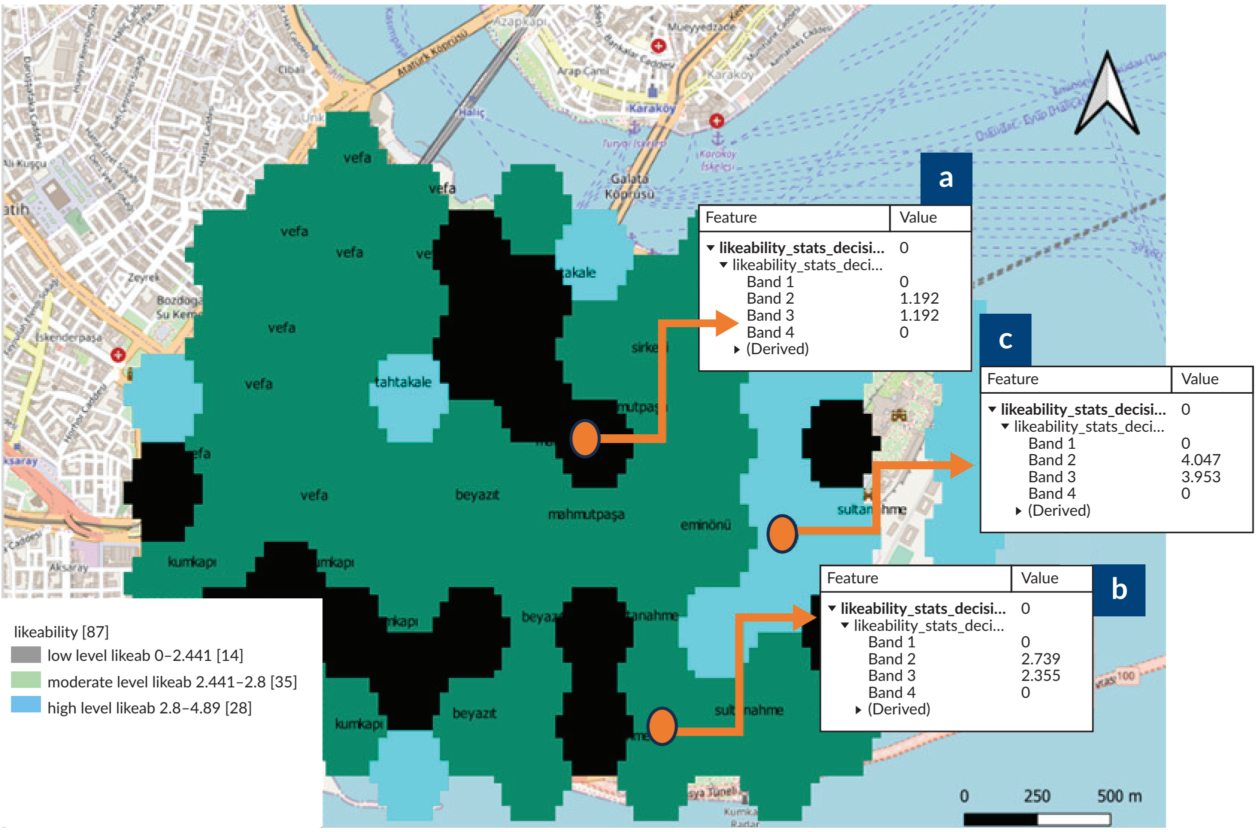


**Figure 5.** Different likeability states: (a) low level likability, (b) moderate level likeability, and (c) high level likeability.

of Molla Hüsrev neighborhood in the Vefa district changed from low to moderate level likability. Conversely, the number of grids with moderate level likability attributes increased from 40.23% (35/87) to 55.17% (48/87), indicating a significant 15% change, particularly in Vefa, Kumkap, Mahmutpaşa, and Beyazıt Districts. However, the number of grids with high level likability attributes decreased from 32.18% (28/87) to 19.54% (17/87), a 12.64% change. These shifts suggest clustering in moderate-level likability following BBN propagation. The HUGIN QGIS results also reveal meaningful variations in the distribution of moderate likability levels, with both low and high level likability probabilities dispersed. In general, the likability results show greater dispersion in HUGIN QGIS results compared to more clustering in gBay results. There is a decrease in both high, moderate, and low likability levels, with 37.5% in low, 20% in moderate, and 50% in high likability levels. HUGIN QGIS results also display uncomputed areas with no data, accounting for 12.64%, corresponding to 20% in gBay. These uncomputed areas are mostly low-likable zones. Considering the user interaction and result evaluation, gBay is selected for spatial decision-making. A comparison between HUGIN QGIS and gBay results is presented in Figure 6.

The decisions regarding individual variables were also subject to testing to assess their influence on the spatial distribution of likability. Consequently, optimal decisions were identified to enhance likability. The study revealed that continuous variables such as urban greening, traffic density, and building enclosure rate exhibit more noticeable alterations in likability compared to discrete variables like signboards, vistas, and cultural landmarks. The results of the statistical validity percent support this observation, as displayed in

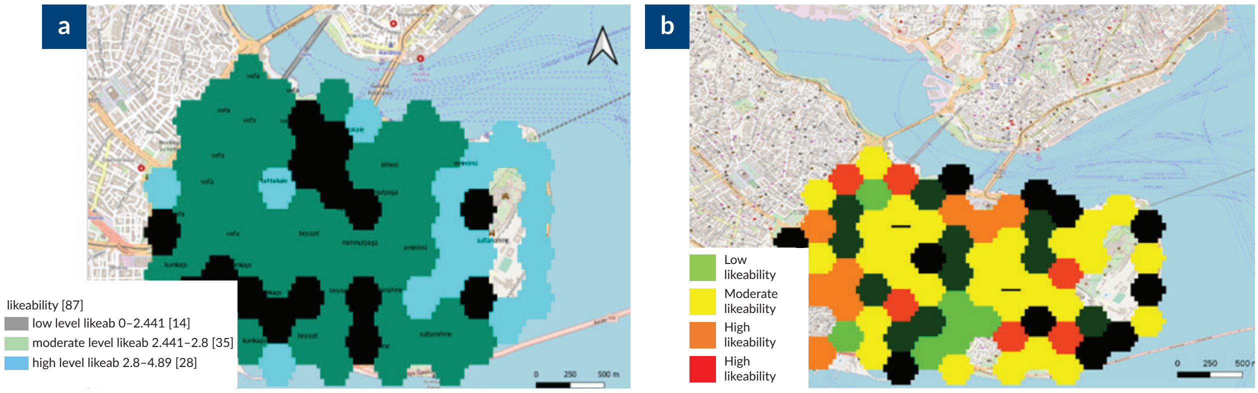


**Figure 6.** The comparison of the two spatial BBN outputs for likability variable: (a) HUGIN GIS results and (b) gBay results.

Table 5. The "Statistics valid percent" signifies the proportion of valid data within the bands. By comparing the percentages of valid data across various variables, it becomes apparent that building enclosure has the highest percentage at 66.31%, followed by urban greening at 56.72%, and traffic density at 51.49%, among continuous variables. In contrast, among discrete variables, cultural significance stood at 34.89%, vista at 33.22%, and signboard at 31.28%. Overall, the findings indicate that the most substantial impact on likability occurs when the building enclosure rate is reduced (Decision 3). Subsequently, increasing urban greening (Decision 2) has the second most significant effect, while decreasing traffic density (Decision 1) ranks third in terms of its impact on likability. Interestingly, the survey did not support the notion that traffic density significantly affects likability. Conversely, enhancing the presence of cultural landscapes (Decision 5) and reducing signboard density (Decision 4) has the least impact on likability. Curiously, the survey did not highlight the influence of cultural landscapes on likability either.

**Table 5.** The effect of variables on likability (target node).

| Variable | Band | Statistics Maximum | Statistics Mean | Statistics Minimum | Statistics StdDev | Statistics Valid Percent |
|---|---|---|---|---|---|---|
| D2 Increasing Urban Greening | Band 1 | 0.99 | 0.87 | 0.83 | 0.06 | 56.72 |
| | Band 2 | 2.66 | 2.59 | 2.59 | 0.06 | |
| | Band 3 | 2.37 | 2.37 | 2.31 | 0.02 | |
| D5 Enhancing Cultural landscape | Band 1 | 0.97 | 0.97 | 0.97 | 0 | 34.89 |
| | Band 2 | 2.48 | 2.48 | 2.48 | 0 | |
| | Band 3 | 2.29 | 2.29 | 2.29 | 0 | |
| D1 Decreasing traffic density | Band 1 | 0.98 | 0.98 | 0.97 | 0.07 | 51.49 |
| | Band 2 | 2.63 | 2.63 | 2.48 | 0.05 | |
| | Band 3 | 2.35 | 2.35 | 2.26 | 0.03 | |
| D4 Decreasing signboard density | Band 1 | 0.98 | 0.98 | 0.98 | 0 | 31.28 |
| | Band 2 | 2.54 | 2.54 | 2.54 | 0 | |
| | Band 3 | 2.32 | 2.32 | 2.32 | 0 | |
| D3 Controlling Building enclosure rate | Band 1 | 0.96 | 0.84 | 0.73 | 0.09 | 66.31 |
| | Band 2 | 2.88 | 2.43 | 2.04 | 0.34 | |
| | Band 3 | 2.62 | 2.31 | 2.08 | 0.22 | |

## 6. Discussion

This study utilized spatial BBNs to simultaneously assess causal relationships between variables and their spatial interactions, shedding light on the spatial clustering and dispersion of likability. Spatial BBNs offer valuable insights into how decisions impact specific locations, helping decision-makers target interventions more effectively. The research revealed that areas with low level likability are concentrated in districts with dense signboards, while high level likability is associated with cultural landmarks, urban greening, and pleasant vistas. This understanding allows for more targeted interventions, prioritizing signboard regulation in the Tahtakale commercial district, cultural landmark enhancement in Sultanahmet and Vefa districts, building enclosure rate arrangement in Vefa and Mahmutpaşa districts, and increased urban greening in Eminönü and Mahmutpaşa districts.

When site decisions were implemented, the results showed an anticipated increase in likability in the Kumkapı, Vefa, and Sultanahmet districts. Reducing the building enclosure rate had the most significant impact on likability, and increasing urban greening also made a substantial contribution. Interestingly, increasing cultural landscapes and reducing signboard density had relatively less significant effects. These findings underscore the importance of prioritizing strategies that reduce building enclosures, promote urban greening, and address traffic congestion in urban planning to create more attractive and likable streetscapes. According to the results, the ideal scenario for likable streets involves green, pedestrian-friendly, human-scaled streets with appropriate building enclosures. However, this study faced limitations related to the operational principles of spatial BBN tools. These tools primarily handle raster data, and converting vector data to raster may result in information loss due to image resolution. Careful resolution settings can help mitigate this issue. Notably, the gBay platform is sensitive to changes in raster image resolution, which can significantly affect outputs. Additionally, gBay lacks the ability to process all variables' spatial data simultaneously. Moreover, HUGIN QGIS does not offer user interaction since it is a QGIS extension of HUGIN designed solely for result monitoring, unlike gBay. However, even user interaction with gBay is limited by its interface, restricting users from modifying the BBN and observing spatial results simultaneously. These platforms should work on enhancing their interoperability and interaction capabilities. Furthermore, they may pose challenges for experts lacking prior knowledge of BBN.

## 7. Conclusion

This study introduces a decision support model based on BBN and spatial BBN to assist in urban vibrancy decisions, significantly contributing to urban planning decision-making processes. It enhances participatory practices by evaluating urban vibrancy through "what-if" scenarios based on the conditional probabilistic relationships of variables. BBN tools allow for instant reflection of changes in conditional probabilities on the target variable, enabling what-if analyses. However, spatial impacts are often overlooked. Spatial BBNs, on the other hand, enhance what-if scenarios by considering spatial dependencies, allowing experts to assess which parameters to prioritize and their spatial implications. This study has the potential to enhance decision-making by integrating both conditional and spatial dependencies, increasing expert engagement with the BBN model.

The novelty of this research lies in adapting BBN-based evaluation and participation, commonly used in ecosystem services and landscape planning, into the urban planning decision-making process. It enhances expert engagement and enables targeted interventions based on economic, use, and image value measures. This approach fosters a more comprehensive understanding of urban vibrancy and significantly advances digital participation in urban planning decisions. Considering the widespread use of computational systems as digital participatory tools, this study aims to boost expert engagement with the proposed model. While the current study focuses on experts, future research will emphasize citizen engagement. This research lays the groundwork for an information dissemination platform designed to inform and involve citizens in urban vibrancy decisions. The BBN-based decision model is expected to evolve into a digital participatory platform, displaying and interactively altering probabilistic relational networks and spatial maps to monitor decision outcomes. Involving citizens in the decision-making process is anticipated to empower them to create more vibrant and livable urban spaces.

## Acknowledgments

This article constitutes an integral part of the thesis study titled *A Decision Support Model Based on Bayesian Belief Network to Evaluate Urban Vibrancy*. We would like to express our gratitude for the support provided by the Istanbul Technical University Scientific Research Project Coordination Unit under project number 42708. This article is based upon work from COST Action DOPMADE, CA18204, supported by COST (European Cooperation in Science and Technology).

## Conflict of Interests

The authors declare no conflict of interests.

## References

Abadi, M., Agarwal, A., Barham, P., Brevdo, E., Chen, Z., Citro, C., & Zheng, X. (2016). *Tensorflow: Large-scale machine learning on heterogeneous distributed systems*. Arxiv. https://arxiv.org/abs/1603.04467

Çalışır Adem, P., & Çağdaş, G. (2022). Cellular automata for infill designs in historic urban quarters. *Nexus Network Journal*, *24*(3), 567–586. https://doi.org/10.1007/s00004-022-00602-2

Carmona, M. (2019). Place value: Place quality and its impact on health, social, economic and environmental outcomes. *Journal of Urban Design*, *24*(1), 1–48. https://doi.org/10.1080/13574809.2018.1472523

Commission for Architecture and the Built Environment. (2006). *The value handbook: Getting the most from your buildings and spaces*. https://www.designcouncil.org.uk/fileadmin/uploads/dc/Documents/the-value-handbook.pdf

Duarte, J. P., Beirão, J. N., Montenegro, N., & Gil, J. (2012). City induction: A model for formulating, generating, and evaluating urban designs. In S. M. Arisona, G. Aschwanden, J. Halatsch, & P. Wonka (Eds.), *Digital urban modeling and simulation* (pp. 73–98). Springer. https://doi.org/10.1007/978-3-642-29758-8_5

Erhan, H. (2003). *Interactive computational support for modeling and generating building design requirements* [Unpublished doctoral dissertation]. Carnegie Mellon University. http://code.arc.cmu.edu/archive/upload/Dissertation_hie.0.pdf

Fusco, G. (2004). Looking for sustainable urban mobility through Bayesian networks. *European Journal of Geography*, *2004*(292). https://doi.org/10.4000/cybergeo.2777

Fusco, G. (2008). Spatial dynamics in France. In O. Pourret, P. Naim, & B. Marcot (Eds.), *Bayesian networks: A practical guide to applications* (pp. 87–112). Wiley. https://people.bath.ac.uk/man54/SAMBa/ITTs/ITT1/DNV/PourretEtAl.pdf

Heckerman, D. (1997). Bayesian networks for data mining. *Data Mining and Knowledge Discovery*, *1*, 79–119. https://doi.org/10.1023/A:1009730122752

Hollands, R. (2008). Will the real smart city please stand up? *City*, *12*(3), 303–320. https://doi.org/10.1080/13604810802479126

HUGIN Expert. (2013). *HUGIN Expert white paper*. https://hugin.com/wp-content/uploads/2016/05/HUGIN-WHITE-PAPER-NEW-AND-REVISED_2013.pdf

Jacobs, A., & Appleyard, D. (1987). Toward an urban design manifesto. *Journal of the American Planning Association*, *53*(1), 112–120. https://doi.org/10.1080/01944368708976642

Jacobs, J. (1961). *The death and life of great American cities*. Random House.

Karlsen, M., & Madsen, A. L. (2018). *HUGIN QGIS plugin: How to* [Technical report]. Unpublished manuscript. https://raw.githubusercontent.com/huginexpert/HUGIN-QGIS/master/src/QGIS_HUGIN_HOWTO.pdf

Kingston, R. (1998, October 3–7). *Accessing GIS over the web: An aid to public participation in environmental decision making* [Paper presentation]. Workshop of the International Association of Public Participation, Tempe, AZ, USA.

Kitchin, R. (2013). The real-time city? Big data and smart urbanism. *GeoJournal*, *79*, 1–14. https://doi.org/10.1007/s10708-013-9516-8

Landuyt, D., Van der Biest, K., Broekx, S., Staes, J., Meire, P., & Goethals, P. L. M. (2015). A GIS plugin for Bayesian belief networks: Towards a transparent software framework to assess and visualise uncertainties in ecosystem service mapping. *Environmental Modelling & Software*, *71*, 30–38. https://doi.org/10.1016/j.envsoft.2015.05.002

Langemeyer, J., Wedgwood, D., McPhearson, T., Baró, F., Madsen, A. L., & Barton, D. N. (2020). Creating urban green infrastructure where it is needed—A spatial ecosystem service-based decision analysis of green roofs in Barcelona. *Science of The Total Environment*, *707*, Article 135487. https://doi.org/10.1016/j.scitotenv.2019.135487

Lima, F. T., Brown, N. C., & Duarte, J. P. (2022). A grammar-based optimization approach for walkable urban fabrics considering pedestrian accessibility and infrastructure cost. *Environment and Planning B: Urban Analytics and City Science*, *49*(5), 1489–1506. https://doi.org/10.1177/23998083211048496

Lin, S., Xie, R., Xie, Q., Zhao, H., & Chen, Y. (2017). Understanding user activity patterns of the swarm app: A data-driven study. In *UbiComp '17: Proceedings of the 2017 ACM International Joint Conference on Pervasive and Ubiquitous Computing and Proceedings of the 2017 ACM International Symposium on Wearable Computers* (pp. 125–128). Association for Computing Machinery. https://doi.org/10.1145/3123024.3123086

Loo, B. P. Y., & Tang, W. S. M. (2019). "Mapping" smart cities. *Journal of Urban Technology*, *26*(2), 129–146. https://doi.org/10.1080/10630732.2019.1576467

Luger, G., & Chakrabarti, C. (2008). Expert systems. In T. Rudas (Ed.), *Handbook of probability: Theory and applications* (pp. 383–403). SAGE. https://doi.org/https://doi.org/10.4135/9781452226620

Martí, P., Serrano-Estrada, L., & Nolasco-Cirugeda, A. (2019). Social media data: Challenges, opportunities and limitations in urban studies. *Computers, Environment and Urban Systems*, *74*, 161–174. https://doi.org/10.1016/j.compenvurbsys.2018.11.001

McCloskey, J. T., Lilieholm, R. J., Boone, R., Reid, R., Sader, S., Nkedianye, D., & Worden, J. (2011). A participatory approach for modeling alternative future land use scenarios around Nairobi National Park using Bayesian belief networks. *WIT Transactions on Ecology and the Environment*, *144*, 43–57. http://doi.org/10.2495/ECO110041

Montgomery, J. (1998). Making a city: Urbanity, vitality and urban design. *Journal of Urban Design*, *3*(1), 93–116. https://doi.org/10.1080/13574809808724418

Moura, A. C., & Campagna, M. (2018). Co-design: Digital tools for knowledge-building and decision-making in planning and design. *Disegnarecon*, *11*(20), 1–3. https://doi.org/10.20365/disegnarecon.20.2018.ed

Nasar, J. L. (1998). *The evaluative image of the city*. SAGE.

Norsys Software Corporation. (n.d.). *GeoNetica*. https://www.norsys.com/WebHelp/NETICA/X_GeoNetica.htm

Pearl, J. (1986). Fusion, propagation, and structuring in belief networks. *Artificial Intelligence*, *29*(3), 241–288. https://doi.org/10.1016/0004-3702(86)90072-X

Rinner, C., & Bird, M. (2009). Evaluating community engagement through argumentation maps—A public participation GIS case study. *Environment and Planning B: Planning and Design*, *36*(4), 588–601. https://doi.org/10.1068/b34084

Sanoff, H. (1992). *Integrating programming, evaluation and participation in design (Routledge revivals): A theory Z approach* (1st ed.). Routledge. https://www.routledge.com/Integrating-Programming-Evaluation-and-Participation-in-Design-Routledge/Sanoff/p/book/9781138203396

Site Management Directorate of Istanbul Historic Peninsula. (2011). *Istanbul Historic Peninsula site management plan (October 2011)*. https://www.praha.eu/public/2a/40/af/1595575_386437_Istanbul_Historic_Peninsula_Site_Management_Plan.pdf

Site Management Directorate of Istanbul Historic Peninsula. (2018). *Istanbul Historic Peninsula management plan (May 2018)*. http://www.alanbaskanligi.gov.tr/evrak/engtyp.pdf

Skogheim, R., & Atkinson, R. (2013). Urban regeneration and the use of "urban knowledge" in English and Norwegian cities: Knowledge producers, interests and inclusion/exclusion of knowledge. In R. Atkinson & H. T. Andersen (Eds.), *Production and use of urban knowledge: European experiences* (pp. 35–54). Springer. https://doi.org/10.1007/978-90-481-8936-6_3

Sohtorik, A. S. (2016). *A knowledge discovery approach to urban analysis: The Beyoğlu Preservation Area as a data mine* [Unpublished doctoral dissertation]. Istanbul Technical University. https://tez.yok.gov.tr/UlusalTezMerkezi/TezGoster?key=cbOXH84ZayrLjc0tI-QXKmlOgclEmpqWt1b79s9hcADGviYR79b7NqupZUoWDXDG

Sprague, R. H., & Carlson, E. D. (1982). *Building effective decision support systems*. Prentice-Hall International Inc.

Steck, H., & Tresp, V. (1999). Bayesian belief networks for data mining. In *Proceedings of the 2. Workshop On Data Mining and Data Warehousing Als Grundlage Moderner Entscheidungsunterstützender Systeme* [Proceedings of the 2nd Workshop on Data Mining and Data Warehousing as a Basis for Modern Decision Support Systems] (pp. 145–154). Citeseer.

Stritih, A., Rabe, S.-E., Robaina, O., Grêt-Regamey, A., & Celio, E. (2020). An online platform for spatial and iterative modelling with Bayesian networks. *Environmental Modelling & Software*, *127*, Article 104658. https://doi.org/10.1016/j.envsoft.2020.104658

Talen, E. (2006). Design that enables diversity: The complications of a planning ideal. *Journal of Planning Literature*, *20*(3), 233–249. https://doi.org/10.1177/0885412205283104

Tang, L., Lin, Y., Li, S., Li, S., Li, J., Ren, F., & Wu, C. (2018). Exploring the influence of urban form on urban vibrancy in Shenzhen based on mobile phone data. *Sustainability*, *10*(12), Article 4565. https://doi.org/10.3390/su10124565

Tekeli, İ. (2009). *Akılcı planlamadan bir demokrasi projesi olarak planlamaya*. Yurt Publication.

Wilken, R., & Goggin, G. (2014). *Locative media* (1st ed.). Routledge. https://doi.org/10.4324/9781315887036

Yanık, S., Aktas, E., & Topcu, Y. I. (2017). Traveler satisfaction in rapid rail systems: The case of Istanbul metro. *International Journal of Sustainable Transportation*, *11*(9), 642–658. https://doi.org/10.1080/15568318.2017.1301602

Zhang, L., Ye, Y., Zeng, W., & Chiaradia, A. (2019). A systematic measurement of street quality through multi-sourced urban data: A human-oriented analysis. *International Journal of Environmental Research and Public Health*, *16*(10), Article 1782. https://doi.org/10.3390/ijerph16101782

## About the Authors

**Gülce Kırdar** completed her undergraduate studies in architecture at Bahcesehir University and earned her MSc degree from Istanbul Technical University in architectural design computing. Since 2017, she has pursued a PhD in the same program. She also instructs architectural design courses at respected private foundation universities in Turkey, including Altinbas, Kultur, Medipol, and Yeditepe Universities. Her research interests encompass big data, urban decision support systems, data analysis, and urban vibrancy and livability. Since 2022, she has actively participated in the COST Action CA18204—Dynamics of Placemaking and Digitization in Europe's Cities (DOPMADE).

**Gülen Çağdaş** graduated from Istanbul Technical University, Faculty of Architecture. She began as a teaching assistant in 1981 at the same faculty, later earning her PhD in architectural design from the same university in 1986. Over the years, she progressed through the academic ranks, becoming an assistant professor in 1987, an associate professor in 1989, and full professor in 1997. She held various leadership roles, including vice dean of the Faculty of Architecture from 1997 to 2000, head of the Architectural Design Chair from 2004 to 2007, and department head of Architecture from 2008 to 2012. Additionally, she served as the coordinator of the Architectural Computing Graduate Program from 2000 to 2015 and as department head of Informatics at the Institute of Science, Engineering, and Technology, at Istanbul Technical University, from 2006 to 2018. Her primary research area centers on architectural design computing, with more information available on her web page (https://avesis.itu.edu.tr/cagdas).