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Evidence-Based Interior Analysis Model: An ICT-Based Methodological Framework for Analyzing Spatial Behavior in Interior Environments

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Abstract

Despite the increasing availability of digital tools for analyzing spatial behavior in interior environments, interior design studies often rely on conventional methods that do not fully integrate both objective and subjective insights, thereby limiting a comprehensive understanding of how users interact with space. This article proposes the Evidence-Based Interior Analysis (EBIA) model, an original methodological framework specifically designed for public-use interiors. The model offers a unique integration of Indoor Positioning Systems with user perception surveys within a unified structure. This integration enables the capture of both behavioral patterns and experiential feedback, facilitating their joint analysis for interior design decisions. The model is grounded in three foundational pillars: Spatial behavior studies, evidence-based design, and information and communication technologies. Rather than reporting a specific case study, the article outlines the conceptual and methodological formulation of the EBIA model. It proposes a dynamic, iterative approach that challenges conventional linear design processes and facilitates the development of responsive, user-centered, and sustainable interior environments by aligning spatial configurations with user behavior and long-term functionality. Scalable and applicable across diverse spatial contexts, the EBIA model addresses a critical methodological gap by bridging data-driven analysis with behavior-informed spatial design.

Keywords

spatial behavior, evidence-based design, information and communication technologies (ICT), interior environment, methodological framework

Introduction

Designing interior environments that prioritize user satisfaction, enhance quality of life, and support sustainability has emerged as a central challenge in contemporary interior design research (Celadyn, 2020; Obeidat et al., 2022; Pistore et al., 2023; Rashdan & Ashour, 2024; Schaumann & Kapadia, 2019). The relationship between people and physical environments encompasses interactions, perceptions, and individual experiences, while also revealing how environments influence human behavior, attitudes, and well-being (Gehl, 2010; Low & Altman, 1992; Zeisel, 2006). Understanding spatial behavior, which can be defined as dynamic and multifaceted ways in which people (as individuals or groups) perceive, navigate, and interact with their surrounding built environments, is crucial for creating adaptable and user-centered interior solutions (Aktan Abraham & Deniz, 2025a). However, interior design has yet to develop specialized methodologies tailored to interior spatial analysis, and often borrows theories and methods from other fields due to the absence of established theories and frameworks (Bae et al., 2019; Clemons and Eckman, 2011). Studies assessing spatial behavior in interior environments frequently utilize conventional methodologies that do not integrate quantitative and qualitative insights or employ advanced digital tools for a more comprehensive evaluation.

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Information and communication technologies (ICT), including sensors, electronics, and signal processing, have provided assistive systems and advanced tools for data-driven knowledge extraction and reuse, ultimately enhancing the analysis of environments and improving quality of life (Andò et al., 2018; Parisi et al., 2021). Utilizing ICT infrastructure, indoor positioning systems (IPS) facilitate precise location tracking and the collection of accurate, objective, real-time data (Battarra et al., 2024; Deng et al., 2022). IPS connects physical environments with digital systems to improve user experience and operational efficiency. Simultaneously, evidence-based design (EBD) principles underscore the necessity of basing design decisions on most up-to-date evidence from research and practice to improve the quality, usability, and effectiveness of interior design solutions (Bae et al., 2019; Hamilton & Watkins, 2009). However, these tools and approaches are rarely integrated into a framework designed for interior environments.

Although some studies have explored links between tracked spatial behavior and self-reported experiences through mixed-method approaches (East et al., 2017; Pettersson & Zillinger, 2011; Rubino et al., 2013), these applications are still fragmented and limited in scope. Existing approaches often use objective tracking technologies or subjective perception surveys separately, which limits their ability to capture the full complexity of interactions between users and their environments. While IPS provides accurate behavioral data, it is not equipped to reveal experiential dimensions such as satisfaction or perceived comfort. Surveys, on the other hand, capture these subjective insights, but their temporal and spatial precision is limited by recall bias and spatial generalization. Previous studies on sensory-inclusive environments highlight how user-centered feedback mechanisms reveal affective responses such as stress reduction and comfort, emphasizing the importance of integrating perceptual data into behavioral analysis (Gopan, 2025). A unifying methodological structure that brings these complementary approaches together is still lacking.

To address these gaps in the literature and practical studies, this article introduces the evidence-based interior analysis (EBIA) model, an original methodological framework for systematically analyzing spatial behavior in interior environments, with a particular focus on public-use spaces. The study aims to explore how integrating objective tools such as IPS with user perception surveys can inform the development of sustainable and adaptive design solutions. In interior contexts, adaptability refers to the capacity of spaces to respond and transform through the reconfiguration, reuse, and alteration of spatial conditions in ways that enhance resilience and support sustainability by reducing the need for new construction, minimizing waste, and extending spatial lifecycles (Atmodiwirjo & Yatmo, 2022; Brooker & Stone, 2018; Plevoets & van Cleempoel, 2019; Rashdan & Ashour, 2024). The EBIA model supports adaptability and sustainability through the evaluation of measurable spatial responses by capturing behavioral patterns and perceived spatial qualities. The study positions the EBIA model as a comprehensive, interdisciplinary approach that bridges ICT and EBD. This approach reinforces the role of user-centered evidence in shaping more responsive interior environments.

By positioning spatial behavior as a central component of design inquiry, the EBIA model invites a rethinking of how user experience is captured and translated into evidence-based interior solutions. In doing so, the EBIA model not only supports data-informed decision making but also contributes to an evolving discourse around how interior environments can be understood, evaluated, and designed through behavior-centered epistemologies.

> **...the EBIA model invites a rethinking of how user experience is captured and translated into evidence-based interior solutions.**

Accordingly, the article first examines the conceptual pillars underlying the EBIA model. It then outlines the development process and operational structure of the framework, followed by a discussion on its scalability across diverse interior typologies, stakeholder relevance, and iterative and sustainable nature. The article concludes by reflecting on its contributions to spatial behavior analysis and its implications for future interior design practices.

Conceptual Foundations and Pillars of the EBIA Model

Acknowledging the significance of spatial behavior, the EBIA model is structured around three fundamental pillars: *Spatial Behavior Studies, ICT, and EBD* (Figure 1). The theoretical framework integrates insights from spatial behavior research and EBD principles to deepen the understanding of user interaction patterns and interior spatial dynamics. Moreover, the EBIA model provides more accurate and reliable spatial data collection through the application of advanced methods provided by ICTs. Collectively, these three pillars form a structured approach to assess and improve interior environments.

Spatial Behavior in Interior Environments

The first pillar, spatial behavior, constitutes the foundational component of the EBIA model, considering studies on how individuals interact within interior environments from a behavioral design perspective. Spatial behavior has been a subject

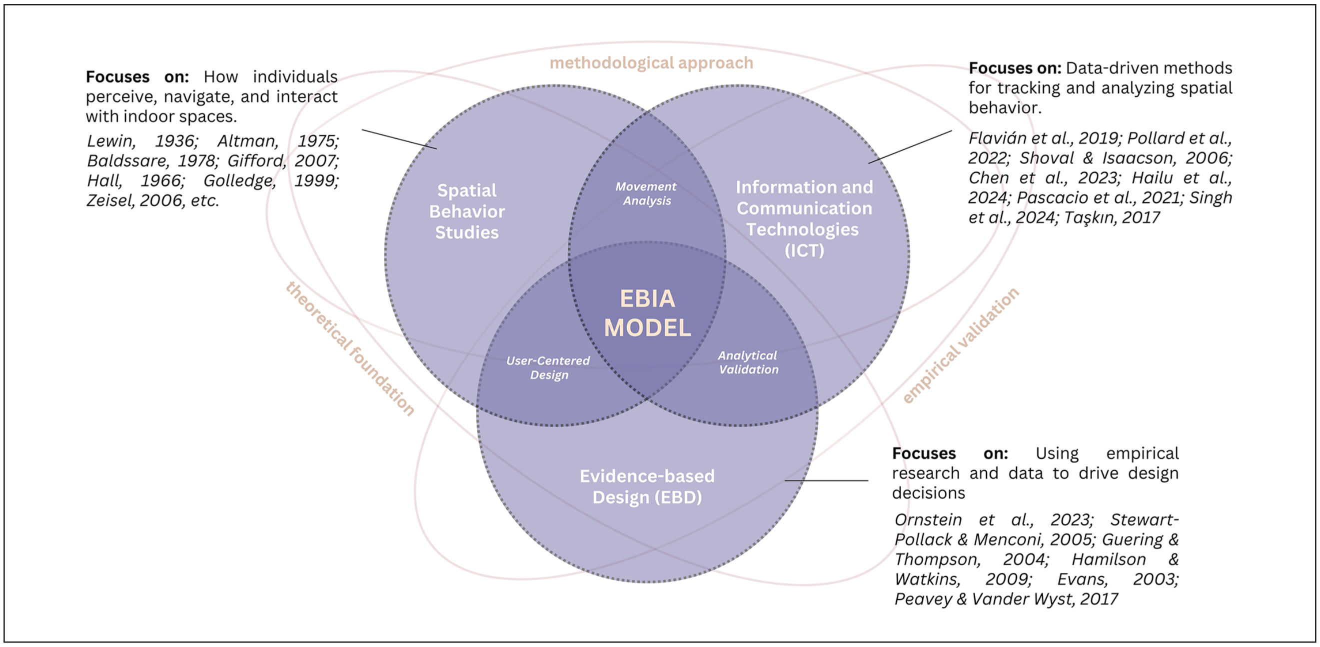

Figure 1. Pillars of the EBIA model.
Source. Aktan Abraham, 2025.
Note. EBIA = Evidence-based interior analysis.

of discourse across various disciplines with diverse objectives especially for the past 60-70 years. The study of spatial behavior has a multidisciplinary nature with a background in environment-behavior studies. Initial research on human spatial behavior can be traced back to Kurt Lewin's (1963) equation for behavior in 1936, stating people's behavior can be explained through the consideration of both person and environment. However, these studies gained prominence in the early 1960s with a psychological focus concerning cognitive processes to understand how individuals perceive and organize spatial information. Since the 1960s, spatial behavior has been studied under several disciplines including, but not limited to *environmental psychology, geography, sociology, neuroscience, urban design, architecture, interior design, and environmental studies* (Altman, 1975; Baldassare, 1978; Gifford, 2007; Hall, 1966). Therefore, the concept of spatial behavior in interior environments is inherently multidisciplinary, as illustrated in the diagram (Figure 2).

Many scholars illustrate how human spatial behavior is distributed in various contexts and scales (Mennis et al., 2013). Conventional approaches including observational and self-reported methods are used to record and examine patterns, frequencies, and dynamics of movement in given spaces. Observational methods involve the systematic observation and recording of human behavior within physical settings. Those methods include direct and indirect observation, time-use studies as video recording or diary studies and behavioral mapping, and have been widely used across different disciplines (Cosco et al., 2010; Downs & Stea, 1973; Golledge, 1999; Proshansky et al., 1970). While observational methods have been extensively documented and widely acknowledged, their implementation within particular research contexts is crucial for obtaining valuable insights into spatial behavior dynamics (Cresswell, 2004; Ewing & Handy, 2009). However, their ability to capture nuanced user experiences in interior contexts remains limited, especially when aiming to inform design decisions.

As another part of conventional approaches, self-reported methods in spatial behavior analysis involve collecting data directly from individuals about their perceptions, experiences, or behaviors in various spatial contexts. These include a great variety of different methods, including questionnaires and inventories, interviews, focus groups, and driving diaries (Lajunen & Özkan, 2011). These methods are used to gather data to evaluate cognitive concerns, along with travel patterns, route preferences, satisfaction with built environments. Post-occupancy evaluation (POE) survey became one of the most common self-reported techniques in spatial behavior analysis, specifically in evaluating built environments. As Li et al. (2018) defines, POE surveys are used to obtain feedback about a building's performance in use, including energy performance, interior environment quality, occupants' satisfaction, productivity, etc. They provide a means of understanding how people perceive and interact with a space after occupancy, and this allows researchers to gather detailed information on the effectiveness of design, spatial layout and environmental conditions (Preiser & Vischer, 2005; Zeisel, 2006). While traditional

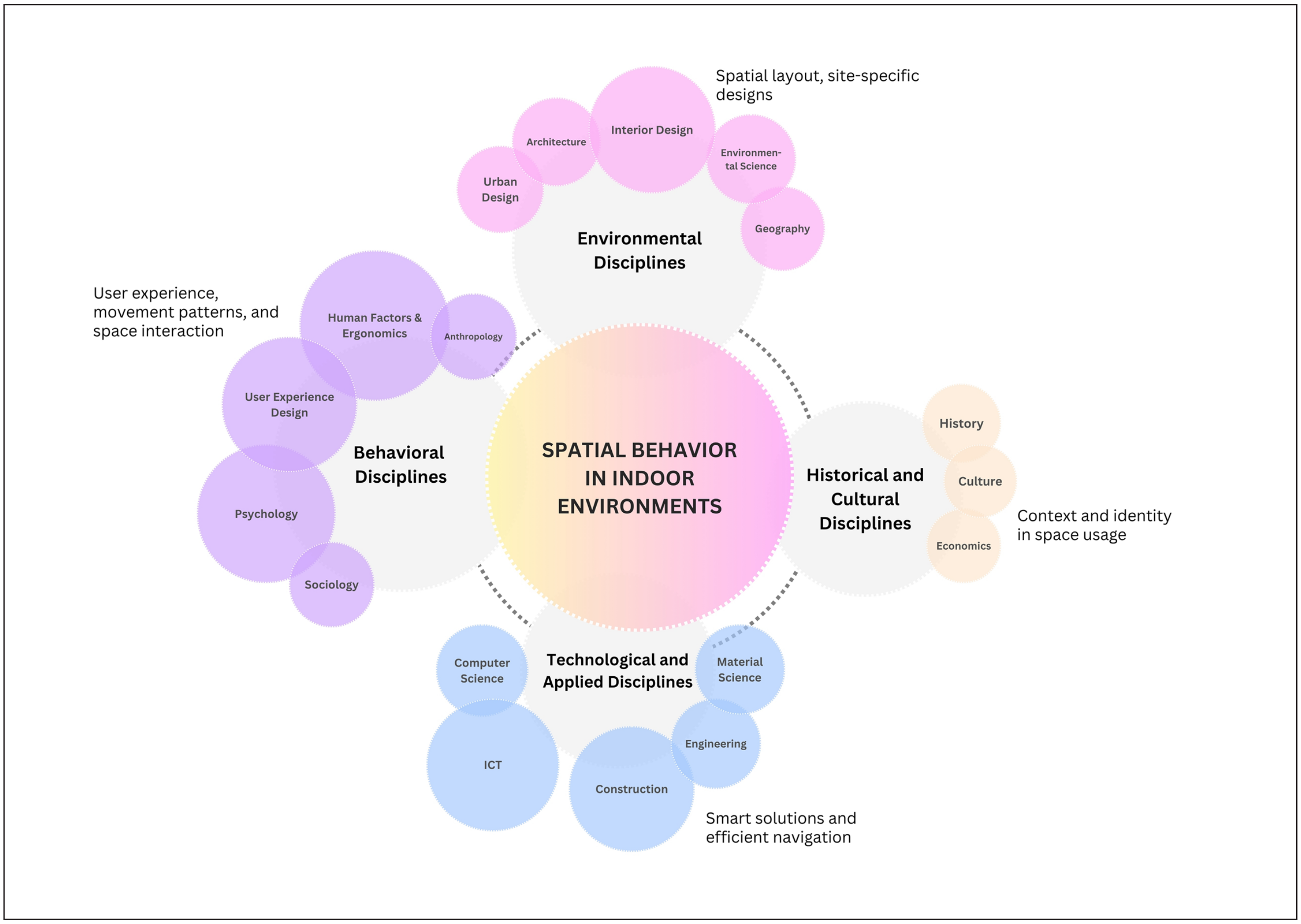

Figure 2. Spatial behavior considerations in interior environments.
Source. Aktan Abraham, 2025.

methods offer valuable insights, they often fall short in delivering the precision, scalability, and behavioral depth required to address the complexities of contemporary interior environments. Therefore, understanding spatial dynamics in design contexts requires a comprehensive approach that integrates qualitative and quantitative insights, linking empirical behavioral data with interior design thinking. This shift moves beyond merely observing user behavior toward actively informing adaptive, evidence-based, and experientially-grounded spatial decisions.

ICT for Data-Driven Spatial Analysis

The second pillar, Information and Communication Technologies (or ICT), strengthens spatial behavior analysis by providing objective and real-time data collection methods. Space syntax was one of the first quantitative approaches to investigate the layout of spaces, shifting the perceptual emphasis toward spatial configuration (Hillier & Hanson, 1984). Although space syntax is still utilized and has paved the way for the development of subsequent methods, it remains limited in its capacity to capture users' real-time, behavior-specific data. As Ericson et al. (2020) also underline, it lacks robustness when applied across varying spatial and temporal scales. This limitation has driven academics to explore alternate methods that tackle the dynamic and evolving dimensions of spatial behavior.

In the 21st century, advances in digital technologies have expanded the methodological possibilities for spatial behavior research, enabling the use of diverse tools to capture behavior-based data within built environments (Flavián et al., 2019; Pollard et al., 2022; Shoval & Isaacson, 2007). While earlier definitions of ICT emphasized telecommunications, computing devices and applications for storing/retrieving/transmitting information, more recent studies view ICT as encompassing applications that enable data generation, access, collection, processing, storage, and transmission (W. Chen et al., 2023). The development of tracking and navigating technologies help to track human spatial activity from the 1990s and offer new possibilities for collecting high resolution and accurate spatial and temporal data (Shoval & Isaacson, 2006).

Due to the evolution of ICTs, especially since the 21st century began, new tools such as the global positioning system (GPS) have emerged for data collection with higher spatial accuracy. GPS data provides individual-centered and continuous location data that help to identify reliable activity locations in time and space (Jones & Pebley, 2014). According to Huang & Wang (2022), GPS has great potential for applications in behavioral studies considering the fact that GPS trajectory data tends to complement conventional data sources and behavioral observations. Extracting patterns from these datasets requires advanced computational tools such as Geographic Information Systems (GIS) and data mining algorithms to reveal latent behavioral insights.

Nevertheless, GPS systems cannot be used in interior environments because reinforced concrete and other structural materials typically block satellite signals (Huang & Wang, 2022). In response, a range of IPS, including Wi-Fi, Bluetooth, radio-frequency identification (RFID), and ultrawideband (UWB), have been developed to identify and track movement behaviors in indoor contexts (Pollard et al., 2022). Indoor Positioning Systems offer the ability to locate both users and mobile devices regardless of the complexity of the interior environment (Hailu et al., 2024). They can be used in several interior environments to give information about user behaviors, navigation, and interactions between spaces and users with algorithms. Algorithms are employed to monitor location in real-time and acquire a trajectory that closely approximates a person's actual journey; therefore, subsequently creating potential for identifying regular pathways, queues, and bottlenecks in diverse interior environments (Vladislav & Marina, 2021).

Since interior environments present more diverse and dynamic scenarios with complex geometries compared to outdoor settings, they demand higher accuracy and adaptive coverage, making it difficult to apply a single IPS method across all contexts (Pascacio et al., 2021). As Singh et al. (2024) also highlight, there is no universal IPS method, considering that some interior environments require special hardware installations such as RFID and Bluetooth Low Energy (BLE) beacons, while others can be supported with Wi-Fi. Therefore, IPS data collection relies on two types of signal sources: existing signal sources such as Wi-Fi and geomagnetic fields that lack accuracy and have weak capabilities, and new signal sources such as BLE and UWB radio tags (Taşkın, 2017; Vladislav & Marina, 2021). To increase algorithmic precision, IPS receivers can also be paired with wearable devices or mobile sensors.

Among diverse IPS technologies, BLE beacons have emerged as a reliable and economical solution for monitoring indoor movements with higher spatial and temporal resolution. BLE beacons operate by transmitting data at consistent intervals and enable nearby devices to determine their proximity and location through received signal strength indicator values (Zafari et al., 2019). BLE devices are small, cost-effective, and energy-efficient; thereby offering an alternative to Wi-Fi for indoor positioning due to their extensive smartphone compatibility and low cost, despite their susceptibility to signal fading in complex environments (Faragher & Harle, 2015). Given these advantages, BLE technology allows spatial behavior researchers to analyze movement patterns, optimize circulation design, and enhance user experience.

Empirical findings from IPS and BLE beacon-based studies further demonstrate the relevance of these technologies in interior contexts. Recent literature has demonstrated practical outcomes across diverse typologies. In healthcare environments, IPS have been deployed to track patient movement and locate medical assets, enhance operational efficiency and safety, improve navigation and user experience for patients, staff and visitors (Shipkovenski et al., 2020; Wichmann, 2022; Yang et al., 2015). In workplace settings, they have been used to map mobility and occupancy patterns. In some cases, those applications uncovered spatial dynamics associated with communication and productivity, identified underutilized zones, and supported data-driven decisions for optimized desk allocation (Pollard et al., 2021, 2023). Similarly, in cultural venues, analyses of visitor routes and dwell times have informed layout and exhibition design decisions, improving navigation, visitor experience, accessibility and comfort (Philippopoulos et al., 2024; Spachos & Plataniotis, 2020). In educational contexts, IPS technologies have been deployed to automate attendance tracking, map occupancy patterns, and analyze students' behavioral dynamics. The outcomes provide real-time insights into classroom allocation, campus navigation, and spatial usage that inform adaptive and data-driven learning environment design (Griffiths et al., 2019; Simas et al., 2024).

These cases illustrate that the integration of objective movement data with user-oriented evaluation has been associated with enhancements in space usage. Additionally, this integration fosters adaptability and sustainability through data-informed reconfiguration, efficient resource allocation, and lifecycle extension of interior environments. As discussed, the literature indicates a paradigmatic shift from predominantly qualitative methods to ICT-enhanced, sensor-based systems. These technologies facilitate real-time, scalable, and behavior-specific data collection that enriches our understanding of spatial interaction in interior settings. By systematically integrating empirical observation into design thinking, ICT-based methods strengthen the analytical foundation of spatial research, aligning with EBD principles and supporting informed spatial planning in interior environments. Rather than replacing conventional approaches, these systems enhance their precision and continuity by revealing subtle behavioral patterns that may remain unnoticed through manual methods.

EBD for Decision-Making

The third foundational pillar of the EBIA model is Evidence-Based Design (or EBD), which ensures that spatial interventions are grounded in empirical research and validated knowledge rather than intuition or convention. EBD provides a structured framework for making design decisions informed by data from a variety of sources, such as a rigorous analysis of user needs, behavioral data, and environmental impact (Hamilton, 2003). EBD is positioned as the practice of basing design solutions and decisions on a researched and documented knowledge base, including the interpretation and synthesis of empirical findings from both academic studies and real-world applications (Stewart-Pollack & Menconi, 2005). It relies on empirical research and the latest findings from both research and practice to inform and justify design decisions effectively (Guerin & Thompson, 2004; Hamilton & Watkins, 2009). While EBD originally emerged within the healthcare domain to evaluate how physical environments affect patient outcomes, safety, and staff performance (Carr et al., 2011; Ulrich et al., 2008, 2010; Van Hoof et al., 2014), its application in other domains has started to expand recently (Aktan Abraham & Deniz, 2025b; Colenberg & Jylhä, 2022; Zhang et al., 2023).

Despite its growing adaptation beyond healthcare, EBD continues to face critical challenges. These include the fragmented nature of current research, the lack of discipline-specific frameworks and standardized evaluation protocols, and the limited dissemination of research knowledge into professional practice (Bae et al., 2019; Ornstein et al., 2023). As Ornstein et al. (2023) underlines, the growing emphasis on integrating technologies highlights a shift toward more adaptive EBD methodologies to address existing challenges for data collection, analysis, and visualization. These limitations often stem from difficulties in collecting and interpreting reliable, longitudinal, and context-specific data within complex spatial settings.

Within the EBIA model, EBD is reconceptualized through its integration with ICT-based spatial analysis and behaviorally grounded design strategies. This alignment enables the transformation of raw movement and perceptual data into design intelligence, bridging evidence with decision-making. The model operationalizes the collected data as spatial parameters under defined categories, and creates a dynamic feedback system for the continuous evaluation and improvement of the interior environment. Defined categories can include underused areas, activity overlaps, and circulation inefficiencies, and inform design interventions through applications such as spatial reconfiguration, adaptive zoning, or material optimization. These iterative adjustments promote adaptability by allowing spaces to evolve in alignment with changing user needs, and support sustainability by maximizing the use of existing spatial and material resources, thereby reducing the need for new construction or excessive refurbishment (Atmodiwirjo & Yatmo, 2022; Brooker & Stone, 2018; Plevoets & van Cleempoel, 2019). In this way, the EBIA model demonstrates how EBD can serve as a robust framework for operationalizing insights from spatial behavior studies and ICT tools into actionable design strategies that enhance user satisfaction, well-being, and productivity while fostering resilient and resource-efficient interior environments. The iterative and dynamic nature of the EBIA model further ensures its relevance to evolving spatial demands, offering a flexible and future-oriented approach for addressing contemporary design challenges.

Methodology

The EBIA model is proposed as a structured and systematic methodology for analyzing spatial behavior in interior environments, particularly within educational, healthcare, workplace, and other public-use settings. The transition from the conceptual pillars of the EBIA model to its methodological framework is rooted in the previously underlined gaps. Each pillar has a distinct role in structuring the EBIA model: spatial behavior defines the dimensions to be analyzed, ICT provides the technical infrastructure for data collection, and EBD anchors the model in an evidence-based decision-making framework.

While the EBIA model provides tools to examine spatial behavior in terms of movement, perception, and perceived configuration, it also offers a means to evaluate users' spatial experiences and translate them into actionable design interventions. The second pillar, ICT, supplies the technological infrastructure for the model, enabling precise, real-time, and scalable data acquisition. Through the use of BLE beacons and mobile software, IPS facilitate continuous tracking of user movement patterns in interior spaces. The third pillar, EBD, establishes the model's epistemological foundation, ensuring that all analyses and recommendations are anchored in data-driven, research-supported insights.

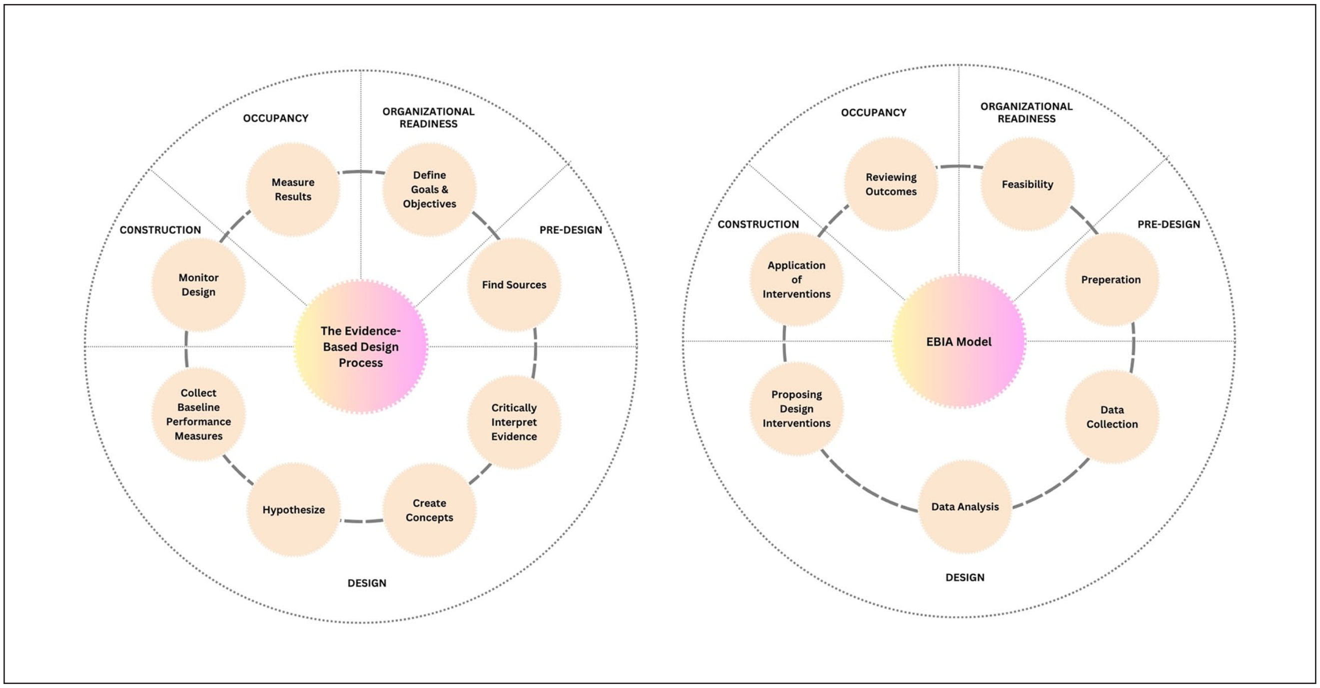

Figure 3. The evidence-based design process.
Source. Aktan Abraham, 2025 (Adapted from Center for Health Design).

The Center for Health Design (CHD) defines the EBD process as a structured cycle with five stages: (a) organizational readiness, in which goals and objectives are clarified; (b) predesign, focused on identifying and critically interpreting relevant evidence; (c) design, where hypotheses are developed and innovative solutions are created; (d) construction, where implementation and baseline performance monitoring are carried out; and (e) occupancy, where postoccupancy performance is measured and outcomes disseminated (Malone et al., 2008). This process has been instrumental in framing how evidence can inform design practice within healthcare environments, particularly in demonstrating how spatial features affect recovery, safety, and staff efficiency. Several studies have built upon the CHD framework to refine its methodological structure and broaden its relevance beyond healthcare environments, introducing extensions such as simulation-supported assessment models, performance-based evaluation frameworks, and standardized postoccupancy toolkits that support the knowledge base of EBD (Davoodi et al., 2017; Joseph et al., 2014).

As a new approach, EBIA addresses the limitations of EBD by reinterpreting it as a behavior-centered, ICT-enabled methodology tailored for different types of interior environments beyond healthcare. In this reframing, EBD's evidence-gathering stage corresponds to Phase 1 (objective tracking via IPS), while user involvement is operationalized as Phase 2 (subjective perception surveys). Unlike the CHD model, which primarily evaluates outcomes after occupancy, EBIA incorporates iterative, real-time feedback loops throughout all stages. Thus, interventions can remain adaptive, beyond previous postoccupancy measures. Figure 3 illustrates how EBD is reframed as interior-specific outcomes.

Despite the methodological differences, EBIA and EBD share a common theoretical foundation: both prioritize the use of empirical evidence in shaping interior environments. However, while EBD is primarily literature and precedent-based, the EBIA model operationalizes these principles through the collection of live, site-specific behavioral data, resulting in an adaptive framework capable of informing real-time spatial modifications and evidence-informed decision-making. The nature of the EBIA model allows revisions, refinements, and potential reapplication of the methodology.

Design of the EBIA Model as a Methodological Framework

The methodological framework of the EBIA model is structured along intersecting horizontal and vertical axes. Adapted from the CHD framework, the horizontal axis outlines the five main stages and their corresponding steps. The vertical axes represent three core operational components of the EBIA model as (a) Spatial decision/implementation; (b) Phase

1 objective tracking; and (c) Phase 2 subjective evaluation. The first vertical axis involves spatial decision-making and implementation processes, emphasizing interior-design-specific actions and interventions. The second axis, referred to as Phase 1, is grounded in objective data collection, detailing the technological procedures required to capture real-time spatial behavior using ICT tools. The third axis, Phase 2, focuses on subjective data collection through the application of structured user perception surveys, aiming to capture qualitative feedback regarding spatial experience. These three dimensions intersect across multiple stages, creating a dynamic, iterative structure that supports both analysis and responsive design. The methodological framework of the EBIA model is illustrated in Figure 4.

The steps of the methodological framework are defined as follows.

Step 1: Feasibility (Organizational Readiness Stage)

The process begins with defining the objectives, expected outcomes, contextual boundaries, and target users of the selected interior space in which spatial interventions will be applied. As emphasized in POE literature, early consideration of organizational conditions and stakeholder engagement is essential to secure technical feasibility and to align design intentions with user needs (Alvaro et al., 2015; Li et al., 2018; Riley et al., 2010; Roberts & Edwards, 2022). Thus, identifying user groups and typology-specific requirements at this stage provides a grounded basis for evidence-based evaluation, as performance criteria are shaped by both functional programs and occupant needs, which vary across different building types (Zimmerman & Martin, 2001). In practical terms, feasibility can be operationalized through preliminary stakeholder meetings to clarify priorities (Alvaro et al., 2015; Riley et al., 2010), technical reviews of IPS infrastructure to ensure spatial coverage (Li et al., 2018; Roberts & Edwards, 2022), and securing ethical approval where required (Riley et al., 2010; Roberts & Edwards, 2022). All together, this step establishes the organizational readiness for applying the EBIA model.

Step 2: Preparation (Pre-Design Stage)

The preparation stage focuses on developing the tools and infrastructure necessary for data collection. In Phase 1 (objective tracking), preparation begins with the creation of an initial layout plan for BLE beacon placement, followed by a feasibility check to ensure coverage of activity zones and alignment with research objectives. As IPS literature emphasizes, careful calibration of beacon density, positioning, and signal testing is essential to achieve accuracy and reliability in spatial tracking (Benaissa et al., 2025; Faragher & Harle, 2015; Ke et al., 2018). A compatible mobile application must then be selected or developed, with configuration features such as timestamped recording, recognition of beacon IDs, and anonymized user codes. Such integration of hardware and software prior to deployment is supported by BLE localization studies (Karabtcev et al., 2019).

In Phase 2 (subjective evaluation), the preparatory step involves the design of a questionnaire combining rating scales and open-ended questions to capture user perceptions and experiences. Here, key evaluation metrics should be determined in relation to the interior type and study objectives. Survey design in POE studies demonstrates that early attention to context-specific variables and participant demographics strengthens the validity of perception data (Asojo et al., 2021; Hay et al., 2017; Zhao et al., 2024). The distribution method of the questionnaire (e.g. digital vs. in-person) should be defined at this stage to ensure sufficient response rates and comparability across participant groups. This preparatory step establishes the reliability of subsequent data collection and analysis.

Step 3: Data Collection (Design Stage)

At this stage, the EBIA process transitions from preparatory setup to empirical application through the core datasets. In line with mixed-methods reasoning (Creswell & Plano Clark, 2018; Fetters et al., 2013), data are collected in two phases. As demonstrated in previous studies, BLE-based IPS operates in real conditions to capture timestamped movement trajectories across defined zones, enabling the mapping of behavioral patterns and spatial density (Wang et al., 2025; Zhao et al., 2021). Therefore, in Phase 1, data are collected in real time as participants carry tablets or mobile devices running the configured software, which receive signals from fixed BLE beacons installed in the space. To protect anonymity and ensure ethical compliance, each participant registers with a self-selected username within the application. This allows data collection under anonymized identifiers consistent with ethical protocols in BLE-based tracking studies (Wang et al., 2025; Zhao et al., 2021).

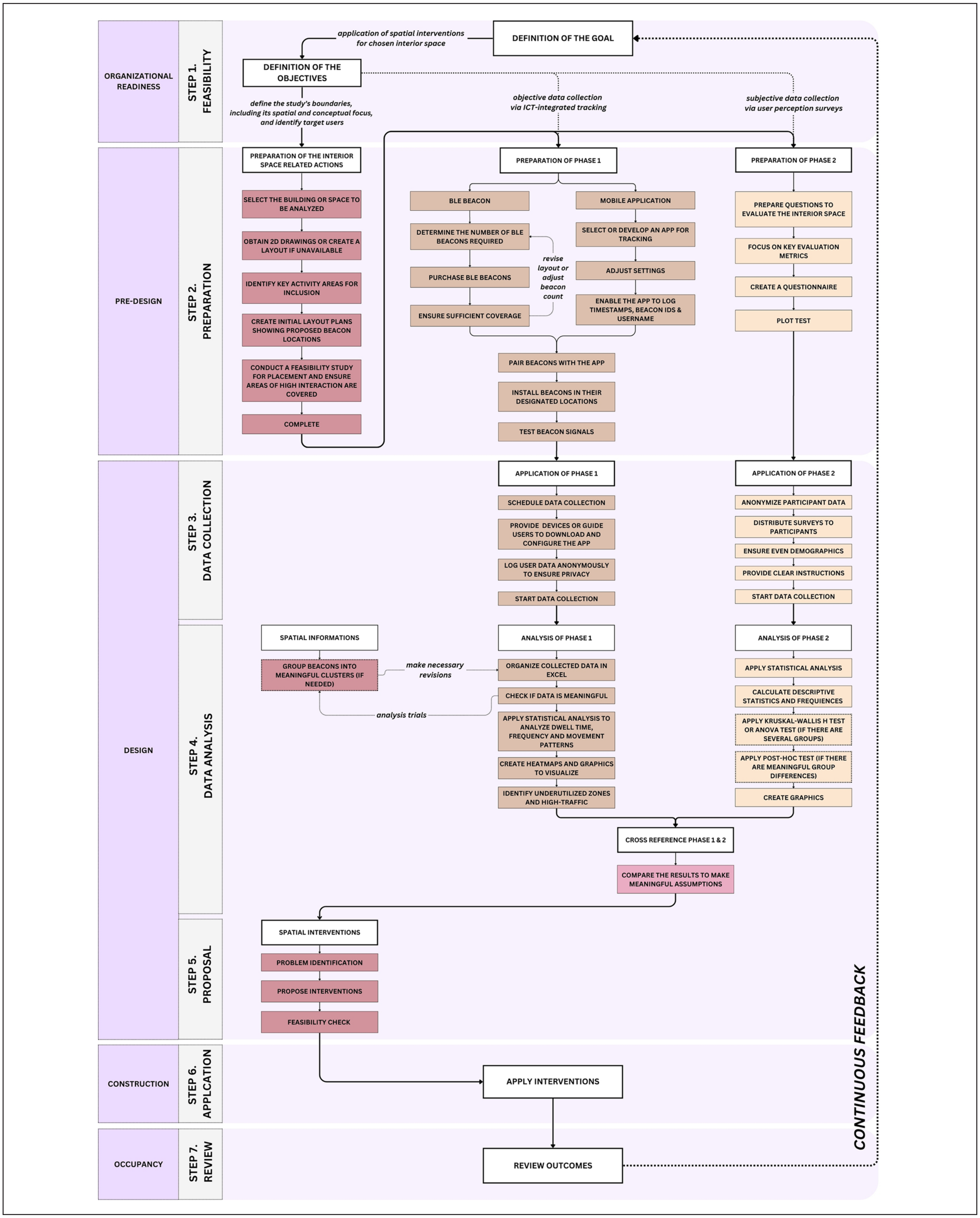

Figure 4. Methodological framework of the EBIA model.
Source. Aktan Abraham, 2025.
Note. EBIA = Evidence-based interior analysis.

In parallel, Phase 2 is administered to capture user perceptions of chosen spatial attributes based on the context. Using consistent anonymized codes across both phases enables behavioral data to be directly paired with perception data. By the end of this step, the two datasets are synchronized, linking observed behaviors with reported experiences. This synchronization aligns with mixed-methods integration principles, and emphasizes coherence in timing and consistency in procedures across data strands (Fàbregues et al., 2024; Fetters et al., 2013; Müller et al., 2019).

Step 4: Data Analysis (Design Stage)

After data collection, both datasets are analyzed through an integrative process to extract patterns and generate evidence for interpretation. Objective data are processed to extract movement patterns, dwell times, and frequently used routes, visualized through heatmaps or flow diagrams to reveal spatiotemporal trends (X. Chen et al., 2025; Ni et al., 2017). Prior to analysis, the quality and consistency of the IPS dataset must be validated by checking for missing signals or spatial overlaps between beacons. In cases where individual beacon IDs exhibit inconsistent coverage or lack meaningful spatial relationships, clustering can be performed to group adjacent beacons representing functionally similar zones to evaluate broader behavioral trends within activity areas. Similar clustering approaches have been applied in indoor tracking research to interpret behavioral patterns across functional zones by grouping proximate positioning points into meaningful spatial areas, such as thematic groupings (Cheng et al., 2021; Delafontaine et al., 2012). Statistical summaries and spatial visualization tools such as SPSS (IBM, USA) and GIS/QGIS (QGIS Development Team, USA) support this phase to interpret the behavioral patterns across spatial and temporal dimensions (Mennis et al., 2013).

For Phase 2, the questionnaire is analyzed using descriptive and inferential statistical methods to identify significant differences across user groups. Descriptive analysis summarizes frequencies, distributions, and measures of central tendency, while inferential tests such as t-tests, ANOVA, or Kruskal–Wallis H tests determine the statistical significance of group variations based on sample characteristics and data normality. Post-hoc tests may be used to identify specific group differences when needed. Visual representations such as bar charts, box plots, or radar diagrams can be created to effectively communicate the findings.

Following the individual analyses of both phases, the final step involves integrating the results to identify relationships between observed spatial behavior (Phase 1) and user perception (Phase 2). This integration follows a comparative strategy in which findings from each dataset are aligned under shared or complementary analytical themes to identify convergent or divergent patterns and the generation of meta-inferences (Åkerblad et al., 2020; Fetters et al., 2013; Johnson et al., 2017). These results reveal the areas of alignment or discrepancy between behavioral intensity and satisfaction levels. For instance, zones with high dwell but low satisfaction can be prioritized for reconfiguration proposals. These correlations serve as the analytical foundation for developing design recommendations by identifying clusters of optimal alignment, underutilized potential, or functional mismatch.

Step 5: Proposal (Design Stage)

Spatial interventions are formulated to address areas that display underused potential or functional mismatch. This translation from evidence to design aligns with the EBD principle of generating prescriptive strategies based on documented performance outcomes rather than subjective intuition (Hamilton & Watkins, 2009; Ulrich et al., 2010). Accordingly, each proposal is grounded in empirical findings, targeting specific spatial issues such as circulation bottlenecks, inefficient layouts, or promising spatial zones. Proposed interventions encompass physical modifications, ranging from small-scale modifications such as furniture repositioning, layout adjustments to larger-scale spatial reconfigurations through the stakeholder evaluation. In this step, the EBIA model operationalizes the transition from analytical interpretation to design action, highlighting the model's feedback-oriented character.

Step 6: Application (Construction Stage)

At this step, proposed spatial interventions are physically implemented and examined empirically within the real interior environment. Crucially, application is not limited to construction activity but includes a process of systematic monitoring and documentation to ensure that the implemented changes remain consistent with both the original design intentions and the evidence generated during earlier steps. As emphasized in EBD literature, implementation must work closely with evaluation protocols to verify that design decisions are carried through into practice and to reduce the risk of deviation during construction phases (Hamilton & Watkins, 2009). Similarly, recent POE studies highlight that iterative and longitudinal observation throughout the postoccupancy phase provides an essential mechanism for detecting emerging performance gaps and unintended consequences early in a building's operational life (Hay et al., 2017). Within the EBIA framework, the application step functions as a translational bridge into tangible modifications while simultaneously embedding a feedback mechanism that prepares for subsequent review and refinement.

Step 7: Review (Occupancy Stage)

The final step focuses on postimplementation evaluation to assess whether the applied spatial interventions have met the defined objectives and identify emerging issues that may require further action. In alignment with established POE and EBD literature, systematic review at the occupancy stage provides the strongest evidence base for linking design decisions with measurable outcomes (Boissonneault & Peters, 2022; Hay et al., 2017). Continuous review ensures that design outcomes evolve throughout the building's life cycle, supporting a performance-oriented feedback (Hay et al., 2017; Preiser & Vischer, 2005; Zhao et al., 2024). This step functions as a closing and re-opening cycle in the EBIA model: findings inform organizational readiness for subsequent iterations, and creates a self-sustaining model.

Evaluation of the EBIA Model as a Methodological Framework

Utility

The methodological framework of the EBIA model offers a structured yet adaptable approach for evaluating interior spaces. The structure allows a systematic progress from defining the conceptual and spatial boundaries of a study to applying targeted design interventions and evaluating their outcomes. The EBIA model operationalizes data interpretation into empirically testable design actions and measurable spatial outcomes. Therefore, a notable strength of the model is its methodological flexibility, which allows adaptation across diverse interior typologies while maintaining contextual specificity and analytical consistency. This adaptability derives from its process-oriented structure, and allows researchers to calibrate each phase according to the spatial, functional, and user-specific characteristics of a given interior context. Through the mixed-method integration, the framework provides a holistic understanding of how interior environments are experienced and utilized. As both a research method and a practical design tool, the EBIA model enables designers and researchers to make informed, user-centered spatial decisions grounded in empirical data and lived experience. This dual grounding in ICT-enabled evidence and human-centered interpretation ensures that design strategies remain analytically rigorous yet contextually responsive. Ultimately, its cyclical structure fosters continuous spatial improvement, aligning with adaptive and sustainable design principles.

Stakeholders

The EBIA model involves a diverse range of stakeholders whose engagement varies across different steps of the methodology. As summarized in Table 1, stakeholders contribute in differentiated ways according to each step's operational needs. While core actors, such as project owners, facility managers, end-users, interior designers, researchers, and technical staff, have crucial roles in the model, optional stakeholders such as decision-makers may be involved depending on the project's context, scale, and institutional setting. Integrating these multiple perspectives enhances the model's basis of evidence by ensuring that empirical findings are interpreted in light of practical, managerial, and experiential insights. This variation underscores the necessity for careful stakeholder planning and coordination at the initial stage of a project. A comprehensive definition of responsibilities is instrumental in facilitating effective communication, minimizing role overlap, and ensuring the timely execution of spatial interventions that are tailored to the specific needs of each interior environment.

Practical Implications and Scalability

The EBIA model is proposed considering its scalability across a wide range of interior types where beacon deployment is feasible. In adaptation to different interior settings, the core structure of the framework remains consistent with minor tailoring based on the specific context. As explained, the model supports contextual specificity by defining context-specific objectives and stakeholders in early stages, while maintaining the main goal and application. To clarify this scope, this article distinguishes four analytical dimensions: *category, spatial setting, user profile, and research intention.* In all cases, Phase 1 (objective tracking) serves as a default pre-design step, with beacon placement determined by coverage and spatial layout; data collection and storage follow a standardized protocol within ethical and legal constraints. Phase 2 (subjective analysis)

Table 1. Involvement of Stakeholders in EBIA Model.

Stakeholders	Step 1: Feasibility	Step 2: Preparation	Step 3: Data collection	Step 4: Analysis	Step 5: Proposal	Step 6: Application	Step 7: Review
Project owners	X						
Facility managers	X	X			X		X
Interior designers	X	X			X	X	
Researchers	X	X	X	X			X
IT specialists		X	X				
Data analysts				X			
End-users			X				

Note. EBIA = Evidence-based interior analysis.

Table 2. Scalability of the EBIA Model.

Category	Spatial setting	User profile	Examples for research intention
Commercial interiors	Office spaces, retail stores, shopping malls, restaurants and cafés, hotels & hospitality	Employees, customers, guests (short-term/temporary users)	Analyze circulation patterns, optimize customer experience, evaluate service/workplace efficiency
Educational interiors	Universities, schools, libraries	Students (continuous), teachers, academic and administrative staff	Understand learning space use, compare user groups, assess satisfaction with study/work environments
Healthcare interiors	Hospitals, health clinics	Patients (temporary), doctors and nurses (continuous), visitors, healthcare administrators	Evaluate waiting area crowding, patient/visitor flows, staff mobility, and workload
Cultural & recreational interiors	Museums, exhibition halls, theaters, galleries, cultural centers	Visitors (temporary), artists/performers, staff	Study visitor routes and dwell times, optimize wayfinding, evaluate comfort and accessibility
Transportation-related interiors	Airport terminals, train and bus stations, ports, and cruise terminals	Passengers (temporary), transportation staff, security, airline/cruise personnel	Monitor passenger flows, identify bottlenecks, improve wayfinding and service allocation

Note. EBIA = Evidence-based interior analysis.

is adaptive and tailored to (a) the research question; (b) the user profile (e.g. temporary visitors/passengers vs. continuous users such as patients, staff, or students); and (c) the interior context.

As summarized in Table 2, the adaptation matrix illustrates how EBIA can be operationalized across different interior domains. This approach aligns with prior IPS and beacon-based studies, where technologies have already demonstrated benefits in healthcare (e.g. enhanced patient navigation, asset tracking, and operational efficiency: Shipkovenski et al., 2020; Yang et al., 2015), workplaces (e.g. mobility mapping and productivity optimization: Pollard et al., 2021, 2023), education (e.g. behavioral mapping and adaptive learning space management: Griffiths et al., 2019; Simas et al., 2024), cultural venues (e.g. visitor routing, accessibility, and experiential enhancement: Philippopoulos et al., 2024; Spachos & Plataniotis, 2020), and transportation hubs (e.g. flow management, real-time navigation, and operational optimization in airport environments: Khadonova et al., 2020; Molina et al., 2018). EBIA builds on these established applications, integrating them into a single adaptable framework by allowing the configurations in the first stage.

Sustainability

As it is shown in Figure 4, the EBIA model has an iterative and cyclical nature. This sustainable nature of the framework allows for a continuous refinement and adaptation over time for chosen interior environments. The iterative components of the framework enable the implementation of diverse interventions at various stages during the application process. As each step provides opportunities for internal revisions in the framework, the model identifies potential challenges and leads to alternative solutions, making context-sensitive adjustments before going into the following step. Overall, the model serves as an ongoing evaluation process in which spatial interventions are regularly reviewed, revised, and re-applied based on the schedule of application.

Beyond its procedural character, this cyclical structure also supports environmental sustainability. Continuous refinement allows for reconfiguration for alternative uses, extending the lifecycle of interior spaces and minimizing resource consumption through adaptive reuse, material efficiency, and spatial flexibility strategies that enhance sustainability across time (Celadyn, 2019; Ramadan, 2025). In this sense, sustainability is not limited to material choices but is embedded in the efficient management and reuse of space. The adaptability embedded in the model supports long-term relevance, especially in dynamic interiors that evolve with time and changing user profiles. Thus, the framework promotes a more resilient design process where decisions are continuously informed by user experience, while also supporting resource efficiency and lifecycle sustainability (Boissonneault & Peters, 2022; Celadyn, 2019; Hay et al., 2017; Ramadan, 2025; Preiser & Vischer, 2005). In addition, other studies have also shown that spatial and environmental modifications can effectively reduce spatial stress while enhancing user experience (Jamshidi & Pati, 2023). Accordingly, the EBIA model promotes sustainability in terms of *(a) Avoided new build (reuse/reconfigure), (b) Material efficiency (targeted interventions), (c) Operational fit (better occupancy alignment)*, leading to outcomes such as improved well-being, user satisfaction, and operational adaptability across diverse contexts.

Limitations

Besides the defined advantages of the EBIA model, the following limitations should be considered to contextualize its implementation and scope:

Stakeholder Coordination and Planning Complexity: One of the major challenges is the coordination and planning between multiple stakeholders involved in different steps of the research process. Because the model is built on a collaborative effort, therefore organizing this coordination can be time-consuming and complicate decision-making can be complicated by the involvement of bureaucratic stages.

Dependence on Technological Infrastructure and IT Expertise: The involvement of ICTs such as the installation of BLE beacons, the creation or application of mobile software, and the pairing of those tools creates potential issues related to system malfunctions, limits on technological access, and data privacy. Since those technologies evolve, ongoing updates and adaptations may also be required. In addition, applying these technologies effectively depends on technical expertise, and involving IT specialists may be difficult if resources for their expertise are limited.

User Participation and Ethical Considerations: The model depends on active user participation and the collection of spatiotemporal data. Particularly in sensitive settings such as healthcare or governmental institutions, ethical considerations can be challenging.

Conclusion

This study introduces the EBIA model as a systematically structured and ICT-based framework for analyzing spatial behavior in interior environments. By integrating objective data through IPS and subjective data from user surveys, the model bridges digital tools with user-centered insights to generate measurable evidence for spatial decision-making. It addresses a methodological gap in spatial behavior studies within the field of interior design and environmental studies by operationalizing data-driven analysis into design-relevant outcomes. Rather than treating interior spaces as static environments, the model approaches interiors as dynamic systems that are shaped by ongoing user interactions, perceptions, and needs.

Through the integration of ICT and EBD principles, the EBIA model establishes a transparent mechanism that translates behavioral evidence into actionable design strategies. This iterative and data-driven approach supports the development of interior spaces that can evolve continuously based on empirical evidence. By establishing a cyclical evaluation process, the framework enables designers and stakeholders to engage in a reflective and responsive design practice. Therefore, the framework aligns with contemporary priorities in sustainable development, considering resource-efficient and user-responsive interior environments.

In doing so, the model contributes to reframing interiors not only as functional environments but also as behavioral interfaces, spaces continuously shaped by empirical and experiential feedback. It expands upon existing postoccupancy and EBD methods by integrating ICT-based behavioral tracking within an iterative design framework. This integration overcomes the challenges of conventional evaluation models and contributes to greater methodological precision. In conclusion, the EBIA model offers a foundation for rethinking the future of interior environments through the lens of evidence-based, user-centered, and sustainability-oriented design. It encourages the field of interior design to expand its methodological toolkits by integrating digital and technological innovation in pursuit of more resilient and adaptive spatial environments that are not only designed but also lived, measured, and continuously reimagined.

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Data Availability Statement

No empirical data were generated or analyzed in this study. Supporting materials related to the methodological framework are available from the corresponding author upon reasonable request.

Declaration of Conflicting Interests

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This article does not involve human participants, data collection, or experimental procedures, ethical approval and informed consent were not required.

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References

Åkerblad, L., Seppänen-Järvelä, R., & Haapakoski, K. (2020). Integrative strategies in mixed methods research. *Journal of Mixed Methods Research*, *15*(2), 152–170. https://doi.org/10.1177/1558689820957125

Aktan Abraham, S. (2025). *A methodology for improving interior space use through spatial behavior analysis: Case of a design school*. (Publication No. 948756) [Doctoral dissertation, Izmir University of Economics]. YÖK Ulusal Tez Merkezi.

Aktan Abraham, S., & Deniz, D. (2025a). Navigating the nexus: Towards a multidimensional framework for evaluating indoor spatial behaviour. *Journal of Design Research*, *22*(1), 1–25. https://doi.org/10.1504/jdr.2025.147725

Aktan Abraham, S., & Deniz, D. (2025b, May 12–13). Rethinking the interior design process: Advancing circularity through evidence-based design. In M. Karyda, D. Çay, A. K. Bakk, R. Dezső, & J. Hemmings (Eds.), *Data as experiential knowledge and embodied processes*, Budapest, Hungary. https://doi.org/10.21606/eksig2025.113

Altman, I. (1975). *The environment and social behavior*. Brooks/Cole Publishing Company.

Alvaro, C., Wilkinson, A. J., Gallant, S. N., Kostovski, D., & Gardner, P. (2015). Evaluating intention and effect. *HERD Health Environments Research & Design Journal*, *9*(2), 82–104. https://doi.org/10.1177/1937586715605779

Andò, B., Baglio, S., Lombardo, C.O., & Marletta, V. (2018). Smart multisensor strategies for indoor localization. In E. Pissaloux & R. Velazquez (Eds.), *Mobility of visually impaired people* (pp. 585–595). Springer. https://doi.org/10.1007/978-%203-319-54446-5_18

Asojo, A., Vo, H., & Bae, S. (2021). The impact of design interventions on occupant satisfaction: A workplace pre-and post-occupancy evaluation analysis. *Sustainability*, *13*(24), Article 13571. https://doi.org/10.3390/su132413571

Atmodiwirjo, P., & Yatmo, Y. A. (2022). Responsive interior: Tactics for adaptation and resilience. *Interiority*, *5*(2), Article 238. https://doi.org/10.7454/in.v5i2.238

Bae, S., Bhalodia, A., & Runyan, R. C. (2019). Theoretical frameworks in interior design literature between 2006 and 2016 and the implication for evidence-based design. *The Design Journal*, *22*(5), 627–648. https://doi.org/10.1080/14606925.2019.1625177

Baldassare, M. (1978). Human spatial behavior. *Annual Review of Sociology*, *4*, 29–56. https://doi.org/10.1146/annurev.so.04.080178.000333

Battarra, I., Accorsi, R., Manzini, R., & Dardari, D. (2024). A framework to design a scalable and reliable indoor positioning system-IPS for industrial applications. In R. Manzini & R. Accorsi (Eds.), *Warehousing and material handling systems for the digital industry* (pp. 473–503). Springer.

Benaissa, B., Hendrichovsky, F., As, M., & Yoshida, K. (2025). BLE signal reception and localization performance with varying receiver and beacon setups. *Future Internet*, *17*(2), 54. https://doi.org/10.3390/fi17020054

Boissonneault, A., & Peters, T. (2022). Concepts of performance in post-occupancy evaluation post-probe: A literature review. *Building Research & Information*, *51*(4), 369–391. https://doi.org/10.1080/09613218.2022.2132906

Brooker, G., & Stone, S. (2018). *Rereadings 2: Interior architecture and the design principles of remodelling existing buildings*. RIBA Publishing.

Carr, V. L., Sangiorgi, D., Büscher, M., Junginger, S., & Cooper, R. (2011). Integrating Evidence-Based design and Experience-Based approaches in healthcare service design. *HERD Health Environments Research & Design Journal*, *4*(4), 12–33. https://doi.org/10.1177/193758671100400403

Celadyn, M. (2019). Interior architectural design for adaptive reuse in application of environmental sustainability principles. *Sustainability*, *11*(14), Article 3820. https://doi.org/10.3390/su11143820

Celadyn, M. (2020). Integrative design classes for environmental sustainability of interior architectural design. *Sustainability*, *12*(18), Article 7383. https://doi.org/10.3390/su12187383

Chen, W., Zhang, S., Kong, D., Zou, T., Zhang, Y., & Cheshmehzangi, A. (2023). Spatio-temporal evolution and influencing factors of China's ICT service industry. *Scientific Reports*, *13*(1), Article 9703. https://doi.org/10.1038/s41598-023-34994-z

Chen, X., Chen, J., Pu, W., Fan, G., & Lu, Z. (2025). Modeling Spatial–Behavioral dynamics in cultural exhibition architecture through mapping and regression analysis. *Buildings*, *15*(17), Article 3049. https://doi.org/10.3390/buildings15173049

Cheng, D., Yue, G., Pei, T., & Wu, M. (2021). Clustering indoor positioning data using E-DBSCAN. *ISPRS International Journal of Geo-Information*, *10*(10), Article 669. https://doi.org/10.3390/ijgi10100669

Clemons, S. A., & Eckman, M. J. (2011). Exploring theories identified in the Journal of Interior Design. *Journal of Interior Design*, *36*(4), 31–50. https://doi.org/10.1111/j.1939-1668.2011.01065.x

Colenberg, S., & Jylhä, T. (2022). Identifying interior design strategies for healthy workplaces—A literature review. *Journal of Corporate Real Estate*, *24*(3), 173–189. https://doi.org/10.1108/jcre-12-2020-0068

Cosco, N. G., Moore, R. C., & Islam, M. Z. (2010). Behavior mapping. *Medicine & Science in Sports & Exercise*, *42*(3), 513–519. https://doi.org/10.1249/mss.0b013e3181cea27a

Cresswell, T. (2004). *Place: A short introduction*. Blackwell Publishing.

Creswell, J. W., & Plano Clark, V. L. (2018). *Designing and conducting mixed methods research* (3rd ed.). SAGE.

Davoodi, A., Johansson, P., Henricson, M., & Aries, M. (2017). A conceptual framework for integration of evidence-based design with lighting simulation tools. *Buildings*, *7*(4), Article 82. https://doi.org/10.3390/buildings7040082

Delafontaine, M., Versichele, M., Neutens, T., & Van De Weghe, N. (2012). Analysing spatiotemporal sequences in Bluetooth tracking data. *Applied Geography*, *34*, 659–668. https://doi.org/10.1016/j.apgeog.2012.04.003

Deng, Y., Ai, H., Deng, Z., Gao, W., & Shang, J. (2022). An overview of indoor positioning and mapping technology standards. *Standards*, *2*(2), 157–183. https://doi.org/10.3390/standards2020012

Downs, R. M., & Stea, D. (1973). *Image and environment: Cognitive mapping and spatial behavior*. Transaction Publishers.

East, D., Osborne, P., Kemp, S., & Woodfine, T. (2017). Combining GPS & survey data improves understanding of visitor behaviour. *Tourism Management*, *61*, 307–320. https://doi.org/10.1016/j.tourman.2017.02.021

Ericson, J. D., Chrastil, E. R., & Warren, W. H. (2020). Space syntax visibility graph analysis is not robust to changes in spatial and temporal resolution. *Environment and Planning B Urban Analytics and City Science*, *48*(6), 1478–1494. https://doi.org/10.1177/2399808319897624

Evans, G. W. (2003). The built environment and mental health. *Journal of Urban Health*, *80*(4), 536–555. https://doi.org/10.1093/jurban/jtg063

Ewing, R., & Handy, S. (2009). Measuring the unmeasurable: Urban design qualities related to walkability. *Journal of Urban Design*, *14*(1), 65–84. https://doi.org/10.1080/13574800802451155

Fàbregues, S., Younas, A., Escalante-Barrios, E. L., Molina-Azorin, J. F., & Vázquez-Miraz, P. (2024). Toward a framework for appraising the quality of integration in mixed methods research. *Journal of Mixed Methods Research*, *18*(3), 270–280. https://doi.org/10.1177/15586898241257555

Faragher, R., & Harle, R. (2015). Location fingerprinting with Bluetooth low energy beacons. *IEEE Journal on Selected Areas in Communications*, *33*(11), 2418–2428. https://doi.org/10.1109/jsac.2015.2430281

Fetters, M. D., Curry, L. A., & Creswell, J. W. (2013). Achieving integration in mixed methods designs—Principles and practices. *Health Services Research*, *48*(6 Pt 2), 2134–2156. https://doi.org/10.1111/1475-6773.12117

Flavián, C., Ibáñez-Sánchez, S., & Orús, C. (2019). The impact of virtual, augmented and mixed reality technologies on the customer experience. *Journal of Business Research*, *100*, 547–560. https://doi.org/10.1016/j.jbusres.2018.10.050

Gehl, J. (2010). *Cities for people*. Island Press.

Gifford, R. (2007). *Environmental psychology: Principles and practice* (4th edition). Optimal Books.

Golledge, R. G. (Ed.). (1999). *Behavior: Cognitive mapping and other spatial processes*. Johns Hopkins University Press.

Gopan, G. (2025). Sensory inclusivity in retail environments: A design-oriented approach. *Journal of Interior Design*, *50*(2), 118–140. https://doi.org/10.1177/10717641251327928

Griffiths, S., Wong, M. S., Kwok, C. Y. T., Kam, R., Lam, S. C., Yang, L., Yip, T. L., Heo, J., Chan, B. S. B., Xiong, G., & Lu, K. (2019). Exploring Bluetooth beacon use cases in teaching and learning: Increasing the sustainability of physical learning spaces. *Sustainability*, *11*(15), Article 4005. https://doi.org/10.3390/su11154005

Guerin, D. A., & Thompson, J. A. A. (2004). Interior design education in the 21st century: An educational transformation. *Journal of Interior Design*, *30*(2), 1–12. https://doi.org/10.1111/j.1939-1668.2004.tb00401.x

Hailu, T. G., Guo, X., Si, H., Li, L., & Zhang, Y. (2024). Theories and methods for indoor positioning systems: A comparative analysis, challenges, and prospective measures. *Sensors*, *24*(21), Article 6876. https://doi.org/10.3390/s24216876

Hall, E. T. (1966). *The hidden dimension*. Anchor.

Hamilton, D. K. (2003). Four levels of evidence-based practice. *Healthcare Design*, *11*(3), 19–26.

Hamilton, D. K., & Watkins, D. H. (2009). *Evidence-Based design for multiple building types*. John Wiley & Sons.

Hay, R., Samuel, F., Watson, K. J., & Bradbury, S. (2017). Post-occupancy evaluation in architecture: Experiences and perspectives from UK practice. *Building Research & Information*, *46*(6), 698–710. https://doi.org/10.1080/09613218.2017.1314692

Hillier, B., & Hanson, J. (1984). *The social logic of space*. Cambridge University Press.

Huang, W., & Wang, L. (2022). Towards big data behavioral analysis: Rethinking GPS trajectory mining approaches from geographic, semantic, and quantitative perspectives. *Architectural Intelligence*, *1*(1), Article 7. https://doi.org/10.1007/s44223-022-00011-y

Jamshidi, S., & Pati, D. (2023). Identifying environmental elements and attributes that contribute to indoor wayfinding: An exploratory study utilizing think-aloud protocol. *Journal of Interior Design*, *49*(2), 117–138. https://doi.org/10.1177/10717641231207031

Johnson, R. E., Grove, A. L., & Clarke, A. (2017). Pillar Integration Process: A joint display technique to integrate data in mixed methods research. *Journal of Mixed Methods Research*, *13*(3), 301–320. https://doi.org/10.1177/1558689817743108

Jones, M., & Pebley, A. R. (2014). Redefining neighborhoods using common destinations: Social characteristics of activity spaces and home census tracts compared. *Demography*, *51*(3), 727–752. https://doi.org/10.1007/s13524-014-0283-z

Joseph, A., Quan, X., Keller, A. B., Taylor, E., Nanda, U., & Hua, Y. (2014). Building a knowledge base for evidence-based healthcare facility design through a post-occupancy evaluation toolkit. *Intelligent Buildings International*, *6*(3), 155–169. https://doi.org/10.1080/17508975.2014.903163

Karabtcev, S., Khorosheva, T., & Kapkov, N. (2019, March 1–2). *BLE Beacon Interaction module and mobile application in the Indoor-Navigation system* [Conference session]. 2019 International Science and Technology Conference "EastConf," Vladivostok, Russia. https://doi.org/10.1109/eastconf.2019.8725420

Ke, C., Wu, M., Chan, Y., & Lu, K. (2018). Developing a BLE Beacon-Based location system using location fingerprint positioning for smart home power management. *Energies*, *11*(12), Article 3464. https://doi.org/10.3390/en11123464

Khadonova, S. V., Ufimtsev, A. V., & Dymkova, S. S. (2020, October 20–22). Digital smart airport system based on innovative navigation and information technologies [Conference session]. 2020 International Conference on Engineering Management of Communication and Technology (EMCTECH), Vienna, Austria. https://doi.org/10.1109/EMCTECH49634.2020.9261529

Lajunen, T., & Özkan, T. (2011). Self-report instruments and methods. In B. Porter (Eds.), *Handbook of traffic psychology* (pp. 43–59). Elsevier eBooks.

Lewin, K (1936). *Principles of topological psychology*. McGraw-Hill.

Li, P., Froese, T. M., & Brager, G. (2018). Post-occupancy evaluation: State-of-the-art analysis and state-of-the-practice review. *Building and Environment*, *133*, 187–202. https://doi.org/10.1016/j.buildenv.2018.02.024

Low, S. M., & Altman, I. (1992). Place attachment. In I. Altman & S. M. Low (Eds.), *Human behavior and environment* (pp. 1–12). Springer. https://doi.org/10.1007/978-1-4684-8753-4_1

Malone, E., Harmsen, C., Reno, K., Edelstein, E., Hamilton, D., & Salvatore, A. (2008). *An introduction to evidence based design: Exploring healthcare and design* (EDAC Study Guide Series, Vol: 1). The Center for Health Design.

Mennis, J., Mason, M. J., & Cao, Y. (2013). Qualitative GIS and the visualization of narrative activity space data. *International Journal of Geographical Information Science*, *27*(2), 267–291. https://doi.org/10.1080/13658816.2012.678362

Molina, B., Olivares, E., Palau, C. E., & Esteve, M. (2018). A multimodal Fingerprint-Based indoor positioning system for airports. *IEEE Access*, *6*, 10092–10106. https://doi.org/10.1109/access.2018.2798918

Müller, J., Fàbregues, S., Guenther, E. A., & Romano, M. J. (2019). Using sensors in organizational research—Clarifying rationales and validation challenges for mixed methods. *Frontiers in Psychology*, *10*, Article 1188. https://doi.org/10.3389/fpsyg.2019.01188

Ni, B., Shen, Q., Xu, J., & Qu, H. (2017). Spatio-temporal flow maps for visualizing movement and contact patterns. *Visual Informatics*, *1*(1), 57–64. https://doi.org/10.1016/j.visinf.2017.01.007

Obeidat, I., Obeidat, S., Rumman, S. A., & Al-Jubouri, F. (2022). The role of sustainable interior design and its impact on customer's behavior in commercial environments. *IOP Conference Series Earth and Environmental Science*, *1026*(1), Article 012054. https://doi.org/10.1088/1755-1315/1026/1/012054

Ornstein, S. W., Van Der Voordt, T., & Mallory-Hill, S. (2023). Editorial: Design quality: What we learned from evidence-based design and post-occupancy evaluation research during the COVID-19 pandemic. *Frontiers in Built Environment*, *9*, Article 1232682. https://doi.org/10.3389/fbuil.2023.1232682

Parisi, F., Fanti, M. P., & Mangini, A. M. (2021). Information and Communication Technologies applied to intelligent buildings: A review. *Journal of Information Technology in Construction*, *26*, 458–488. https://doi.org/10.36680/j.itcon.2021.025

Pascacio, P., Casteleyn, S., Torres-Sospedra, J., Lohan, E. S., & Nurmi, J. (2021). Collaborative indoor positioning systems: A systematic review. *Sensors*, *21*(3), Article 1002. https://doi.org/10.3390/s21031002

Peavey, E., & Vander Wyst, K. B. (2017). Evidence-based design and research-informed design: What's the difference? Conceptual definitions and comparative analysis. *HERD Health Environments Research & Design Journal*, *10*(5), 143–156. https://doi.org/10.1177/1937586717697683

Pettersson, R., & Zillinger, M. (2011). Time and space in event behaviour: Tracking visitors by GPS. *Tourism Geographies*, *13*(1), 1–20. https://doi.org/10.1080/14616688.2010.529932

Philippopoulos, P. I., Drivas, I. C., Tselikas, N. D., Koutrakis, K. N., Melidi, E., & Kouis, D. (2024). A holistic approach for enhancing museum performance and visitor experience. *Sensors*, *24*(3), Article 966. https://doi.org/10.3390/s24030966

Pistore, L., Konstantinou, T., Pasut, W., & Naboni, E. (2023). A framework to support the design of a regenerative interior environment. *Frontiers in Built Environment*, *9*, Article 1225024. https://doi.org/10.3389/fbuil.2023.1225024

Plevoets, B., & van Cleempoel, K. (2019). *Adaptive reuse of the built heritage: Concepts and cases of an emerging discipline*. Routledge.

Pollard, B., Engelen, L., Held, F., & De Dear, R. (2020). Movement at work: A comparison of real time location system, accelerometer and observational data from an office work environment. *Applied Ergonomics*, *92*, Article 103341. https://doi.org/10.1016/j.apergo.2020.103341

Pollard, B., Engelen, L., Held, F., & De Dear, R. (2022). Activity space, office space: Measuring the spatial movement of office workers. *Applied Ergonomics*, *98*, Article 103600. https://doi.org/10.1016/j.apergo.2021.103600

Pollard, B., Van Buskirk, J., Engelen, L., Held, F., & De Dear, R. (2023). How many days of indoor positioning system data are required to characterise typical movement behaviours of office workers? *Applied Ergonomics*, *106*, Article 103915. https://doi.org/10.1016/j.apergo.2022.103915

Preiser, W. F., & Vischer, J. C. (2005). *Assessing building performance*. Routledge eBooks.

Proshansky, H. M., Ittelson, W. H., & Rivlin, L. G. (1970). *Environmental Psychology: Man and his physical setting*. Holt, Rinehart & Winston.

Ramadan, S. E. (2025). Guide for longevity and flexibility in interior architecture. *Discover Cities*, *2*, Article 46. https://doi.org/10.1007/s44327-025-00066-2

Rashdan, W., & Ashour, A. F. (2024). Exploring sustainability in interior design: A comprehensive systematic review. *Buildings*, *14*(8), Article 2303. https://doi.org/10.3390/buildings14082303

Riley, M., Kokkarinen, N., & Pitt, M. (2010). Assessing post occupancy evaluation in higher education facilities. *Journal of Facilities Management*, *8*(3), 202–213. https://doi.org/10.1108/14725961011058839

Roberts, C., & Edwards, D. (2022). Post-occupancy evaluation: Identifying and mitigating implementation barriers to reduce environmental impact. *Journal of Cleaner Production*, *374*, Article 133957. https://doi.org/10.1016/j.jclepro.2022.133957

Rubino, I., Xhembulla, J., Martina, A., Bottino, A., & Malnati, G. (2013). MUSA: Using indoor positioning and navigation to enhance cultural experiences in a museum. *Sensors*, *13*(12), 17445–17471, doi: 10.3390/s131217445

Schaumann, D., & Kapadia, M. (2019). Modeling social and spatial behavior in built environments: Current methods and future directions. In P. Davis, A. O'Mahony, & J. Pfautz (Eds.), *Social-behavioral modeling for complex systems* (pp. 673–695). Wiley.

Shipkovenski, G., Kalushkov, T., Petkov, E., & Angelov, V. (2020, June 26–28). *A Beacon-Based indoor positioning system for location tracking of patients in a hospital* [Conference session]. 2022 International Congress on Human-Computer Interaction, Optimization and Robotic Applications (HORA, pp. 1–6). https://doi.org/10.1109/hora49412.2020.9152857

Shoval, N., & Isaacson, M. (2007). Tracking tourists in the digital age. *Annals of Tourism Research*, *34*(1), 141–159. https://doi.org/10.1016/j.annals.2006.07.007

Simas, A., Oliveira, A., & Matos, M. (2024, September 18–21). A prototype to enhance academic attendance using BLE beacons [Conference session]. 16th International Conference on Education Technology and Computers (ICETC 2024), Porto, Portugal. https://doi.org/10.1145/3702163.3702422

Singh, J., Tyagi, N., Singh, S., Ali, F., & Kwak, D. (2024). A systematic review of contemporary indoor positioning systems: Taxonomy, techniques, and algorithms. *IEEE Internet of Things Journal*, *11*(21), 34717–34733. https://doi.org/10.1109/jiot.2024.3416255

Spachos, P., & Plataniotis, K. N. (2020). BLE beacons for indoor positioning at an interactive IoT-based smart museum. *IEEE Systems Journal*, *14*(3), 3483–3493. https://doi.org/10.1109/jsyst.2020.2969088

Stewart-Pollack, J., & Menconi, R. M. (2005). *Designing for privacy and related needs*. Fairchild Books.

Taşkın, D. (2017). Design of Bluetooth low energy based indoor positioning system. *Balkan Journal of Electrical and Computer Engineering*, *5*, 60–65. https://doi.org/10.17694/bajece.334388

Ulrich, R. S., Berry, L. L., Quan, X., & Parish, J. T. (2010). A conceptual framework for the domain of evidence-based design. *HERD Health Environments Research & Design Journal*, *4*(1), 95–114. https://doi.org/10.1177/193758671000400107

Ulrich, R. S., Zimring, C., Zhu, X., DuBose, J., Seo, H., Choi, Y., Quan, X., & Joseph, A. (2008). A review of the research literature on evidence-based healthcare design. *HERD Health Environments Research & Design Journal*, *1*(3), 61–125. https://doi.org/10.1177/193758670800100306

Van Hoof, J., Rutten, P. G., Struck, C., Huisman, E. R., & Kort, H. S. (2014). The integrated and evidence-based design of healthcare environments. *Architectural Engineering and Design Management*, *11*(4), 243–263. https://doi.org/10.1080/17452007.2014.892471

Vladislav, V., & Marina, B. (2021). Implementation of indoor positioning methods: Virtual hospital case. *Procedia Computer Science*, *193*, 183–189. https://doi.org/10.1016/j.procs.2021.10.018

Wang, H., Ganesh, G., Zon, M., Ghosh, O., Siu, H., & Fang, Q. (2025). A BLE based turnkey indoor positioning system for mobility assessment in aging-in-place settings. *PLoS Digital Health*, *4*(4), e0000774. https://doi.org/10.1371/journal.pdig.0000774

Wichmann, J. (2022). Indoor positioning systems in hospitals: A scoping review. *Digital Health*, *8*, Article 205520762210816. https://doi.org/10.1177/20552076221081696

Yang, J., Wang, Z., & Zhang, X. (2015). An iBeacon-based indoor positioning systems for hospitals. *International Journal of Smart Home*, *9*(7), 161–168. https://doi.org/10.14257/ijsh.2015.9.7.16

Zafari, F., Gkelias, A., & Leung, K. K. (2019). A survey of indoor localization Systems and technologies. *IEEE Communications Surveys & Tutorials*, *21*(3), 2568–2599. https://doi.org/10.1109/comst.2019.2911558

Zeisel, J. (2006). *Inquiry by design: Environment/behavior/neuroscience in architecture, interiors, landscape, and planning*. W.W Norton.

Zhang, Z., Zou, Y., & Xiao, W. (2023). Exploration of a virtual restoration practice route for architectural heritage based on evidence-based design: A case study of the Bagong House. *Heritage Science*, *11*(1). https://doi.org/10.1186/s40494-023-00878-8

Zhao, J., Aziz, F. A., Deng, Y., Ujang, N., & Xiao, Y. (2024). A review of comprehensive post-occupancy evaluation feedback on occupant-centric thermal comfort and building energy efficiency. *Buildings*, *14*(9), Article 2892. https://doi.org/10.3390/buildings14092892

Zhao, J., Pikas, E., Seppänen, O., & Peltokorpi, A. (2021). Using Real-Time indoor resource positioning to track the progress of tasks in construction sites. *Frontiers in Built Environment*, *7*, Article 661166. https://doi.org/10.3389/fbuil.2021.661166

Zimmerman, A., & Martin, M. (2001). Post-occupancy evaluation: Benefits and barriers. *Building Research & Information*, *29*(2), 168–174. https://doi.org/10.1080/09613210010016857

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