Online Journal of Art and Design
volume 15, issue 2, April 2027
DOI: https://doi.org/10.30935/ojad/2513148

AI Versus Conventional Methods In Spatial Behavior Analysis Of Educational Settings: A Comparative Review Of Methodological Limitations

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"This article is derived from the first author's ongoing PhD dissertation conducted at Gebze Technical University"

ABSTRACT
Spatial behaviour analysis in educational spaces is an important area of research for understanding user–space interaction and evaluating the performance of learning environments. Although the use of AI-supported methods has increased in recent years, the behavioural dimensions addressed or overlooked in AI-based and conventional research have not been systematically compared across educational settings. This study evaluates spatial behaviour research in educational spaces from the perspective of the representation gap and compares the behavioural and environmental dimensions examined by AI-supported and traditional approaches.
A systematic literature review yielded an analysis matrix containing 181 coded publications, including 121 non-AI and 60 AI-supported records. The publications were coded according to educational level, behavioural parameters, environmental variables, data collection tools, and methodological approach. The findings show that AI-supported studies more frequently examine duration, route, and headcount, while user interaction and density are more frequently considered in non-AI studies. Environmental parameters, including temperature, acoustics, air quality, humidity, and lighting, are infrequently represented in both groups.
The results indicate that increased data collection and analytical capacity does not necessarily result in a broader examination of social and environmental dimensions. The differences identified concern the variables addressed in the reviewed publications rather than the inherent capabilities of individual methods. The study therefore emphasises the value of analysis frameworks that integrate behavioural, social, and environmental components in the evaluation of educational buildings.
Keywords: spatial behaviour analysis, educational spaces, artificial intelligence, representation gap, user behaviour, systematic literature review.

1. INTRODUCTION
Educational spaces are characterised as settings in which user behaviours can be observed intensively and continuously and where individual–space interaction becomes clearly apparent (Ali et al., 2026; Kasalı & Doğan, 2010). The movements, interactions, and use preferences of students, academic staff, and other user groups within space provide important information regarding the efficiency of educational processes, user satisfaction, and spatial performance (Guo & Sui, 2025; Ji et al., 2023). For this reason, spatial behaviour analyses conducted in educational buildings have become an important area of research for evaluating and improving learning environments (Wu et al., 2020; Yin et al., 2025).

Spatial behaviour analysis is an interdisciplinary field that examines users' movements, location preferences, intensity of use, interaction patterns, and temporal behaviours within a given physical environment. Studies conducted across different fields, including architecture, environmental psychology, urban and regional planning, educational sciences, and human–computer interaction, focus on understanding the effects of space on user behaviour and developing design decisions accordingly (Kasalı & Doğan, 2010; Tunçok Sarıberberoğlu & Ünlü, 2024). In particular, spatial behaviour analyses conducted in educational buildings are used as an important research tool for identifying spatial characteristics that support learning processes, understanding user needs, and evaluating the performance of educational environments (Ali et al., 2026; Wang et al., 2026). Spatial behaviour analysis is therefore regarded not only as a means of explaining user movement, but also as an important source of evidence for assessing the extent to which design decisions correspond to user needs.

Research carried out in classrooms, circulation areas, and informal learning spaces demonstrates the importance of examining behaviour in relation to spatial organisation. Kasalı and Doğan (2010) investigated the use of non-classroom spaces during recess, while Wu et al. (2020) examined the relationship between spatial openness and student activities within an atrium. More recent work has considered the relationship between configuration and social behaviour in educational buildings (Tunçok Sarıberberoğlu & Ünlü, 2024), as well as the relationship between spatial layout and peer academic support (Ji et al., 2023). These studies show that observable activity is closely related to the opportunities and constraints created by physical space.

For many years, spatial behaviour studies have relied on traditional methods such as direct observation, interviews, surveys, and plan-based evaluations (Kasalı & Doğan, 2010; Wu et al., 2020). These methods allow researchers to interpret the contextual reasons underlying behaviour and to understand user experiences directly. However, they generally depend on time-consuming data collection processes, work with limited observation periods, and may be influenced by the researcher's interpretations. These limitations become particularly apparent in large-scale educational settings with intensive user movement or in studies requiring long-term observation (Arsan & Kepez, 2017; Martínez-Maldonado et al., 2022).

In recent years, developments in sensor technologies, image-processing methods, big data analytics, and the use of artificial intelligence applications have introduced new research approaches to spatial behaviour analysis (Arsan & Kepez, 2017; Song et al., 2026). Camera systems, Wi-Fi-based tracking systems, Bluetooth Low Energy (BLE) networks, RFID systems, wearable sensors, location-based technologies, and machine-learning algorithms enable user behaviours to be recorded and analysed across different spatial and temporal scales (Martínez-Maldonado et al., 2022; Kong et al., 2025). AI-supported approaches may offer particular advantages in identifying movement patterns, detecting occupants, conducting route analyses, and classifying observable activities (Kong et al., 2025; Song et al., 2026). Accordingly, automated techniques have become an important component of recent spatial behaviour research. Spatial behaviour research has thus become capable of generating larger volumes of data, monitoring groups of users, and analysing certain behavioural patterns automatically.

The use of digital devices for data collection should nevertheless be distinguished from the use of artificial intelligence in analysis. Cameras, Wi-Fi, BLE, RFID, and other sensors may record the presence or movement of users without applying a learning-based algorithm. Conversely, studies that use computer vision or machine learning may process camera or sensor records to detect people, classify activities, or examine behavioural patterns. As illustrated by automated behaviour mapping (Arsan & Kepez, 2017), classroom tracking (Martínez-Maldonado et al., 2022), and AI-supported classroom analysis (Kong et al.,

2025), different technological arrangements produce different forms of evidence and should not be evaluated as interchangeable methods.

Nevertheless, the extent to which technological developments have broadened the scope of research remains open to debate. AI-based methods can generate more data and monitor larger user groups. But increased data collection capacity does not necessarily result in a more comprehensive representation of all dimensions of behaviour. Similarly, although traditional methods can reveal social and contextual aspects of behaviour in greater detail, they may have limitations when the research requires large-scale or continuous observation. The central discussion therefore concerns not which approach is more advanced, but which behavioural, environmental, and methodological dimensions different research approaches address and which remain comparatively less visible.

At the same time, a substantial proportion of existing research focuses on the technical performance of the methods used. While most studies evaluate data volume, detection accuracy, or methodological effectiveness, the question of which dimensions of behaviour are represented and which are systematically overlooked receives relatively limited attention. Spatial behaviour, however, consists not only of physical movement, but also of relationships among social interactions, environmental conditions, and temporal patterns of use. For this reason, behavioural analyses need to evaluate not only the technical capabilities of methods but also their representational capacity.

Although several studies have examined spatial behaviour analyses conducted in educational buildings, research addressing the comparative representation of behavioural and environmental dimensions across AI-supported and non-AI approaches remains limited. Existing publications often concentrate on particular technologies, specific educational levels, or selected types of behaviour (Song et al., 2026; Martínez-Maldonado et al., 2022). Research into post-occupancy evaluation and evidence-based design has also demonstrated the importance of relating observed use to building configuration and environmental quality (Guo & Sui, 2025; Wang et al., 2026). Despite these advances, a systematic comparison of the parameters selected by different approaches can provide an additional perspective on the present state of research. This situation makes it necessary to distinguish the prevalence of a parameter in the literature from a method's technical capacity to measure it.

This study aims to address this gap. Within the scope of the research, 181 publication records on spatial behaviour analysis in educational spaces were systematically examined, and the studies were coded through the developed analysis matrix in terms of educational level, behavioural parameters, environmental parameters, data collection tools, methodological approaches, building typologies, and building scales. Using the resulting data, AI-supported and non-AI studies were compared, and the dimensions addressed less frequently by each approach were identified. The study therefore aims not only to reveal current research patterns, but also to make the differences in behavioural representation across the reviewed literature visible and to provide a data-based assessment for the development of more comprehensive analytical frameworks in future research. The central assumption of the study is that research methods should be discussed not only in terms of their capacity to generate data, but also in terms of the behavioural dimensions they have been used to investigate. Accordingly, the study evaluates spatial behaviour research in educational spaces from the perspective of the "representation gap" and focuses on the question of which dimensions of behaviour receive attention within different methodological approaches.

2. METHODS

This study adopts a systematic literature review approach to identify representation gaps in spatial behaviour research conducted in educational spaces. Accordingly, the research

process consists of literature searching, study selection, development of the analysis matrix, coding, and comparative evaluation.

2.1 Literature Review and Study Selection Process

A systematic literature review was conducted to identify the scope, trends, and methodological limitations of spatial behaviour analysis studies carried out in educational spaces. The review process was structured around three main conceptual axes: educational spaces, spatial behaviour analysis, and case studies. The search began in 2023 and was extended iteratively as the doctoral research developed.

During the search process, English terms referring to educational spaces, including "educational building", "school building", "learning space", "academic building", "classroom", "library", "corridor", "atrium", and "cafeteria", were used together with their Turkish equivalents. For the spatial behaviour dimension, concepts such as "spatial behavior", "space use", "space utilization", "user behavior", "behavioral mapping", "activity mapping", "mekânsal davranış", and "mekân kullanımı" were included in the search. In addition, the terms "case study", "field study", "empirical study", "observational study", "vaka çalışması", and "saha çalışması" were used to identify applied studies based specifically on case studies.

To broaden the scope of the search, keywords describing behavioural parameters and data collection tools were also included. Accordingly, concepts referring to behavioural parameters such as location, direction, route, speed, density, headcount, duration, interaction, and spatial preference, as well as terms describing data collection tools such as observation, camera, sensor, Wi-Fi, BLE, RFID, UWB, wearable sensor, and computer vision, were repeatedly searched in different combinations. New concepts and synonymous expressions encountered throughout the review process were added to the keyword pool and used in subsequent searches.

The identification stage recorded 5,892 records distributed across Scopus (n = 2,103), Web of Science (n = 1,764), ScienceDirect (n = 1,205), and Google Scholar (n = 820). The search was conducted in English and Turkish. Related publications and the Connected Papers platform were also used to identify potentially relevant material. The exact dates of individual database queries and their complete exported search histories were not archived. These limitations are distinguished from the numerical selection record in Figure 1 and are taken into account when interpreting the reproducibility of the review.

Six main criteria were used to determine which publications would be included in the research. Accordingly, publications were required to:

- be conducted in physical educational buildings or their functionally associated nearby outdoor areas,
- examine spatial behaviour or the effect of space on user behaviour,
- include direct or indirect observation of actual behaviour,
- analyse at least one observable behavioural parameter,
- include student users, either alone or together with other user groups,
- focus on behaviour-based indicators rather than exclusively on emotional states or cognitive performance.

The scope of the research was not limited to classroom spaces. Corridors, libraries, entrance areas, atriums, cafeterias, courtyards, and nearby outdoor areas associated with educational buildings, all of which are integral parts of educational facilities, were also included in the evaluation. Purely virtual learning environments, studies without observed spatial behaviour, and exclusively theoretical accounts were not treated as eligible empirical cases. In this way, the study aimed to examine behavioural patterns occurring in educational spaces in a holistic manner (Figure 1).

Online Journal of Art and Design
volume 15, issue 2, April 2027
DOI: https://doi.org/10.30935/ojad/2513148

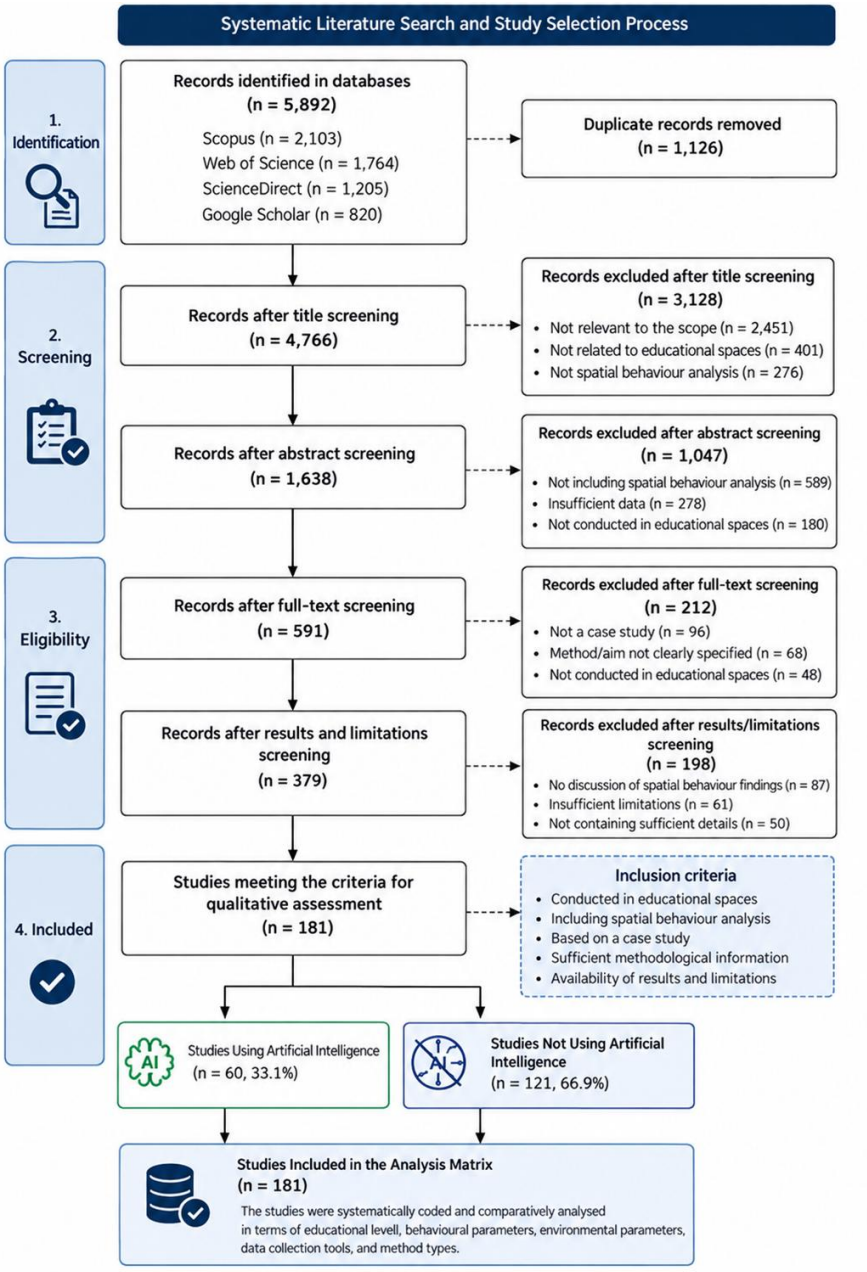


Figure 1. Literature review and case study selection process.

A total of 181 coded publication records were retained following the search and screening processes, including 121 non-AI and 60 AI-supported records.

Figure 1 shows the original numerical transitions between screening stages. After 1,126 duplicate records were removed from the 5,892 identified records, 4,766 remained for title screening. The exclusions recorded at the subsequent stages were 3,128 during title screening, 1,047 during abstract screening, 212 during full-text assessment, and 198 during the final review of reported results and limitations. These steps left 181 coded records for analysis. The final review concerned the availability of findings and sufficient reporting for extraction, rather than a standardised methodological quality appraisal. The selection stages are described in relation to established systematic-review reporting principles (Page et al., 2021), without treating missing original search logs as if they had been retrospectively reconstructed.

The main purpose of this literature review is not merely to identify the diversity of methods used in educational spaces. The research also aims to determine which dimensions of behaviour are represented by different studies and which dimensions are neglected. For this reason, the selection process considered not only the technologies used, but also behavioural parameters, environmental variables, and data collection approaches. In this way, a common and comparable basis for analysis was established across the studies.

2.2 Analysis Matrix and Coding System

A multivariable analysis matrix was developed to enable the selected publications to be compared systematically. The matrix was designed to reveal which behavioural, environmental, and methodological dimensions are represented in spatial behaviour research conducted in educational spaces. The unit of analysis was a coded publication record rather than an individual building, classroom, or behavioural event.

In developing the analysis matrix, spatial behaviour was considered a multidimensional phenomenon. Accordingly, user behaviour was evaluated not simply as a dataset consisting of movement patterns, but as the result of relationships among behavioural indicators, environmental conditions, and research methods. Based on this approach, the matrix was designed to identify which dimensions of behaviour each study makes visible rather than focusing primarily on the methodological characteristics of the studies. Each study was coded in terms of:

- educational level,
- behavioural parameters,
- environmental parameters,
- data collection tools,
- method type,
- building typology,
- building scale.

Behavioural parameters consist of behaviour type, location, direction/route, speed, duration, frequency, density, headcount, and user interaction variables. Environmental parameters include temperature, humidity, air quality, acoustic characteristics, lighting, and colour.

Data collection tools were classified as direct observation, interview, survey, camera systems, digital plan analyses, GPS, Wi-Fi, BLE, RFID, UWB, wearable sensors, speed measurement devices, sound level meters, and LiDAR systems. Data collection tools were distinguished from analytical techniques and research designs. The original master matrix contains tool-level indicators, but does not provide a complete, mutually exclusive qualitative, quantitative, and mixed-method research-design code for every publication. Consequently, the available tool indicators were used for the descriptive profile presented in Table 5, rather than assigning unverified research-design categories.

Studies were classified according to educational level as preschool, primary-secondary education, high school, and university. Studies using artificial intelligence were also evaluated as a separate group. In the coding system, studies using artificial intelligence were indicated by adding the suffix “Y” to the code representing the relevant educational level. For example, code A refers to non-AI studies at the preschool level, whereas code AY refers to AI-based studies at the preschool level. A record was treated as AI-supported when learning-based procedures, such as machine learning, deep learning, or learning-based computer vision, contributed to the collection, processing, classification, or interpretation of behavioural data. Use of a camera or sensor alone did not constitute artificial intelligence. This distinction was also applicable to studies combining conventional observation with AI-based analysis. The original AI/non-AI assignments were retained for the descriptive comparison.

2.2.1. Coding Process

The coding process was carried out through a full-text review of the included publications. Each publication was evaluated according to the predefined coding scheme and assigned to the relevant categories by a single researcher. No independent second-coder assessment or inter-rater agreement calculation was undertaken.

When a study used more than one behavioural parameter or data collection tool, all relevant variables were coded separately. In this way, the studies were evaluated not only in terms of their dominant methods, but also in terms of the behavioural and environmental dimensions they represented.

For the purposes of comparison, location and route were treated as separate characteristics, as were duration and frequency, and headcount and density. Behaviour/activity type concerned the type of observable activity, while interaction concerned a reported relationship or engagement between users rather than proximity alone. Environmental variables were recorded as dimensions examined by the publication; their presence did not necessarily indicate an objective instrumental measurement or a demonstrated relationship with behaviour. The analysis therefore identified reported research content, not the validity or explanatory completeness of each measurement.
This approach made it possible to comparatively analyse the topics on which spatial behaviour research in educational spaces has concentrated and the dimensions in which representation gaps exist.

2.3. The Representation Gap Approach

The theoretical framework of this study is based on the "representation gap" approach. Representation gap refers to a situation in which certain dimensions of behaviour become highly visible within a body of research, while other dimensions systematically remain in the background. In the present study, representation is operationalised as whether a publication examines a specified behavioural or environmental variable.

Although movement-based indicators such as location, route, and duration are frequently examined in spatial behaviour research, user interactions, social behaviours, environmental conditions, and contextual components may receive different levels of attention. For this reason, the study evaluates AI and non-AI research not only in terms of technological characteristics, but also in terms of the parameters documented in the reviewed publications. A low frequency does not automatically establish that a parameter ought to have been measured in every study or that the technique used cannot address it. Within this approach, the main aim of the study is not to determine the superiority of one method over another, but to make the representational imbalances in the existing literature visible.

2.4. Comparative Analysis Approach

The coded data were evaluated using frequency and percentage analyses. In the first stage, the distribution of AI and non-AI studies across educational levels was examined. Differences between the two groups were then compared in terms of behavioural parameters, environmental parameters, data collection tools, and data-collection profiles. The denominators for the within-group percentages were 121 non-AI and 60 AI-coded records. Because several different parameters or tools could be coded for the same publication, percentages across variables were not expected to sum to 100%.

During the comparisons, not only variables with high levels of representation but also those with low levels of representation or no representation were evaluated. Rather than assessing the inherent strengths of particular technologies, the study sought to identify the differences in research emphasis and the representation gaps that emerge in spatial behaviour analyses conducted in educational spaces.

Accordingly, the focus of the study is not to demonstrate the superiority of particular methods, but to answer which behavioural and environmental dimensions each approach makes visible in the reviewed literature. The comparison is descriptive. It does not measure the accuracy, validity, explanatory depth, or technical capacity of the methods used in individual studies, and differences in educational level and research aims may also influence the observed distributions.

2.5 Scope and Limitations of the Research

The research covers empirical publications conducted in educational buildings and the nearby outdoor areas functionally associated with them. Theoretical studies, methodological proposals without physical educational-space cases, laboratory-only experiments, and spatial behaviour studies conducted outside the specified setting were excluded from the scope. Therefore, the findings should be interpreted only within the context of educational spaces. In addition, evaluating different research designs within a common analytical framework involves a certain degree of generalisation. The coding was undertaken by one researcher and did not include a standardised assessment of methodological quality; the classification and search records also have documentary limitations. Nevertheless, the developed analysis matrix provides a systematic framework for comparatively evaluating the dimensions examined in spatial behaviour research conducted in educational spaces.

3. FINDINGS

This section presents the findings obtained from the 181 coded publication records evaluated within the scope of the systematic review. The findings were comparatively assessed in terms of educational levels, behavioural parameters, environmental variables, data collection tools, and tool-use profiles, followed by an analysis of the representation gaps identified in the literature.

3.1 Distribution of AI and Non-AI Studies by Educational Level

Of the 181 coded records examined within the scope of the research, 121 were classified without the use of artificial intelligence, while 60 were AI-supported studies. When the distribution by educational level is examined, it can be seen that the majority of records are concentrated at the university level (Table 1).

Table 1. Distribution of AI and Non-AI Studies by Educational Level

Educational Level	Non-AI	AI	Total	AI Rate (%)
Preschool	18	1	19	5.3
Primary-Secondary Education	41	12	53	22.6
High School	8	7	15	46.7
University	54	40	94	42.6
Total	121	60	181	33.1

As shown in Table 1, more than half of the studies (51.9%) were conducted at the university level. The university level constitutes the most highly represented research context in both AI and non-AI studies. In contrast, research conducted in preschool educational environments remains quite limited.

When the distribution of AI-supported studies is considered separately, these studies are seen to be largely concentrated on higher education buildings. Exactly two-thirds of the studies using artificial intelligence (40 of 60; 66.7%) concerned the university level. At the preschool level, only one AI-based record was identified.

This indicates a clear representational imbalance across educational levels within the reviewed sample. While a substantial proportion of the research concerns young adult user groups, spatial behaviour patterns in early childhood are represented to a more limited extent. The unequal distribution of educational levels should also be considered when

comparing the behavioural parameters of AI and non-AI studies, since the type of educational setting may influence the questions investigated.

3.2 Representation of Behavioural Parameters

Clear differences can be observed between AI and non-AI studies when the behavioural parameters addressed in spatial behaviour research are examined (Table 2).

Table 2. Behavioural Parameters Examined in AI and Non-AI Studies

Parameter	Non-AI n (%)	AI n (%)
Location	79 (65.3)	35 (58.3)
Route (Direction/Route)	28 (23.1)	19 (31.7)
Speed	8 (6.6)	4 (6.7)
Duration	23 (19.0)	34 (56.7)
Frequency	42 (34.7)	18 (30.0)
Density	61 (50.4)	20 (33.3)
User Interaction	60 (49.6)	14 (23.3)
Headcount	22 (18.2)	17 (28.3)
Behaviour/Activity Type	68 (56.2)	44 (73.3)

Location is among the most frequently examined behavioural variables in both approaches. User locations within space were evaluated in 65.3% of non-AI studies and 58.3% of AI studies. Behaviour/activity type was addressed in 56.2% of non-AI records and 73.3% of AI-supported records; this parameter is included in Table 2 to maintain consistency with the comparative analysis in Table 6.

Duration stands out clearly in studies using artificial intelligence. Duration analysis was used in 56.7% of AI studies, compared with only 19.0% of non-AI studies. Similarly, route and headcount analyses are also represented at higher rates in AI-supported research. These differences describe the variables examined by publications within the sample.

In contrast, user interaction and density parameters are more highly represented in traditional approaches. User interaction was evaluated in nearly half of non-AI studies (49.6%), whereas this rate decreased to 23.3% in AI studies. Similarly, density analyses were more common in non-AI studies (50.4% compared with 33.3%).

These results show that different groups of studies make different dimensions of behaviour visible. In the reviewed literature, AI-supported studies place comparatively greater emphasis on movement-related and temporal indicators, while social interactions and collective patterns of space use appear more often in the non-AI group. This difference should not be understood as evidence that AI-supported methods are inherently unable to represent social behaviour or that conventional methods are necessarily more accurate.

The percentages in Table 2 indicate the proportion of publications examining each parameter, not the proportion of behaviour explained by a method. Because a publication could examine more than one parameter, the totals are not expected to add up to 100%. The comparison therefore concerns research emphasis rather than mutually exclusive categories of behaviour.

3.3 Representation of Environmental Parameters

Spatial behaviour is known to be influenced not only by user movement, but also by environmental conditions. For this reason, the extent to which studies evaluated environmental parameters was also examined separately (Table 3).

Online Journal of Art and Design
volume 15, issue 2, April 2027
DOI: https://doi.org/10.30935/ojad/2513148

Table 3. Environmental Parameters Examined in AI and Non-AI Studies

Environmental Parameter	Non-AI n (%)	AI n (%)
Temperature	8 (6.6)	2 (3.3)
Air Quality	2 (1.7)	1 (1.7)
Humidity	1 (0.8)	1 (1.7)
Colour	1 (0.8)	0 (0.0)
Acoustics	5 (4.1)	0 (0.0)
Lighting	18 (14.9)	1 (1.7)

The results show that environmental parameters are represented at very low levels in both AI and non-AI research. Although lighting has the highest representation rate, even this variable was evaluated in only a limited proportion of the studies.

Environmental variables such as temperature, air quality, humidity, acoustic characteristics, and colour were examined in only a very small proportion of the studies. In particular, no examples addressing acoustics or colour were identified among the studies using artificial intelligence.

This finding indicates that the environmental context in which behaviour occurs is examined less frequently than many movement-related variables in the selected corpus. Consequently, one of the most prominent representation gaps in spatial behaviour research conducted in educational spaces emerges in relation to environmental parameters. A low frequency, however, should not be interpreted as evidence that every publication needed to measure environmental conditions, nor does recording an environmental variable alone establish its influence on behaviour.

3.4. Data Collection Tools and Methodological Differences

The distribution of data collection tools reveals clear methodological differences between AI and non-AI studies (Table 4).

Table 4. Usage Rates of Data Collection Tools

Tool	Non-AI n (%)	AI n (%)
Direct Observation	79 (65.3)	3 (5.0)
Interview	25 (20.7)	1 (1.7)
Survey	29 (24.0)	3 (5.0)
Camera	20 (16.5)	38 (63.3)
Digital Plan Analysis	20 (16.5)	1 (1.7)
GPS	5 (4.1)	2 (3.3)
Wi-Fi	2 (1.7)	9 (15.0)
BLE	1 (0.8)	7 (11.7)
RFID	1 (0.8)	1 (1.7)
UWB	1 (0.8)	3 (5.0)
Wearable Sensor	8 (6.6)	6 (10.0)
Speed Measurement Device	4 (3.3)	1 (1.7)
Sound Level Meter	3 (2.5)	1 (1.7)
LiDAR	0 (0.0)	1 (1.7)

Direct observation is the most common data collection method in non-AI studies. User-oriented data collection tools such as interviews and surveys are also frequently used. In contrast, camera systems are by far the most common data collection tool in AI studies. Technologies such as Wi-Fi, BLE, UWB, and wearable sensors are also used at higher rates in AI-supported studies. However, an individual tool does not determine whether the analysis is AI-supported, since cameras and sensors may also be used without machine-learning algorithms.

This distribution indicates that the AI-supported and non-AI publications within the reviewed sample differ substantially in the tools employed for data collection. It does not, by itself, demonstrate that observation-based methods have been replaced over time. Moreover, increased data collection capacity does not automatically lead to a more comprehensive representation of all dimensions of behaviour.

3.5 Data Collection Profiles

When evaluated in terms of the combinations of data collection tools employed, clear differences can also be observed between AI and non-AI studies (Table 5).

Table 5. Data Collection Profiles of AI and Non-AI Studies

Data Collection Profile	Non-AI n (%)	AI n (%)
Human-mediated tools only	68 (56.2)	4 (6.7)
Digital/instrumented tools only	29 (24.0)	54 (90.0)
Both tool groups	24 (19.8)	2 (3.3)

Non-AI studies are largely concentrated in the group using human-mediated data collection tools alone (56.2%). In contrast, a substantial proportion of AI-supported records use only digital or instrumented tools (90.0%). The combined use of human-mediated and digital tools is found in 19.8% of non-AI studies and 3.3% of AI studies. These groups refer to the tools recorded in the analysis matrix; they do not correspond directly to qualitative, quantitative, or mixed-method research designs.

These results reveal different data collection profiles within the reviewed publications. The distinction is useful for interpreting how spatial behaviour has been documented, but no temporal transformation or difference in methodological quality can be established from these data alone.

For Table 5, direct observation, interviews, and surveys were grouped as human-mediated tools. Cameras, digital plan analyses, GPS, Wi-Fi, BLE, RFID, UWB, wearable sensors, speed and sound measurement devices, and LiDAR were grouped as digital or instrumented tools. Each publication was assigned to one of three mutually exclusive profiles according to the indicators available in the original matrix; the resulting totals are 121 non-AI and 60 AI-coded records.

3.6. Overall Pattern of Representational Imbalance

When the preceding findings are considered together, a clear representational imbalance can be observed within the reviewed spatial behaviour publications on educational spaces. Users' locations, activities, movements, routes, and durations of use are represented at different levels, while user interactions and many environmental conditions are addressed less frequently. This tendency is particularly apparent for certain environmental variables in AI-supported studies.

This indicates that increased data production capacity does not necessarily lead to an equally broad selection of behavioural and environmental variables. In other words, the knowledge produced in the literature makes certain dimensions of behaviour visible while leaving others comparatively less examined.

This finding supports the representation gap approach that forms the main conceptual framework of the research.

3.7 Comparative Analysis of Representation Gaps

The findings presented in the previous sections show that AI and non-AI studies represent different dimensions of behaviour at different levels. To clarify these differences, the largest representation gaps between the two approaches were comparatively evaluated (Table 6).

Table 6. Largest Representation Differences Between AI and Non-AI Approaches

Parameter	Non-AI (%)	AI (%)	Difference (percentage points)
Duration	19.0	56.7	+37.7
User Interaction	49.6	23.3	-26.3
Density	50.4	33.3	-17.1
Behaviour/Activity Type	56.2	73.3	+17.1
Headcount	18.2	28.3	+10.1
Route	23.1	31.7	+8.6

As shown in Table 6, the most pronounced difference between AI and non-AI studies occurs in the temporal dimension of behaviour. Duration analysis was used in 56.7% of AI studies, compared with 19.0% of non-AI studies. The difference between the two approaches reaches 37.7 percentage points. This indicates that duration receives greater attention in the AI-supported portion of the reviewed research, although the frequency alone does not establish the measurement capability or accuracy of the methods.

In contrast, the opposite tendency is observed for user interaction. User interactions were evaluated in approximately half of non-AI studies (49.6%), whereas this rate decreased to 23.3% in AI studies. Similarly, density analyses are more highly represented in non-AI studies. These results indicate that the selected non-AI publications more frequently address certain social and collective dimensions of behaviour.

The differences observed in route and headcount parameters may be associated with differences in research objectives and in the tools selected for observing users. The higher occurrence of route analysis in the AI group is consistent with the attention given to movement-related components of behaviour in those publications. In contrast, collective behavioural indicators such as social interaction and density are not represented to the same extent.

Taken together, the findings show that AI and traditional approaches have been used to make different dimensions of behaviour visible in the selected literature. AI-supported studies more frequently address indicators such as route and duration, whereas traditional studies more frequently consider user interactions and density. Therefore, the principal difference established by the present analysis lies in which dimensions of behaviour are represented in the publications, rather than in the inherent technological capability of each approach.

The results support the representation gap approach that forms the main conceptual framework of the study. While some dimensions of behaviour are highly represented in the literature, environmental conditions and behavioural patterns relating to younger age groups are represented at comparatively lower levels. This indicates a potential value in analytical frameworks that consider movement-based, social, and environmental components together when required by the research question.

4. DISCUSSION

This section evaluates the findings in light of the existing literature and discusses the theoretical and methodological implications of spatial behaviour research conducted in educational spaces. Particular attention is given to the representation gaps observed in AI and non-AI studies, the visibility of social behaviour, and the place of environmental context within research.

The findings show that both approaches have different patterns of research emphasis and that neither group addresses all dimensions of behaviour equally. The findings also indicate that the main issue in spatial behaviour research is not the choice of method itself, but the extent to which different dimensions of behaviour are included in the research design. This distinction is relevant to architectural evaluation, where a method may provide reliable occupancy data while leaving other questions about social use or environmental comfort unanswered.

4.1 The AI Paradox and the Representation Gap

One of the most notable points raised by the findings is that the increasing capacity of AI-supported systems to collect and process data does not necessarily imply a more comprehensive interpretation of behaviour. This issue may be discussed conceptually as an "AI paradox". Camera systems, sensor networks, and automated tracking technologies can record certain forms of user behaviour at high temporal resolution; however, an

understanding of why users display particular behaviours may also depend on contextual evidence, spatial configuration, and user experience. The present study did not measure data volume or explanatory depth directly. Accordingly, the proposed paradox is a conceptual interpretation rather than a tested empirical relationship (Table 7).

Table 7. Main Representation Patterns Identified in AI and Non-AI Studies

Analysis Dimension	Situation in Non-AI Studies	Situation in AI Studies
Educational levels	Mainly concentrated on university and secondary education; preschool representation is low	Concentrated at university level; preschool and early educational levels are very limited
Temporal dimension of behaviour	Duration analyses are limited (19.0%)	Duration analyses are common (56.7%)
Social interaction	Relatively highly represented (49.6%)	Poorly represented (23.3%)
Density analysis	Widely used (50.4%)	More limited (33.3%)
Movement patterns (route/trajectory)	Relatively limited (23.1%)	More highly represented (31.7%)
Environmental parameters	Represented at a low level	Represented at a very low level
Acoustics	Very limited representation (4.1%)	Not represented (0.0%)
Lighting	Limited representation (14.9%)	Very low representation (1.7%)
Air quality and humidity	Almost never represented	Almost never represented
Data collection approach	More frequent use of direct observation and user feedback in the reviewed sample	More frequent use of camera- and sensor-based data collection in the reviewed sample
Data-collection profile	Human-mediated tools only: 56.2%; digital/instrumented only: 24.0%	Human-mediated tools only: 6.7%; digital/instrumented only: 90.0%

As shown in Table 7, AI and non-AI studies have different representation profiles. AI-supported publications more frequently examine duration and other movement-related dimensions of behaviour, while traditional studies address user interaction and density at higher rates. In contrast, both approaches consider the environmental context of behaviour only to a limited extent. The profile should be interpreted in relation to the research objectives and educational settings represented in the sample.

These results support the representation gap approach that forms the main conceptual framework of the study. The findings show that the main difference between the reviewed groups is related less to technological capacity than to which dimensions of behaviour are examined. Therefore, methods used in spatial behaviour research should be evaluated not only in terms of their capacity to generate data, but also in terms of how the collected evidence relates to the questions asked in architectural research.

Existing studies help clarify the meaning of this distinction. An atrium evaluation may require observation of activities alongside an analysis of openness and circulation (Wu et al., 2020), whereas an investigation of informal learning spaces may combine the observed distribution of users with accounts of perceived spatial quality (Guo & Sui, 2025; Yin et al., 2025). Similarly, recent post-occupancy evaluation research has considered space syntax, behavioural observations, and user feedback together (Wang et al., 2026). These examples suggest that the relevance of a parameter is dependent on the research objective. A low overall frequency may therefore reflect legitimate specialisation in individual studies, even while drawing attention to dimensions that have received limited consideration across the wider literature.

4.2. The Problem of Representing Social Behaviour

The findings show that the reviewed AI-supported studies more frequently examine movements and temporal indicators, while user interactions and social behaviour patterns receive less attention within this group. However, learning processes in educational spaces are influenced not only by individual movement, but also by social relationships and interaction networks among students. The relatively low frequency of user interaction in the AI subset cannot be taken as evidence that AI methods are unable to analyse it. Recent

research on classroom interaction using spatiotemporal models demonstrates that such analysis is technically possible (Kong et al., 2025).

Traditional methods offer a different advantage in this respect. Approaches such as observation, interviews, and surveys can make the contextual reasons underlying user behaviour visible and contribute to the interpretation of behaviour. However, these methods have various limitations when continuously monitoring large user groups. Therefore, it appears more appropriate to consider the two approaches as complementary rather than as alternatives to one another.

This situation points to a methodological tension between measurability and interpretability in spatial behaviour research. In future studies, integrating movement data with social interaction data may contribute to a more comprehensive representation of behaviour.
The significance of social interaction is also apparent in studies examining the architectural organisation of learning environments. The spatial configuration of educational buildings has been examined in relation to the occurrence of social encounters (Tunçok Sarıberberoğlu & Ünlü, 2024), while work on peer academic support has related spatial layout to patterns of interaction among university students (Ji et al., 2023). In this context, the interpretation of social behaviour requires attention not only to the number or location of users, but also to the relationships established between activities and particular spatial settings.

4.3. Detachment of Behaviour from Environmental Context

One of the most notable findings of the study concerns the level at which environmental parameters are represented. Environmental variables such as temperature, air quality, humidity, acoustic characteristics, and lighting are represented at very low levels in both AI and non-AI studies. This points to an area of comparatively limited attention in the reviewed behavioural research.

Users' movements within space can often be directly observed or measured through sensors. However, the environmental conditions under which these behaviours occur are not investigated as frequently in the present sample. As a result, while many publications address the question of "what the user does", the relationship between observable behaviour and the environmental setting may remain in the background. Furthermore, measuring an environmental variable does not in itself establish its influence on users' actions.

This is particularly important in educational spaces. Variables such as thermal comfort, lighting conditions, acoustic environment, and air quality can be relevant to students' spatial preferences, duration of stay, and interaction patterns. Observational research on acoustical design (Kanakri et al., 2017) and recent studies of informal learning areas (Yin et al., 2025; Shu et al., 2026) indicate how environmental conditions can be related to use and user experience. Environmental data may therefore be integrated more systematically into spatial behaviour analyses when these relationships are relevant to the research question.

4.4. Implications for the Design of Educational Spaces

The findings also have important implications for the design of educational spaces. Learning environments are currently often evaluated through circulation analyses, usage densities, or space utilisation rates. However, the present comparison suggests that user behaviour cannot be fully understood solely through movement patterns. Post-occupancy evaluations have shown the value of comparing measured or observed use with spatial organisation and user experience (Guo & Sui, 2025; Wang et al., 2026).

Unless students' spatial preferences, tendencies towards social interaction, and environmental comfort conditions are considered where relevant, design decisions may be

based on incomplete information. For this reason, future evaluations of educational spaces should select behavioural, social, and environmental data in relation to the specific architectural problem being examined. In a classroom, for example, observations of group activities can be considered alongside furniture arrangements and sightlines. In circulation and transition areas, the spatial distribution of movement and stationary activities may help distinguish places used for passage from those supporting informal social encounters. The findings also show that combining AI-supported data collection systems with traditional user evaluation methods may enable more comprehensive knowledge production when the research question calls for different forms of evidence. Such an approach can be relevant to library areas, informal learning environments, and student gathering spaces where occupancy patterns alone may not explain spatial preference or environmental comfort. Adopting an appropriately selected combination of methods in the future design and evaluation of educational buildings may contribute to a more balanced understanding of user behaviour.

Architectural implications should nevertheless be linked to identifiable decisions rather than treated only as general recommendations. In a library, for instance, maps of occupancy and dwell time may indicate frequently used areas, while acoustic measurements and user feedback can help evaluate the suitability of quiet and collaborative zones. In a corridor, movement counts may describe circulation demand, whereas behavioural mapping can indicate whether furniture placement encourages informal encounters or obstructs passage. Such comparisons can support decisions about flexibility, seating, circulation, visibility, accessibility, and the distribution of shared spaces. These examples illustrate possible applications of the analytical framework; they are not additional empirical findings obtained from the reviewed publications.

The use of observation and automated monitoring also raises ethical concerns. Research involving cameras, location tracking, and behavioural recognition requires careful consideration of informed consent, data minimisation, secure storage, restricted access, and the risks associated with identifying individuals. Particular care is required when research involves children and other potentially vulnerable user groups. Algorithmic differences across populations may also affect the interpretation of automatically classified behaviour. These considerations should form part of the selection of analytical tools rather than being treated as separate technical issues.

The present findings have several limitations. The literature search was developed iteratively, and complete dated database-query exports were not retained. Studies from different educational levels, publication periods, and research objectives were compared within one analytical framework. Coding was undertaken by a single researcher, without independent agreement assessment, and no formal methodological quality appraisal was performed. The numerical findings describe the presence of reported variables and tools rather than the validity of their measurement or the effectiveness of the methods. Although the original coding matrix provides a consistent basis for comparing the recorded entries, publication identity and the AI classification in technically ambiguous cases require caution when interpreting the totals. These conditions limit the extent to which the descriptive findings can be generalised beyond the reviewed corpus.

5. CONCLUSION

This study aimed to comparatively examine the dimensions represented and neglected by AI and non-AI approaches in spatial behaviour analysis research conducted in educational spaces. Accordingly, 181 coded publication records relating to educational buildings were systematically evaluated, and the studies were compared in terms of educational levels, behavioural parameters, environmental variables, data collection tools, and data collection profiles through the developed analysis matrix.

The findings show that although spatial behaviour research in educational spaces has become methodologically diverse, it does not represent all dimensions of behaviour at equal levels. AI-supported studies more frequently examine movement-based indicators such as duration, route, and headcount, while user interactions and density are more frequently reported in traditional studies. These patterns reveal differences in the focus of the publications examined, rather than demonstrating that one method is inherently superior or more capable than another.

One of the most notable findings of the study is that environmental parameters are represented at very low levels in both AI and non-AI studies. Variables that may be related to user behaviour, such as acoustic conditions, air quality, humidity, temperature, and lighting, receive relatively limited attention within the sample. This indicates the value of considering the environmental conditions in which behaviour occurs, particularly when the objective is to explain spatial preference or patterns of space use.

The theoretical contribution of the study is that it proposes an approach that evaluates spatial behaviour research not only according to the technologies used, but also according to the dimensions of behaviour represented. In this regard, the proposed "representation gap" approach makes visible which aspects of behaviour receive attention across a body of literature. The findings indicate that evaluating methods solely in terms of their capacity to generate data is insufficient, and that the nature of the evidence collected should also be considered.

The methodological contribution of the study is the development of a multivariable analysis matrix that enables spatial behaviour research conducted in educational spaces to be compared systematically. The developed matrix provides a flexible evaluation framework that can be used not only for educational buildings but also in future systematic reviews conducted across different building types.

The practical contribution of the study is that it demonstrates the limits of evaluating educational spaces through user movement alone. To understand user behaviour more comprehensively, movement patterns, social interactions, and environmental performance indicators can be evaluated together where the research objective requires them. Therefore, research designs that combine behavioural, environmental, and technological data may be particularly useful for evidence-based evaluation and design in educational spaces.

The study has several limitations. The review includes only publications concerned with spatial behaviour in educational buildings and their associated spaces, and the results are limited to the coded research corpus. In addition, comparing different educational levels and research designs within a common coding system involves a certain degree of generalisation. The single-researcher coding procedure and the absence of a formal methodological quality assessment should also be considered. Despite these limitations, the study contributes to the identification of representation gaps in spatial behaviour research and provides a comparative framework for future evaluation studies.

Future research is recommended to focus particularly on three areas: increasing the number of studies on preschool and younger age groups, integrating environmental parameters more strongly into behavioural analyses, and using AI-based data collection systems together with observation, interviews, and user experience-oriented methods. In this way, it may be possible to develop research approaches that represent user behaviour in educational spaces in a more balanced and comprehensive manner.

Conflict of Interest: The author(s) declare that they do not have a conflict of interest with themselves and/or other third parties and institutions, or if so, how this conflict of

interest arose and will be resolved, and author contribution declaration forms are added to the article process files with wet signatures.

Ethics Committee Permission: In this article, ethics committee approval is not required, and a consent form affirming that a wet-signed ethics committee decision is not necessary has been added to the article process files on the system.

Financial Support: No financial support was received in this studyç

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