Scientific and Social Research, 2026, Volume 8, Issue 7
http://ojs.bbwpublisher.com/index.php/ssr
Online ISSN: 2981-9946
Print ISSN: 2661-4332

Integrating Space Syntax, Behavioral Sensing, and Machine Learning for Campus Public Space Optimization: A Critical Review

Haopeng Li[1], **Mustafa Muwafak Alobaedy**[1], **Mohd Nurul Hafiz Bin Ibrahim**[1]*, **Enci Chen**[2]

[1]Faculty of Information Technology, City University Malaysia, Petaling Jaya 46100, Malaysia
[2]Information Center, Wenzhou Kean University, Wenzhou, 325060 China

Author to whom correspondence should be addressed.

Abstract: Most university campuses still decide where to put public spaces the old way—by walking the site, asking a few people, and trusting experience. That works until the campus grows fast or the student body becomes more mixed. Then the gaps show up: underused plazas, overcrowded paths, places that look good on plan but feel empty in real life. Over the last ten years, researchers have started bringing together Space Syntax measures, Wi-Fi movement data, GIS multi-criteria tools, and machine learning weight adjustments. The combination looks promising on paper. In practice, the pieces rarely talk to each other. This review looks at what has been tried, where the methods still fall short—especially on international campuses—and what a more joined-up approach might look like.

Keywords: Campus public space; Space Syntax; Wi-Fi sensing; GIS-MCDA; Machine learning; Smart campus

Online publication: August 14, 2026

1. Introduction

Campus public spaces are not merely residual areas between buildings; they support circulation, informal learning, recreation, social contact and institutional identity. Spatial configuration influences which routes are encountered and which places remain visually or topologically isolated, a proposition established in foundational Space Syntax research [1–2]. At the same time, public-life studies show that movement alone does not explain staying behavior: seating, shade, active edges, perceived safety and opportunities for social observation strongly affect whether optional and social activities occur [3–4]. Campus-specific studies further demonstrate that the quality and use of outdoor space depend on the interaction between layout, environmental comfort, program distribution and users' everyday routines [5–7].

No single method captures all of these relationships. Geographic Information System-based multi-criteria decision analysis (GIS-MCDA) provides a transparent way to combine heterogeneous spatial criteria, while the Analytic Hierarchy Process (AHP) is widely used to elicit expert preferences [8–9]. Network logs and mobile sensing can reveal aggregate occupancy and mobility patterns at much finer temporal resolution than occasional observations [10–12]. Machine-learning models, particularly Random Forests, can then estimate nonlinear associations between spatial attributes and observed use, although feature-importance measures require careful interpretation when predictors are correlated [13–14]. Explainability methods such as SHapley Additive exPlanations (SHAP) can make these models more interpretable for planners [15].

Smart-campus research has begun to connect real-time space-use measurement with facilities management and decision dashboards, but integrated applications to campus public-space optimization remain fragmented [16–17]. This review therefore combines foundational scholarship with recent studies published through 2026. It examines how Space Syntax, behavioral sensing, GIS-MCDA, and machine learning can be organized into a coherent analytical workflow, with particular attention to multicultural residential and joint-venture campuses.

2. Theoretical and methodological foundations

2.1. Spatial configuration and movement potential

Space Syntax treats the built environment as a relational system rather than a collection of isolated objects. In axial or segment representations, paths are converted into connected elements and analyzed according to how easily they can be reached or traversed from the rest of the network. Integration estimates closeness to other elements and is commonly interpreted as movement-to potential, whereas choice estimates how frequently an element lies on shortest paths and is interpreted as movement-through potential [1–2]. Later segment-based work improved metric and angular representations of route choice, making the approach more suitable for irregular pedestrian networks and large urban systems [3–5].

For campus analysis, scale selection is critical. Global integration may identify a central spine connecting major precincts, while local radii reveal neighborhood-scale accessibility around dormitories, libraries, canteens, or teaching clusters. Angular distance is often more behaviorally plausible than Euclidean distance because pedestrians tend to minimize directional changes, yet metric distance remains important when slopes, weather exposure, or long walking distances create additional effort. A robust study should therefore report the spatial representation, radius, distance definition, and treatment of gates, covered walkways, internal passages, and vertical connections. Without these details, apparently comparable syntax values may describe different movement systems.

Configurational measures should be interpreted as affordances rather than deterministic predictions. A highly integrated plaza may still be underused if it offers little shade, has no active frontage, or is separated from destinations by level changes. Conversely, a topologically peripheral courtyard can be busy because it is adjacent to a popular café or residence hall. The most informative use of Space Syntax is therefore diagnostic: it establishes a baseline expectation derived from layout, after which deviations between predicted and observed use can be investigated as evidence of environmental, functional, or social effects.

2.2. Behavioral and environmental affordances

Behavioral theories complement configuration by distinguishing between movement that is obligatory and activity that depends on environmental quality. Gehl's categories of necessary, optional and social activities and Whyte's systematic observation of sitting, gathering and edge behavior remain useful for interpreting why some accessible places support prolonged occupation while others function only as corridors [5–7]. Campus studies similarly identify shade, seating variety, greenery, enclosure, proximity to services and perceived safety as recurrent determinants of outdoor-space use [8]. These variables should not be treated as independent checkboxes; their effects are often conditional. Shade matters most during hot periods, movable seating may matter during group work, and active edges may be valued differently in quiet study areas and event spaces.

Operationalization requires clear spatial units and measurable definitions. For example, seating can be represented by seats per 100 m^2, shade by the proportion of usable area shaded at specified times, active frontage by the length of transparent or publicly accessible ground-floor edge, and acoustic comfort by measured or modeled sound levels. Equity-oriented studies may additionally calculate walking access from each residential or academic zone and compare the distribution of high-quality spaces across user groups [9]. Public-space quality indices can organize these observations into dimensions such as inclusiveness, meaningful activities, comfort, safety and pleasurability, while evidence from neighborhood open spaces indicates that quality can be associated with sense of community as well as simple visitation frequency [10–11].

The central methodological implication is that behavioral observation should be used both to validate and to interpret spatial models. Structured scans, behavior mapping, short intercept surveys, and environmental measurements can explain why two spaces with similar syntax values perform differently. They also help detect blind spots in digital traces, such as people who do not carry connected devices, brief passers-by misclassified as occupants, or groups whose use is less visible in aggregate density data.

2.3. GIS-MCDA and machine-learning-assisted weighting

GIS-MCDA converts planning objectives into spatial criteria, standardizes them to comparable scales, and combines them through a decision rule such as weighted linear overlay [12]. A typical campus suitability model may include network accessibility, distance to destinations, thermal comfort, noise, greenery, seating, safety, land-use compatibility, and construction feasibility. AHP supplies weights through pairwise comparisons and provides a consistency ratio that can expose contradictory judgments [13]. However, consistent judgments are not necessarily empirically valid, and results may change when experts, normalization functions, or classification thresholds change. Sensitivity analysis should therefore vary both weights and criterion scores rather than reporting only one final map.

Machine learning can provide an empirical counterweight to expert-driven weighting. A Random Forest can be trained to predict observed occupancy or dwell intensity from the same criteria used in GIS-MCDA [14]. Permutation importance or SHAP values can then indicate which variables contribute most strongly to prediction [15]. These outputs can be used in three ways: as an independent benchmark for AHP weights, as a bounded adjustment to expert weights, or as evidence for revising the criterion set. The third use is often the most valuable because persistent residuals may reveal omitted variables, interaction effects, or inappropriate spatial scales.

Two cautions are essential. First, standard impurity-based Random Forest importance can favor continuous or high-cardinality variables and become unstable when predictors are correlated [16]. Second, predictive importance does not establish that changing a variable will cause a change in space use. A plausible hybrid procedure should therefore combine expert judgment, cross-validated predictive evidence, interpretability analysis and post-intervention evaluation. The result is not a fully automatic ranking but a traceable decision process in which each weight has a theoretical, empirical and practical justification.

Taken together, the methodological foundation supports a four-layer workflow: Space Syntax estimates configurational opportunity; environmental and program variables describe local affordances; behavioral sensing supplies spatiotemporal evidence of actual use; and GIS-MCDA translates the combined evidence into planning alternatives. Machine learning should operate across these layers as a calibration and diagnostic mechanism rather than as a substitute for spatial theory or stakeholder judgment.

3. Behavioral sensing and integration challenges

3.1. Data sources, preprocessing and spatial units

Campus wireless infrastructure creates a potentially valuable record of collective movement. Association logs can indicate when devices connect to access points, while probe requests or network-controller data may provide more frequent but noisier observations. Earlier mobility research demonstrated how Wi-Fi traces can be transformed into probabilistic movement patterns, and large-scale location data have long been used to reveal aggregate urban dynamics [17–18]. Controlled studies also show that Wi-Fi signal observations can track mobility at useful temporal resolution, although accuracy depends strongly on access-point density, device behavior, and the localization method [19].

Raw logs are not equivalent to people counts. One person may carry several devices, devices may remain connected when their owners have left, and operating systems vary in how they scan or randomize identifiers. Preprocessing should therefore specify identifier handling, sessionization rules, inactivity thresholds, access-point mapping, duplicate-device treatment, and temporal aggregation. Counts may be normalized against total active devices or calibrated against manual observations at selected sites. Where access-point coverage overlaps, probabilistic assignment or signal-strength weighting is preferable to simply assigning every device to the nearest access point.

The spatial unit must match the resolution of the sensing system. Building- or floor-level data should not be presented as precise positions within an outdoor plaza. For public-space analysis, access points can instead be linked to service areas, entrances, or adjacent open-space polygons, with uncertainty recorded explicitly. Smart-campus studies emphasize that real-time measurement becomes useful only when data definitions are aligned with facilities-management decisions [20]. Accordingly, the target variable should be selected in advance: pedestrian flow, occupancy, dwell time, peak crowding and repeated visitation answer different planning questions and require different processing rules.

3.2. Spatiotemporal fusion, validation and interpretation

Integration begins by placing syntax, environmental and sensing variables on compatible spatial and temporal supports. Syntax values are generally static for a given network, whereas shade, thermal comfort, timetable demand and occupancy vary by hour, day and season. Rather than averaging all observations into one density surface, studies should create stratified layers for teaching periods, evenings, weekends, examination weeks and major events. This makes it possible to distinguish consistently attractive places from spaces activated only by scheduled demand.

Validation should combine independent data sources. Manual pedestrian counts can evaluate flow estimates; behavior maps can test dwell classifications; booking or timetable records can identify programmed peaks; and short surveys can reveal motivations that are invisible in logs. Predictive models should be tested across days or semesters rather than through random row-wise splits that leak repeated observations from the same place into both training and test sets. Appropriate metrics depend on the task: mean absolute error or root mean square error for counts, precision and recall for crowded/not-crowded classification, and rank correlation for suitability ordering.

The most informative outputs are often mismatches rather than high correlations. High syntax and high occupancy indicate that configuration and use are aligned. High syntax but low occupancy suggests deficient comfort, programming, or identity. Low syntax but high occupancy may reveal a strong destination, a shortcut not represented in the network, or a socially valued enclave. Low values on both layers identify spaces that may require substantial redesign or may legitimately serve low-intensity ecological or contemplative functions. This four-way interpretation prevents optimization from collapsing into the simplistic objective of maximizing footfall everywhere.

Temporal modeling also requires attention to drift. Access-point layouts change, new buildings open, course schedules shift, and student cohorts develop different habits. Models should therefore be recalibrated periodically, and dashboards should display data coverage and confidence alongside predicted density. A closed-loop system is credible only when it can detect that the relationship between spatial features and observed behavior has changed, rather than repeatedly applying weights learned from an obsolete semester.

3.3. Privacy, bias and data governance

Mobility data are sensitive even when names are removed. A small number of spatiotemporal points can be sufficient to distinguish individuals in large mobility datasets, so replacing device identifiers with hashes does not by itself guarantee anonymity. Campus studies should apply data minimization: collect only fields needed for the stated planning purpose, aggregate early, limit retention, separate identity-management systems from analytics, and restrict access through documented governance procedures. Results intended for publication should normally be released as coarse counts or synthetic data rather than trace-level records.

Differential privacy offers a formal way to bound the information disclosed about any individual by adding calibrated noise to aggregate queries. Federated learning can keep raw data within local controllers or institutional units while sharing model updates. Both approaches are promising, but neither removes the need for risk assessment: privacy noise can distort low-count spaces, model updates can still leak information, and technical protections do not resolve questions of consent, proportionality or secondary use. General guidance for data-intensive research therefore stresses ethical review, transparency and anticipation of downstream harms throughout the project lifecycle.

Bias is equally important. Device ownership, operating-system behavior, network login practices and international roaming can produce unequal visibility across student groups. Sensors also capture presence more readily than experience; a crowded space may be uncomfortable or unavoidable. Bias audits should compare sensing estimates with observations and surveys across times, locations and user categories, and reports should state which populations may be underrepresented. In multicultural campuses, governance panels should include student representatives and facilities, IT, planning and ethics staff so that analytical convenience does not override legitimate expectations of privacy and inclusion.

4. Gaps and Contextual Limitations

4.1. External validity and multicultural campus contexts

A central limitation of the literature is external validity. Many studies analyze a single campus, a short observation period, or one type of space, making it difficult to separate general mechanisms from local conditions. Climate, academic calendars, residence patterns, security controls, and transport modes can all change the relationship between configuration and behavior. A model calibrated on a compact temperate campus may not transfer to a hot-humid residential campus where covered routes, air-conditioned interiors, and evening activity dominate. Transfer studies should therefore report which variables and thresholds are portable and which require local recalibration.

Cultural context is usually acknowledged but rarely formalized. Proxemic research shows that expectations about interpersonal distance and spatial interaction vary across social settings. On an international campus, preferences for group size, noise, gender mixing, outdoor study and informal gathering may therefore differ within the same physical environment. Treating "students" as one homogeneous population can conceal conflicting needs. Mixed methods are needed: aggregate sensing can reveal when and where patterns differ, while surveys, interviews and participatory mapping can establish whether those differences reflect preference, exclusion, timetable structure or unequal access to amenities [5–7].

Joint-venture and multicultural residential campuses are particularly valuable test beds because they combine diverse user expectations with a relatively bounded spatial system. Yet they also complicate inference. Nationality is an inadequate proxy for cultural preference, and demographic profiling can create ethical and statistical risks. Researchers should prioritize self-reported activity needs and context-specific behavior over essentialized group labels, use subgroup analysis only when sample sizes and consent are adequate, and present uncertainty rather than deterministic cultural explanations.

4.2. Methodological and operational gaps

Most published workflows remain linear. A study may calculate syntax values, create a Wi-Fi density map or produce a weighted suitability surface, but it rarely completes the full cycle from prediction to intervention and post-occupancy evaluation. Without that cycle, the method cannot show whether a recommended change actually improves use, comfort or equity. Stronger designs would include before-and-after comparisons, phased interventions, temporary prototypes or natural experiments, together with control spaces where feasible.

Causal interpretation is another gap. Machine-learning models can identify stable predictors of occupancy, but high predictive importance may reflect destination placement, timetable demand or unmeasured social factors. For example, shade may appear highly important because shaded areas are located next to canteens, not because shade alone generates the observed activity. Researchers should use directed hypotheses, interaction tests and intervention evidence to distinguish actionable design variables from contextual correlates. This is especially important when model-derived weights are transferred directly into capital-investment decisions.

Operational integration is constrained by incompatible data formats and institutional ownership. Campus planners maintain floor plans and land-use layers, IT units control network logs, facilities teams hold maintenance and booking data, and researchers often create separate syntax models. A sustainable workflow requires a shared spatial identifier, versioned geometry, metadata for time and uncertainty, and clear responsibility for updates. Otherwise the analytical system becomes a one-off research prototype that degrades as soon as buildings, access points or organizational structures change.

4.3. Reproducibility, equity and decision risk

Reproducibility is limited by closed floor plans, proprietary network data, incomplete parameter reporting and unavailable code. Privacy constraints are legitimate, but they do not justify omitting methodological detail. Studies can publish de-identified spatial grids, synthetic traces, criterion definitions, normalization equations, sensitivity ranges, and executable code without releasing identifiable mobility records. At minimum, papers should document software versions, network-cleaning rules, syntax radii, train-test partitions, hyperparameters, and the procedure used to convert model outputs into MCDA weights.

Optimization also introduces decision risk. Maximizing predicted occupancy can disadvantage quiet-space users, students with mobility limitations, people sensitive to crowding, or groups who avoid monitored areas. High footfall is not always desirable, and underuse may signal either poor design or a legitimate low-intensity function. Suitability maps should therefore be multi-objective, reporting accessibility, comfort, social opportunity, ecological value and distributional equity separately before any composite score is accepted. Stakeholders should be able to inspect how priorities alter the ranking and to challenge criteria that encode institutional convenience rather than user well-being.

Finally, evidence quality should determine the degree of automation. Where data coverage is sparse or cultural preferences are poorly understood, the system should flag uncertainty and recommend further observation rather than issue a precise ranking. Human review is particularly important for high-cost or irreversible interventions. The appropriate goal is decision support with auditable evidence, not an opaque algorithm that appears to replace planning judgment.

5. Future directions

Future work should prioritize interoperable and testable pipelines. Open toolkits that connect DepthmapX or QGIS-based syntax analysis with Python workflows for sensing, machine learning, and MCDA would reduce duplicated effort and make assumptions easier to audit. Smart-university research provides a broader information-management context for such integration, while urban digital twins demonstrate how versioned spatial models, sensor feeds, and participatory interfaces can be combined. Campus applications should adopt these ideas cautiously, beginning with clearly defined use cases rather than attempting to model every activity at once.

Three research directions are especially important. First, multi-campus benchmark studies should test model transfer across climate, morphology, and institutional type. Second, intervention studies should evaluate whether model-guided changes improve not only occupancy but also comfort, accessibility, social inclusion, and user satisfaction. Third, privacy-preserving analytics should be assessed empirically at campus scale, including the accuracy loss produced by aggregation or differential privacy. Across all three directions, participatory interpretation is essential: students and staff should help define desirable outcomes, review trade-offs, and evaluate whether recommendations reflect lived experience.

A practical closed-loop platform would update behavioral layers at controlled intervals, detect data or model drift, compare observed patterns with syntax-based expectations, and present alternative suitability maps under different stakeholder priorities. Each recommendation should retain a provenance record linking it to data coverage, model version, criterion weights, and sensitivity results. Such transparency would allow campus managers to use real-time evidence without turning a planning aid into an unaccountable surveillance or optimization system.

6. Conclusion

Campus public-space optimization requires more than adding new data to traditional site selection. Space Syntax can explain configurational opportunity, behavioral and environmental measures can describe the qualities that support staying, sensing can reveal when and where use actually occurs, and GIS-MCDA can translate these layers into comparable alternatives. Machine learning is most valuable when it calibrates, challenges, and explains the weighting process rather than when it replaces theory and judgment. The review also identifies major limitations: weak cross-campus validation, insufficient treatment of multicultural behavior, limited privacy evaluation, a lack of closed-loop intervention studies, and poor reproducibility. Addressing these gaps through transparent, privacy-conscious, and participatory workflows would make data-informed campus planning both more accurate and more legitimate.

Disclosure statement

The authors declare no conflict of interest.

References

[1] Hillier B, Hanson J, 1984, The Social Logic of Space. Cambridge University Press, Cambridge.

[2] Hillier B, Penn A, Hanson J, et al., 1993, Natural Movement: Or, Configuration and Attraction in Urban Pedestrian Movement. Environment and Planning B: Planning and Design, 20(1): 29–66. https://doi.org/10.1068/b200029

[3] Gehl J, 2011, Life Between Buildings: Using Public Space. Island Press, Washington.

[4] Whyte WH, 1980, The Social Life of Small Urban Spaces. Conservation Foundation.

[5] Abu-Ghazzeh, TM, 1999, Communicating Behavioral Research to Campus Design: Factors Affecting the Perception and Use of Outdoor Spaces at the University of Jordan. Environment and Behavior, 31(6): 764–804. https://doi.org/10.1177/00139169921972344

[6] Lau SSY, Gou Z, Liu Y, 2014, Healthy campus by Open Space Design: Approaches and Guidelines. Frontiers of Architectural Research, 3(4): 452–467. https://doi.org/10.1016/j.foar.2014.06.006

[7] Hajrasouliha A, 2017, Campus Score: Measuring University Campus Qualities. Landscape and Urban Planning, 2017(158): 166–176. https://doi.org/10.1016/j.landurbplan.2016.10.007

[8] Malczewski J, 2006, GIS-based Multicriteria Decision Analysis: A Survey of the Literature. International Journal of Geographical Information Science, 20(7), 703–726. https://doi.org/10.1080/13658810600661508

[9] Saaty TL, 2008, Decision Making with the Analytic Hierarchy Process. International Journal of Services Sciences, 1(1): 83–98. https://doi.org/10.1504/IJSSCI.2008.017590

[10] Kim M, Kotz D, Kim S, 2006, Extracting a Mobility Model from Real User Traces. In Proceedings of IEEE INFOCOM 2006. https://doi.org/10.1109/INFOCOM.2006.173

[11] Ratti C, Frenchman D, Pulselli RM, et al., 2006, Mobile Landscapes: Using Location Data from Cell Phones for Urban Analysis. Environment and Planning B: Planning and Design, 33(5): 727–748. https://doi.org/10.1068/b32047

[12] Sapiezynski P, Stopczynski A, Gatej R, et al., 2015, Tracking Human Mobility Using WiFi Signals. PLOS ONE, 10(7): e0130824. https://doi.org/10.1371/journal.pone.0130824
[13] Breiman L, 2001, Random Forests. Machine Learning, 45(1): 5–32. https://doi.org/10.1023/A:1010933404324
[14] Strobl C, Boulesteix AL, Zeileis A, et al., 2007, Bias in Random Forest Variable Importance Measures: Illustrations, Sources and a Solution. BMC Bioinformatics, 2007(8): 25. https://doi.org/10.1186/1471-2105-8-25
[15] Lundberg SM, Lee SI, 2017, A Unified Approach to Interpreting Model Predictions. In Advances in Neural Information Processing Systems, 2017(30): 4765–4774.
[16] Valks B, Arkesteijn M, Den Heijer A, 2019, Smart Campus Tools 2.0: Exploring the Use of Real-time Space Use Measurement at Universities and Organizations. Facilities, 37(13/14), 961–980. https://doi.org/10.1108/F-11-2018-0136
[17] Valks B, Arkesteijn M, Koutamanis A, et al., 2021, Towards Smart Campus Management: Defining Information Requirements for Decision Making through Dashboard Design. Buildings, 11(5), 201. https://doi.org/10.3390/buildings11050201
[18] Penn A, Hillier B, Banister D, et al., 1998, Configurational Modelling of Urban Movement Networks. Environment and Planning B: Planning and Design, 25(1): 59–84. https://doi.org/10.1068/b250059
[19] Turner A, 2007, From Axial to Road-centre Lines: A New Representation for Space Syntax and a New Model of Route Choice for Transport Network Analysis. Environment and Planning B: Planning and Design, 34(3): 539–555. https://doi.org/10.1068/b32067
[20] Talen E, Anselin L, 1998, Assessing Spatial Equity: An Evaluation of Measures of Accessibility to Public Playgrounds. Environment and Planning A, 30(4): 595–613. https://doi.org/10.1068/a300595