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# Hybrid Campuses: Optimization Models of Classroom Occupancy and Timetables Based on Digital Data (LMS, Wi-Fi, Access Control Systems) And Their Relationship with Student Achievement and Well-Being

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**Abstract:** In the context of higher education's transition to hybrid learning–campus formats, this study addresses the gap between the operational optimization of infrastructure and the psychological and pedagogical outcomes of the student experience. The aim is to develop and theoretically substantiate an integrated resource management model for the hybrid campus that draws on digital traces from heterogeneous sources (LMS, Wi-Fi, access control systems) not only to increase the efficiency of classroom utilization and timetable construction, but also to design a learning environment that supports growth in academic achievement and student well-being. Methodologically, the work is based on a systematic literature review and content analysis of industry reports, covering publications from the Scopus/WoS databases and materials from leading analytical centers. The results show that incorporating data on students' digital activity into multicriteria optimization models, including genetic algorithms, reveals latent relationships between behavioral patterns, social engagement, and academic achievement. A conceptual framework is proposed that

integrates data collection, analytical processing, resource allocation, and the resulting educational and psychological metrics into a single feedback loop. It is concluded that such an integrated approach, despite ethical and organizational constraints, dissolves the efficiency–experience dichotomy and fosters more adaptive, student-centered educational ecosystems. The work is addressed to university administrators, educational technology specialists, and researchers in learning analytics.

**Keywords:** hybrid campus, timetable optimization, space utilization, learning analytics, digital data, student academic achievement, student well-being, genetic algorithms, Wi-Fi data, LMS.

## Introduction

The modern system of higher education has entered a phase of profound transformation, accelerated by the global shift to hybrid and flexible learning formats in the post-pandemic period [1]. This shift is not situational but sustained in nature and requires universities to rethink management principles for both the physical infrastructure and the campus's digital contours. Leading analytical reviews concur that digital transformation is becoming the primary strategic direction of development. In the Gartner report Hype Cycle for Higher Education 2024, three key trajectories are emphasized: the development of AI literacy, the use of open-source generative AI, and the deployment of composable ERP systems [2]. Notably, 83% of CIOs in the higher education sector place student experience at the top of their priorities [2]. Comparable emphases are shown in the EDUCAUSE Horizon Report 2024, which underscores the increasing importance of data analytics and AI for transforming teaching and learning processes [3]. This technological wave opens up extensive opportunities for optimization, but in the absence of a human-centered framework it carries the risk of dehumanizing the educational environment [4].

At the same time, the research corpus on university resource management remains fragmented and is effectively developing within two weakly coupled paradigms. The first, operational-technical paradigm focuses on solving complex combinatorial problems, from timetable construction to the optimal allocation of the pool of instructional spaces, with objectives of maximizing space utilization, minimizing resource conflicts, and reducing operating costs; metaheuristic approaches and operations research methods dominate

here [5, 6]. The second, psychological-pedagogical paradigm examines the impact of the physical, social, and digital educational environment on student engagement, academic performance, and psychological well-being [7].

The study addresses the identified gap: the absence of an integral conceptual framework that consistently links operational efficiency achieved through the analysis of digital traces with pedagogical outcomes and the psychological state of learners. Optimization models used in practice rarely incorporate into objective functions and constraints indicators of instructional quality, levels of cognitive load, and parameters of social interaction, which generates the strategic antinomy efficiency versus experience. Administrative and IT units, oriented toward cost reduction, seek to maximize capacity utilization, whereas academic units and student support services pursue the goal of enhancing the quality of the educational experience. One-dimensional optimization for efficiency (e.g., overly compressed timetables) can produce adverse effects for students: back-to-back classes in distant buildings without breaks, a shortage of spaces for informal communication and collaborative work, as well as the use of lecture halls for formats that require an interactive environment.

The **objective** of the study is to propose and theoretically substantiate an integrated resource management model for the hybrid campus that leverages heterogeneous sources of digital data (LMS, Wi-Fi network logs, access control systems) not only to optimize room occupancy and construct timetables but also to purposefully organize the learning environment that fosters growth in academic performance and maintains student well-being.

The **scientific novelty** lies in conceptualizing the systemic linkage between the operational and technical optimization of campus infrastructure and the psycho-pedagogical characteristics of the student experience, allowing them to be considered not as competing but as coupled dimensions of a single managerial task.

The **working hypothesis** is that the inclusion of data on students' behavioral patterns (their digital traces) in multi-criteria formulations of resource allocation problems makes it possible to simultaneously increase the efficiency of the use of physical infrastructure and improve academic results and subjective well-being by shaping more adaptive, comfortable, and socially rich learning conditions.

## Materials and methods

The methodological framework of the study is constructed on a combination of a systematic literature review and content analysis of industry reports. This mixed design ensures an integrated synthesis: empirical findings from peer-reviewed studies are combined with conceptual models of academic discourse and with strategic insights from leading consulting and analytics organizations. The systematic review is aimed at identifying, critically appraising, and interpreting the entire body of relevant publications on the topic, whereas content analysis makes it possible to reconstruct the dominant trends, priorities, and problem areas articulated by the professional community.

The source base was formed through a purposive selection of the most significant publications released in recent years, which guarantees the relevance and contemporaneity of the empirical and theoretical material. The corpus is divided into two types of sources.

The first type comprises academic articles. These are publications in leading peer-reviewed journals and conference proceedings indexed in Scopus and Web of Science, including those published by IEEE, ACM, and Springer. They form the theoretical-empirical foundation of the study and cover the following areas: optimization of university timetables using metaheuristics and genetic algorithms; analysis of Wi-Fi data for modeling student mobility, assessing attendance, and predicting academic performance; examination of the impact of physical and hybrid learning environments on learning, engagement, and student well-being; systematic reviews addressing the barriers and challenges of implementing learning analytics in higher education.

The second type includes industry reports. These are analyses produced by organizations that set the agenda in the field of educational technologies, such as Gartner and EDUCAUSE. The key documents are Gartner Hype Cycle for Higher Education 2024 and EDUCAUSE Horizon Report 2024, which are used to substantiate the relevance of the topic, to document macro-trends (including the growing importance of AI and data analytics), and to understand the strategic priorities of university leaders in the context of digital transformation.

## Results and discussion

The foundation of intelligent management of a hybrid

campus is the formation of an integrated data ecosystem that consolidates information from heterogeneous digital sources. Each such source captures specific aspects, from behavioral patterns and the degree of academic engagement to the spatiotemporal trajectories of student movement, thereby complementing the overall analytical picture.

- 1) Learning Management Systems (LMS): Platforms such as Moodle and Canvas accumulate detailed traces of students digital activity. Sequential analysis of event logs enables the reconstruction of login frequency, time spent on course pages, intensity of participation in forums, timeliness of assignment submission, and the dynamics of test results. A body of meta-analytical studies demonstrates a statistically significant positive association between the level of activity in LMS and students final academic performance [14].
- 2) Wi-Fi networks: The wireless access infrastructure generates large-scale telemetry data on the actual behavior and mobility of students. Session parameters — time, duration, and the access point identifier for each connection — serve as a reliable proxy indicator of actual attendance and make it possible to assess the utilization of key campus spaces (classrooms, libraries, coworking spaces) in near real time [11].
- 3) Access control systems: Logs of electronic passes and key cards provide precise, verifiable records of entries and exits, allowing the recording of access to specific buildings and rooms with restricted access, including laboratories, specialized classrooms, and libraries [18].

The alignment of heterogeneous data sources constitutes a key technological and organizational barrier. LMS, Wi-Fi, and access control systems have historically been deployed as autonomous IT segments, depriving the university of a unified view of the student journey. Overcoming this fragmentation requires the construction of centralized data repositories and the use of integration platforms. EAB case studies illustrate successful models: for example, at Erie Community College, streams from the LMS (Canvas) and the student information system (SIS, Colleague) have been consolidated into a unified data model. This provided unified student profiles and enabled the investigation of relationships between digital activity and academic outcomes [19].

Advanced Wi-Fi analytics open horizons that extend

substantially beyond simple accounting for classroom occupancy. Analysis of co-localization patterns — regular and prolonged joint connection to the same access points during the same time intervals — makes it possible to reconstruct informal social and learning networks. A study by Carnegie Mellon University showed a tendency for the academic performance of students to converge with the outcomes of their regularly co-localized peers [11]. Consequently, Wi-Fi telemetry can serve as a proxy metric for the formation of campus social capital — a factor closely associated with retention and psychological well-being. In this perspective, an infrastructure monitoring tool is transformed into a strategic mechanism for student services, enabling the identification of socially isolated learners and the assessment of how shared spaces stimulate collaborative learning activity.

University timetabling represents a classic combinatorial

optimization problem. Formally, it belongs to the class of NP-hard problems: as the numbers of courses, cohorts, instructors, and room resources increase, computational effort grows exponentially [5]. The goal is to allocate a set of events (lectures, seminars) to a limited set of resources (time slots, rooms) while satisfying a collection of hard and soft constraints.

To solve this class of problems, metaheuristics are widely used; among them, genetic algorithms are one of the most studied and effective approaches [10]. They model evolutionary search, operating on a population of candidate solutions (chromosomes) and improving them through selection, crossover, and mutation. The key components of genetic algorithms (GA) for the timetabling optimization setting are systematized in Table 1.

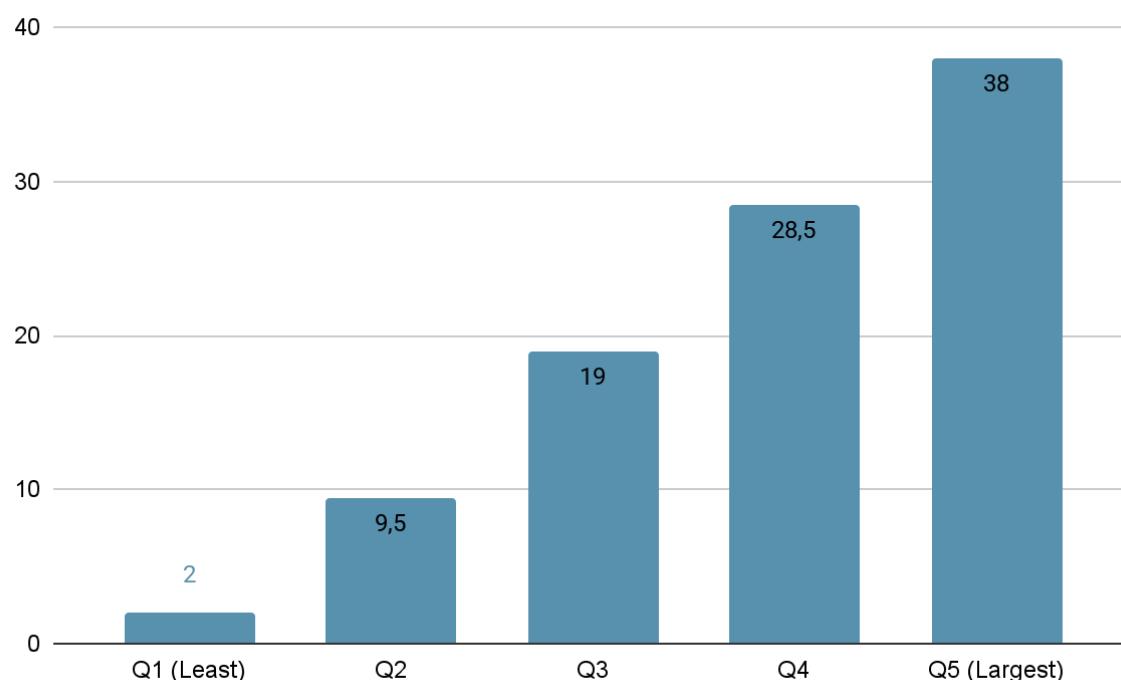
**Table 1. Components of the genetic algorithm for optimizing the university timetable (compiled by the author based on [5, 9, 10, 21]).**

Component	Description in the scheduling context	Example
Representation (Chromosome)	Each chromosome represents a complete, potentially valid timetable. A gene can encode an event (course, instructor, student group) and its assigned time and location.	Array where each element is a tuple (ID_course, ID_room, ID_timeslot).
Objective function (Fitness)	Evaluates the quality of each timetable. Computed as a weighted sum of penalties for constraint violations. The goal is to minimize the value of this function.	$\text{Fitness} = w1 \cdot \sum(\text{hard\_constraint\_violations}) + w2 \cdot \sum(\text{soft\_constraint\_violations})$
Hard constraints	Conditions that cannot be violated (a violation renders the timetable invalid). The penalty for a violation is a very large number.	<ol style="list-style-type: none"> <li>1. One instructor cannot teach two classes at the same time.</li> <li>2. One student group cannot attend two classes at the same time.</li> <li>3. A single room cannot host two classes at the same time.</li> <li>4. Room capacity <math>\geq</math> number of students.</li> </ol>
Soft constraints	Desirable but non-mandatory conditions. A violation adds a small penalty to the objective function.	<ol style="list-style-type: none"> <li>1. Minimization of gaps in student timetables.</li> <li>2. Instructors time preferences.</li> <li>3. Compact arrangement of classes for a single group.</li> </ol>

Despite the demonstrated effectiveness of genetic algorithms in static optimization problems, such as semester timetabling, the modern hybrid campus demands greater operational flexibility. In this context, reinforcement learning methods, particularly deep reinforcement learning (DRL), are promising. Unlike GAs, which target a single optimum on a fixed dataset, DRL agents learn a policy for decision making in a nonstationary environment, relying on a continuous stream of observations and feedback signals [23]. This paves the way from rigid pre-semester planning to adaptive dynamic reconfiguration of resources in real time, for example to the prompt reallocation of the classroom pool under unforeseen changes.

Integrative data analysis makes it possible to detect not only regularities in the use of infrastructural resources but also direct and mediated links between students' behavioral patterns and their educational outcomes.

A longitudinal study at a European university covering 3030 students over five consecutive semesters revealed a statistically significant positive correlation between the intensity of campus Wi-Fi usage and academic performance [11, 12]. It was established that learners in the top quintile by time online demonstrate results (by mean grade and number of successfully completed courses) that are on average 38% higher than those of students in the bottom quintile. The effect is most pronounced for daytime usage (8:00–20:00) and among senior students (from the third year of study). This observation supports the hypothesis that, as learning experience accumulates, the campus digital infrastructure is used more purposefully and productively, whereas for junior cohorts the internet more often acts as a distracting factor. The visualization of the relationship is provided in Fig. 1.



**Fig. 1. Dependence of academic performance on the intensity of Wi-Fi use on campus (compiled by the author based on [2, 3, 11, 12]).**

Beyond direct correlations, the analysis of spatiotemporal mobility trajectories reveals statistically significant indirect social effects (peer effects). It has been found that a student's academic performance over time tends to converge toward the average level of results of their collocated peers, those with whom they most frequently appear within the same Wi-Fi coverage zone [11]. This phenomenon enables the use of mobility data as an indirect indicator for reconstructing informal learning communities, describing their structure, and

assessing their contribution to educational outcomes for individual students as well as for the cohort as a whole.

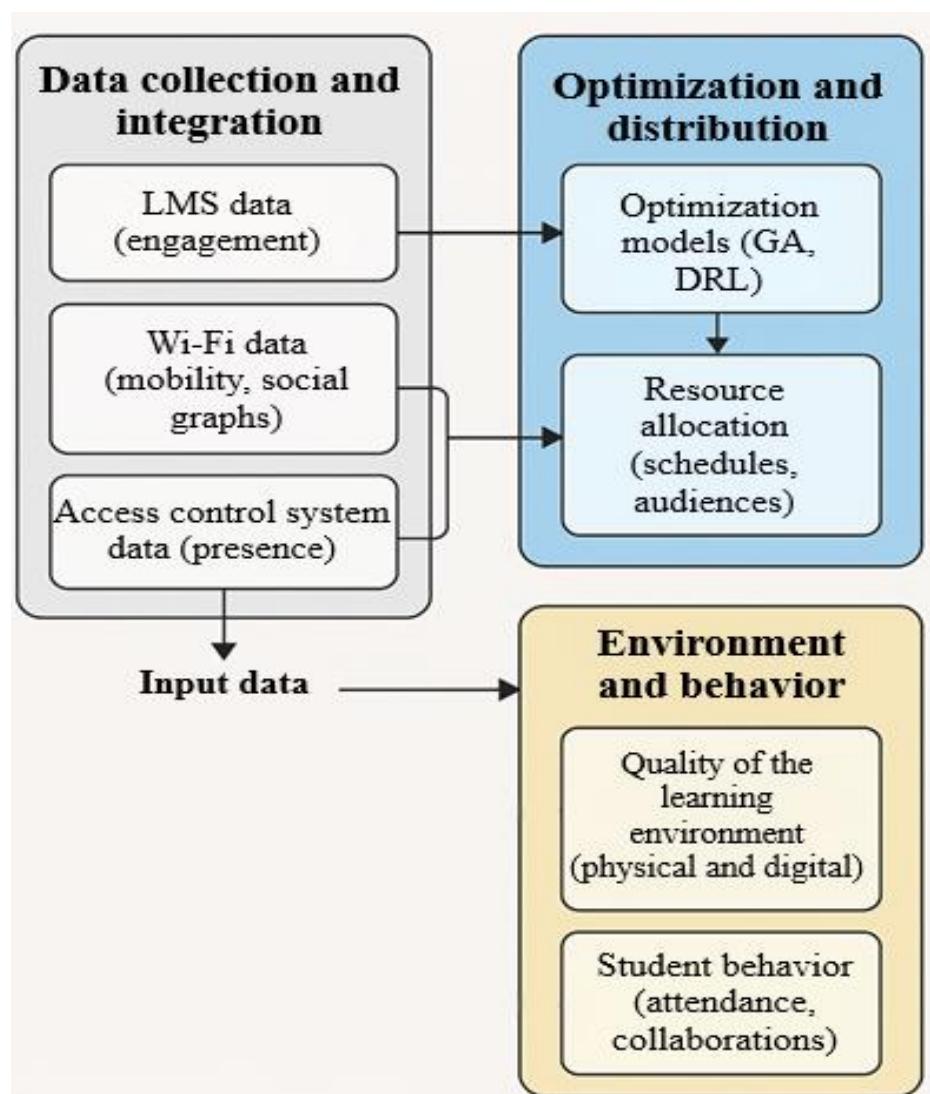
An integrated campus management approach implies a shift in emphasis from purely quantitative utilization metrics to qualitative characteristics of the educational environment. Optimization should not be reduced to the mechanical filling of classrooms. Its goal is to create conditions that support learning activities and promote psychological well-being.

Interdisciplinary evidence from psychology and

pedagogy confirms the direct influence of the physical properties of learning spaces on cognitive functions and, consequently, on academic performance. Parameters of illumination, thermal conditions, air quality (including CO<sub>2</sub> concentration), and acoustic comfort act as significant predictors of educational outcomes. In particular, insufficient ventilation systematically reduces attention and concentration, and extreme temperatures, both high and low, markedly impair performance on cognitive tasks [7]. At the same time, the subjective perception of the environment plays a critical mediating role: a sense of comfort, safety, and the aesthetic appeal of a space correlates with greater engagement in the learning process, which in turn is associated with improved academic outcomes [7]. The experience of implementing hybrid learning demonstrates the difficulty of balancing efficiency and quality. An analysis of the City St George's, University of London case, one of the pioneers of large-scale deployment of hybrid technologies in the United

Kingdom, reveals both the advantages and the limitations of this model [1]. The clear benefits include increased flexibility and inclusivity, allowing students with health constraints, family, or work obligations to continue their studies. At the same time, significant drawbacks are documented: regular technical failures, a mixed and often low level of engagement among students connecting online, and a markedly increased cognitive load on instructors forced to manage physical and virtual classrooms in parallel [17, 18, 20].

Based on the results of the analysis, a conceptual integrated model for optimizing hybrid campus resources has been formulated, visualized in Fig. 2. Its architecture implements a closed loop: empirical data on students' behavioral patterns and educational outcomes serve as input for decision-making on resource allocation. These decisions shape the environment, which, in turn, predetermines subsequent behavior and achieved outcomes.



**Fig. 2. Integrated model for optimizing hybrid campus resources (compiled by the author based on [8, 15, 16, 18]).**

The implementation of an integrated model inevitably confronts the organization with a set of critical constraints that must be embedded from the outset in the digital transformation strategy.

- 1) Ethics and data privacy: The collection, linkage, and interpretation of highly granular information about students' behavior, movements, and elements of social activity give rise to significant ethical risks. Unconditional compliance with applicable data protection regulations is required, including the GDPR in Europe and FERPA in the USA [18]. The foundational pillars should be transparency of rules for data collection and use, obtaining informed consent, and the systematic application of anonymization and pseudonymization as standard mechanisms for minimizing identifiability.
- 2) Organizational and cultural barriers: Effective learning analytics is not only about technology but also about a deep transformation of institutional practices. Key obstacles include a shortage of qualified analysts, a low level of data literacy among faculty and administrators, and persistent resistance to revising established procedures [13]. Overcoming these obstacles presupposes a clear strategic vision on the part of leadership, targeted investments in the development of staff competencies, and the gradual formation of a culture in which managerial decisions are based on data [22, 24].
- 3) Technological complexity: Implementing an integrated model is a task of high engineering complexity. It requires substantial investments in infrastructure: creating unified repositories, deploying platforms for integrating heterogeneous sources, and ensuring data integrity, quality, and cleanliness. Additionally, the development, validation, and maintenance of advanced analytical and optimization models are necessary, which implies the presence within the university of a highly qualified team of Data Science and machine learning specialists.

The analysis conducted shows that students' digital traces within university ecosystems (LMS, Wi-Fi) constitute a highly valuable resource whose potential extends beyond the customary optimization of space and time. These datasets make it possible to reconstruct behavioral patterns, the degree of social inclusion, and the determinants of the student experience.

## Conclusion

A hybrid campus is not the sum of physical and digital spaces, but a multilayered sociotechnical system whose management requires a shift from addressing discrete operational tasks to a holistic, data-driven strategy. The results obtained confirm the initial hypothesis: augmenting classical models of timetabling and instructional space allocation with behavioral indicators and environmental quality parameters produces a pronounced synergistic effect. This approach ensures not only gains in operational efficiency (cost reduction, increased utilization) but also progress toward key educational objectives — improving academic outcomes and sustaining students' psychological well-being. The identified relationships between the intensity of digital resource use, the structure of in-person social interactions, and academic performance open avenues for proactive, personalized measures to support students.

The practical significance of the study lies in the fact that the proposed integrated model can serve as a conceptual guide for university leaders in designing and implementing digital transformation strategies. The model demonstrates the need to overcome departmental fragmentation and to build close interdisciplinary cooperation among IT units, facilities and administrative services, academic affairs, and student support services. Only coordinated efforts make it possible to form a balanced ecosystem in which technological innovation is subordinated to the university's core mission — the holistic development of the student's personality.

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