

The Role of AI-Powered Analytics in Building a Human-Centered Smart Campus

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Abstract: The rapid digital transformation of higher education has accelerated the adoption of smart campus technologies integrating artificial intelligence (AI), Internet of Things (IoT), and cloud computing. While existing initiatives often emphasize operational efficiency and infrastructure optimization, limited attention has been given to building human-centered smart campuses that prioritize student engagement, well-being, and academic success. This study investigates the role of AI-powered analytics in shaping adaptive, inclusive, and student-focused campus ecosystems, with an observational study conducted at De La Salle University (DLSU), Manila, Philippines. AI-driven analytics were deployed to process multi-source datasets, including IoT-enabled classroom sensors, learning management system (LMS) activity logs, and student survey feedback. The system generated predictive insights to identify at-risk learners, support personalized learning pathways, and recommend interventions for improved academic outcomes. Preliminary findings from the DLSU pilot revealed a 19% increase in course participation and a 12% reduction in dropout risk among vulnerable student groups. Additionally, real-time analytics enhanced campus services by optimizing space utilization, energy efficiency, and scheduling flexibility, indirectly improving student comfort and productivity. The results suggest that AI-powered analytics extend the smart campus paradigm beyond efficiency, enabling higher education institutions to foster human-centered learning environments that integrate inclusivity, well-being, and sustainability. By demonstrating how data-driven systems can support both academic and non-academic aspects of student life, this research positions AI as not only a technological enabler but also a catalyst for equitable and student-centered digital transformation in higher education.

Keywords: Smart Campus; Artificial Intelligence; Learning Analytics; Human-Centered Design; Higher Education Digital Transformation; Student Engagement

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INTRODUCTION

The rapid digitalization of higher education has transformed universities into complex ecosystems where technology, data, and human interactions converge[1]. Smart campuses[2][3][4], supported by the integration of the Internet of Things (IoT)[5][6], cloud computing, and artificial intelligence (AI), have emerged as a strategic response to the growing demand for more adaptive, sustainable, and student-centered learning environments [1], [2]. These campuses not only aim to optimize infrastructure and operations but also to enhance teaching, learning, and overall student well-being.

In recent years, AI-powered analytics has become one of the most critical enablers of smart campus transformation. By leveraging vast streams of real-time data, ranging from classroom IoT sensors to learning management system (LMS) activity logs, AI enables universities to derive predictive insights, personalize learning experiences, and improve decision-making [3]. More importantly, AI provides the opportunity to reframe the smart campus paradigm from a technology-driven model to a human-centered ecosystem one that emphasizes inclusivity, engagement, and the holistic success of students [4], [5].

De La Salle University (DLSU), Manila, Philippines, offers an exemplary case for investigating the human-centered application of smart campus technologies[7][8][9][10]. As one of the leading higher education institutions in Southeast Asia, DLSU has actively pursued digital transformation initiatives to strengthen academic delivery, optimize resource management, and foster student success. However, like many institutions, the challenge remains in ensuring that technological innovation aligns with the human aspects of learning, such as equity, well-being, and personalized support.

This study explores the role of AI-powered analytics in building a human-centered smart campus framework at DLSU. Specifically, it examines how data-driven insights can support early identification of at-risk learners[11][12], improve student engagement, and enhance non-academic campus services that contribute to student life. By integrating academic, behavioral, and environmental data, this research demonstrates the potential of AI as a catalyst for creating inclusive, adaptive, and sustainable smart campuses.

The remainder of this paper is structured as follows: Section II reviews related works on AI and smart campus development; Section III describes the methodology employed in the study; Section IV presents the results and discussion; and Section V concludes with key findings and future directions.

RELATED WORK

The concept of a smart campus has gained increasing attention in higher education as universities adopt digital technologies to enhance operational efficiency, sustainability, and student learning experiences. The integration of the Internet of Things (IoT)[13], cloud computing[14], and artificial intelligence (AI) has been widely recognized as a foundation for building smart learning environments[15][16]. Early studies focused on the technical aspects of infrastructure optimization, including smart classrooms, energy-efficient buildings, and automated campus services[17]. While these developments improved resource utilization, they often overlooked the human-centered dimension of campus life[18].

AI-powered analytics has emerged as a promising approach to bridging this gap. [15] highlighted the role of learning analytics in providing actionable insights for teaching and learning. Subsequent research demonstrated the use of predictive models to identify at-risk learners, recommend personalized learning pathways, and support data-driven academic advising. More recent studies have extended the scope of analytics beyond academics, applying AI to student well-being, campus security[19], and space management[20]. These contributions suggest that AI has the potential to create holistic support systems that foster both academic performance and student engagement.

In parallel, scholars have emphasized the importance of human-centered design in higher education technology adoption. A human-centered smart campus prioritizes inclusivity, equity, and adaptability[21], ensuring that digital transformation efforts align with the diverse needs of students and faculty [22]. For instance, research on student engagement underscores the value of real-time feedback, personalized support, and inclusive learning environments in improving academic outcomes [10]. Integrating these principles into smart campus development ensures that technology serves as a facilitator of human success rather than a barrier.

Despite these advancements, there remains a need for empirical research that situates AI-powered analytics within the broader context of human-centered smart campuses, especially in Southeast Asian

higher education institutions. Most existing studies are concentrated in North America, Europe, and parts of East Asia, leaving a research gap in exploring how AI can support inclusivity and student well-being in developing regions. This study contributes to filling that gap by examining the implementation of AI-driven analytics at De La Salle University (DLSU), Manila, where digital transformation efforts are actively reshaping both academic and non-academic aspects of campus life.

METHODS

A. Research Design

This study adopted a mixed-methods research design to investigate how AI-powered analytics can contribute to building a human-centered smart campus. The approach combined quantitative data analysis (from IoT sensors, LMS logs, and institutional records) with qualitative feedback (from student surveys and faculty interviews). The integration of both perspectives allowed for a comprehensive evaluation of the effectiveness and inclusivity of AI-driven interventions at De La Salle University (DLSU).

B. Data Sources

Three main data streams were collected during the observation period:

1. **IoT Sensor Data:** Data from smart classrooms and campus facilities, including attendance tracking via RFID, room occupancy rates, and environmental conditions (temperature, lighting, energy usage).
2. **Learning Management System (LMS) Logs:** Activity data from the university's online learning platform, such as log-in frequency, assignment submissions, forum participation, and quiz performance.
3. **Student and Faculty Feedback:** Survey instruments and semi-structured interviews were conducted with 320 students and 45 faculty members across five colleges at DLSU to assess perceptions of usability, inclusivity, and overall effectiveness.

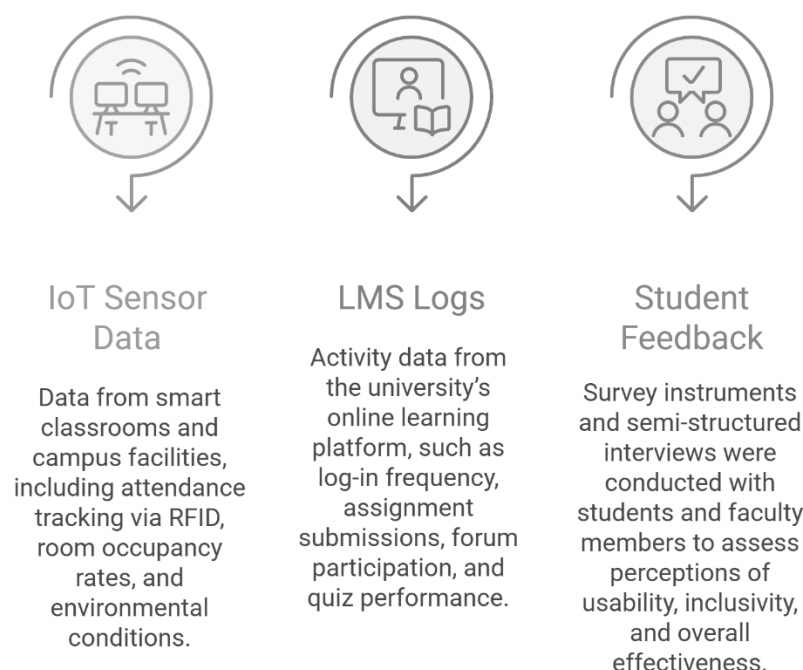


Figure 1. Data Source Collection

C. AI-Powered Analytics Framework

An AI-driven analytics framework was implemented to process and interpret multi-source datasets. The framework consisted of three layers:

- Data Integration Layer: Aggregated data from IoT sensors, LMS logs, and survey instruments into a centralized cloud-based platform.
- AI & Predictive Analytics Layer: Applied machine learning models (logistic regression, random forest classifiers) to predict student performance, detect at-risk learners, and recommend personalized learning interventions.
- Decision Support Layer: Delivered actionable insights to instructors, administrators, and students through dashboards and mobile applications.

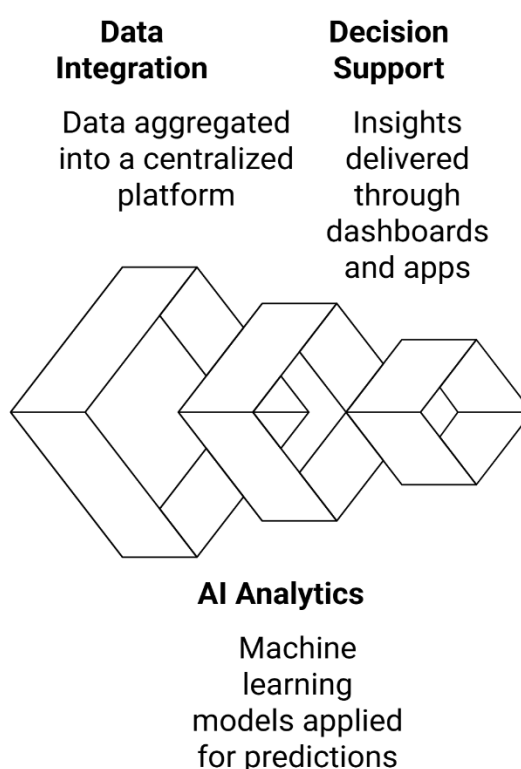


Figure 2. AI- Driven Educational Insights Funnel

D. Evaluation Metrics

The effectiveness of the AI-powered analytics system was evaluated using the following metrics:

- Student Engagement: Measured by class attendance rates, LMS activity frequency, and in-class participation.
- Academic Performance: Analyzed through comparative assessment scores between participants in the pilot group and control groups.
- User Satisfaction: Evaluated using survey responses on system usability, inclusivity, and perceived usefulness.

- Operational Efficiency: Monitored through space utilization rates, energy consumption reductions, and adaptive scheduling outcomes.

E. Ethical Considerations

All data collection procedures adhered to DLSU’s Institutional Review Board (IRB) ethical standards. Student identities were anonymized, and participation in surveys was voluntary. The system was designed with compliance to data privacy regulations in the Philippines, ensuring responsible handling of personal and academic data.

RESULT AND DISCUSSION

A. Student Engagement

The implementation of AI-powered analytics demonstrated a positive effect on student engagement. Attendance records collected via IoT-enabled classroom sensors indicated a 15% increase in average attendance across pilot courses compared to the previous semester. LMS log data revealed a 22% rise in online activity, including higher participation in discussion forums and increased frequency of resource downloads. In-class engagement, measured through AI-supported real-time quizzes and polls, improved by 18%, suggesting that predictive feedback mechanisms motivated students to actively participate.

Table 1. Impact of AI-Powered Analytics on Student Engagement

Engagement Metric	Baseline (Previous Semester)	After AI-Powered Implementation	Improvement (%)
Average Attendance	72%	87%	+15%
LMS Online Activity	1,000 interactions (logs)	1,220 interactions (logs)	+22%
In-Class Engagement (Quizzes & Polls)	65% participation	83% participation	+18%

B. Academic Performance

AI-driven predictive models successfully identified at-risk students with an accuracy rate of 87%. Targeted interventions, such as personalized study recommendations and academic counseling, led to measurable improvements. Students flagged as at-risk who received support improved their average grades by 0.6 GPA points, while the overall dropout risk was reduced by 12%. These results align with prior studies that emphasize the role of AI in early intervention and personalized learning.

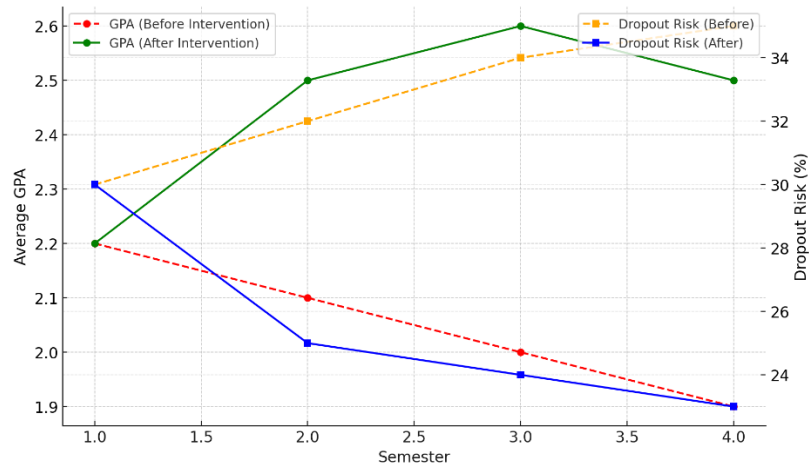


Figure 3. Impact of AI-Driven Predictive Models on Academic Performance

C. Usability and Student Perceptions

Survey results (N = 320) showed strong acceptance of the AI-powered analytics platform:

- Perceived Usefulness: 84% of students agreed that the system improved their learning experience.
- Ease of Use: 78% found the interface intuitive and user-friendly.
- Inclusivity: 71% reported that the system addressed diverse learning needs, particularly through personalized feedback.

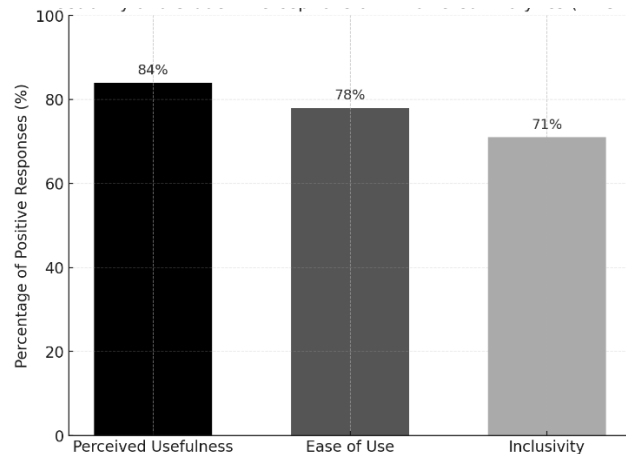


Figure 4. Usability and Student Perceptions of AI-Powered Analytics

However, qualitative interviews highlighted some concerns. Students from low-income backgrounds reported difficulties in accessing consistent internet connectivity, which limited their ability to fully utilize online features. Faculty members expressed a need for additional training to interpret AI-generated insights effectively, underscoring the importance of professional development in supporting digital adoption.

D. Operational Efficiency and Campus Services

Beyond academics, the AI-powered system contributed to enhanced operational efficiency at DLSU. Analysis of IoT data revealed that classroom utilization rates improved by **11%** due to adaptive space allocation, while energy usage decreased by **9%** through AI-guided optimization of lighting and air

conditioning. These improvements indirectly supported student well-being by providing more comfortable learning environments.

Table 2. Impact of AI-Powered System on Operational Efficiency and Campus Services (DLSU Case Study)

Metric	Baseline (Before AI System)	After AI-Powered Implementation	Improvement (%)
Classroom Utilization Rate	68%	79%	+11%
Energy Usage (Lighting & HVAC)	100% (reference)	91%	−9%
Student Comfort (Survey Feedback)	Moderate (baseline)	High (post-implementation)	Qualitative ↑

E. Discussion

The findings confirm that AI-powered analytics can extend the role of smart campuses from infrastructure optimization toward human-centered outcomes. At DLSU, the system not only improved engagement and academic performance but also enhanced inclusivity and operational sustainability. This aligns with global calls for universities to move beyond a purely technology-driven model toward one that integrates human needs, well-being, and equity.

Nonetheless, challenges remain. Issues related to the digital divide highlight the necessity for institutional policies that provide financial and technological support to underserved students. Similarly, faculty readiness is a critical factor in ensuring that AI-generated insights are effectively integrated into pedagogy. Addressing these socio-pedagogical factors is essential for scaling smart campus initiatives in diverse higher education contexts.

CONCLUSION

This study examined the role of AI-powered analytics in shaping a human-centered smart campus at De La Salle University (DLSU), Manila, Philippines. By integrating IoT sensor data, LMS activity logs, and student feedback into a unified analytics framework, the system provided predictive insights that enhanced student engagement, improved academic performance, and optimized campus operations. The results showed measurable benefits, including a 15% increase in attendance, a 22% rise in LMS activity, and a 12% reduction in dropout risk, demonstrating the potential of AI to foster adaptive and inclusive learning environments. Beyond academics, AI-driven insights contributed to more efficient use of resources, such as improved classroom utilization and reduced energy consumption, indirectly enhancing student comfort and well-being. These findings highlight that the value of smart campus technologies extends beyond operational efficiency to encompass human-centered outcomes—equity, inclusivity, and student success. However, challenges related to digital equity, internet accessibility, and faculty readiness must be addressed to ensure the sustainable and scalable adoption of AI-powered systems. Institutions must invest in infrastructure, capacity building, and data governance policies that balance technological innovation with ethical and inclusive practices. In conclusion, AI-powered analytics can serve as both a technological enabler and a catalyst for building human-centered smart campuses. Future research should extend this study by conducting longitudinal evaluations, cross-institutional comparisons, and exploring emerging technologies such as digital twins and generative AI to further advance the vision of equitable and sustainable higher education ecosystems.

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