

System Quality and Perceived Usefulness in Shaping Smart Learning Effectiveness and Smart Campus Design

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Abstract: Smart campus initiatives are increasingly adopted to support the digital transformation of higher education, yet the extent to which system quality translates into meaningful learning benefits remains insufficiently understood. This study examines how key system quality dimensions are associated with smart learning effectiveness and investigates the role of perceived usefulness in this relationship. Drawing on the Information System Success Model and the Technology Acceptance Model, a research model was developed incorporating accessibility, system efficiency, information quality, and real-time capability as system-related antecedents of perceived usefulness and smart learning effectiveness. Data were collected through a questionnaire survey of 420 students and faculty members at the School of Light Industry, North China University of Science and Technology, and analyzed using partial least squares structural equation modeling with 5,000 bootstrap resamples. The results indicate that all four system quality dimensions are positively associated with perceived usefulness and smart learning effectiveness. Information quality exhibited the strongest relationship with both perceived usefulness ($\beta = 0.569$, $p < 0.001$) and smart learning effectiveness ($\beta = 0.342$, $p < 0.001$), while perceived usefulness was positively associated with smart learning effectiveness ($\beta = 0.255$, $p < 0.001$). The findings further indicate differences between students and faculty in selected relationships involving information quality and real-time capability. Building on these empirical findings, the study develops an empirically informed smart campus design framework that translates system quality requirements into architectural and service-design priorities. The study contributes to smart campus research by connecting system-level characteristics, users' perceptions of usefulness, and learning effectiveness within an integrated framework, while providing evidence-based priorities for the design and improvement of smart campus environments.

Keywords: smart campus; smart learning effectiveness; system quality; perceived usefulness; information quality; Technology Acceptance Model; Information System Success Model; PLS-SEM.

1. Introduction

The continuing digital transformation of higher education has expanded the role of information and communication technologies from supporting isolated administrative and instructional functions to enabling integrated, data-driven educational environments. Within this transformation, the smart campus has emerged as an ecosystem in which digital platforms, Internet of Things (IoT) technologies, cloud computing, intelligent services, and connected physical infrastructure are integrated to support teaching, learning, administration, and campus life. Unlike conventional digital campuses, which

primarily digitize existing processes, smart campuses are expected to use interconnected technologies and data to provide adaptive, context-aware, and user-centered services. Accordingly, the value of a smart campus extends beyond technological sophistication and increasingly depends on its capacity to enhance educational experiences and performance while responding to the needs of students, faculty, and other stakeholders (Dong et al., 2020; Ahmed et al., 2020). Recent conceptualizations of smart education similarly emphasize that technological infrastructure should support broader transformations in educational processes rather than function as an end in itself (Demir, 2021).

However, substantial investment in smart infrastructure does not necessarily translate into improved educational outcomes. Universities may deploy integrated information systems, wireless networks, sensing technologies, cloud services, smart classrooms, and automated campus applications without ensuring that these systems provide information and services that users perceive as useful for their learning and teaching activities. Smart-campus development therefore presents both a technological and a socio-technical challenge. A technologically advanced platform may deliver limited educational value when it is difficult to access, inefficient, unreliable, unable to provide timely services, or dependent on information that users consider inaccurate or irrelevant. This concern is particularly important because the fundamental purpose of educational digitalization is not simply to increase the presence of technology but to create environments capable of supporting effective learning and teaching. Human-centered and learning-oriented approaches to smart-campus development consequently argue that technological investments should ultimately be evaluated according to stakeholder needs and educational performance rather than infrastructure deployment alone (Dong et al., 2020).

Existing smart-campus research has provided valuable insights into enabling technologies, architectural frameworks, campus services, sustainability, facilities management, and the characteristics required to transform conventional campuses into connected environments. Studies have examined technologies such as IoT, cloud computing, artificial intelligence, wireless sensing, and data analytics, while other research has proposed frameworks incorporating smart classrooms, smart facilities, energy management, security, transportation, and personalized campus services (Ahmed et al., 2020; Dong et al., 2020). Although this literature has substantially advanced understanding of the technological and organizational components of smart campuses, an important challenge remains in connecting technological capabilities with users' educational experiences. Dong et al. (2020), for example, observed that smart-campus approaches have often been technology-led and argued for a shift toward human-centered and learning-oriented development. Similarly, research on smart learning environments indicates that technological tools require an appropriate theoretical and pedagogical foundation if their contribution to learning processes and outcomes is to be adequately understood (Gambo & Shakir, 2021). Consequently, identifying what technologies a smart campus should contain is insufficient without explaining why particular system characteristics matter to users and how those characteristics are associated with educational effectiveness.

This issue creates an important theoretical problem concerning the mechanisms through which smart-campus system characteristics relate to learning effectiveness. From an information-systems perspective, technological success depends not only on the existence of a system but also on characteristics such as system quality and information quality. The DeLone and McLean Information Systems Success Model identifies system quality and information quality as central dimensions of information-system success and links these characteristics to system use, user satisfaction, and resulting benefits (DeLone & McLean, 2003). From a technology-acceptance perspective, users' evaluations of whether a technology improves their performance are also fundamental. The Technology Acceptance Model identifies perceived usefulness as a central determinant of technology acceptance, with perceived usefulness referring to the degree to which an individual believes that using a particular system can enhance performance (Davis, 1989). Taken together, these perspectives suggest that the educational value of smart-campus technologies may depend not only on objective or perceived characteristics of the systems themselves but also on whether those characteristics translate into perceptions that the systems are useful for learning and teaching.

Despite these complementary theoretical perspectives, a gap remains between research concerned with smart-campus technological design and research concerned with users' perceptions and educational effectiveness. Existing smart-campus frameworks have identified numerous technological components and stakeholder requirements, but they do not necessarily establish which system characteristics are most strongly associated with perceived usefulness and learning effectiveness. Moreover, the relative importance of specific characteristics including accessibility, system efficiency, information quality, and real-time capability requires empirical examination within an integrated explanatory framework. This distinction is consequential for smart-campus design because treating all technological characteristics as equally important may lead universities to allocate resources to technically sophisticated functions that provide comparatively limited educational value. There is therefore a need for an empirically grounded approach that identifies the system characteristics associated with users' evaluations and learning effectiveness and subsequently translates those findings into priorities for smart-campus design.

To address this gap, the present study integrates insights from the Information Systems Success Model (DeLone & McLean, 2003) and the Technology Acceptance Model (Davis, 1989) to examine the relationships among system characteristics, perceived usefulness, and smart learning effectiveness. Four system-related dimensions are considered: accessibility, representing users' ability to access smart-campus services across locations and situations; system efficiency, reflecting responsiveness, stability, and reliability; information quality, representing the accuracy, relevance, and timeliness of information; and real-time capability, reflecting the capacity of the system to provide immediate interaction, notifications, and feedback. Perceived usefulness is incorporated as a user-level evaluation linking technological characteristics with the educational value users associate with smart-campus services. This theoretical integration shifts the focus from asking whether a university possesses smart technologies to examining which

characteristics of those technologies are associated with users' perceptions of usefulness and smart learning effectiveness.

Accordingly, this study investigates two related research questions. RQ1: How are accessibility, system efficiency, information quality, and real-time capability associated with perceived usefulness and smart learning effectiveness in a smart-campus environment? RQ2: How can empirical evidence concerning these relationships inform the design priorities of a user-centered smart-campus framework? To address these questions, questionnaire data were collected from 420 students and faculty members at the School of Light Industry, North China University of Science and Technology, and analyzed using partial least squares structural equation modeling (PLS-SEM). The findings indicate positive relationships between the four system-quality dimensions and both perceived usefulness and smart learning effectiveness. Information quality demonstrates the strongest relationships with perceived usefulness ($\beta = 0.569$, $p < 0.001$) and smart learning effectiveness ($\beta = 0.342$, $p < 0.001$), while perceived usefulness is positively associated with smart learning effectiveness ($\beta = 0.255$, $p < 0.001$). The analysis also identifies differences between students and faculty in selected relationships involving information quality and real-time capability.

This study makes three principal contributions. First, theoretically, it brings together information-systems success and technology-acceptance perspectives to explain smart-campus effectiveness through a framework connecting system characteristics, perceived usefulness, and smart learning effectiveness. Rather than conceptualizing smart-campus success primarily in terms of technological deployment, the study positions users' evaluations of system usefulness as an important component in understanding how technological characteristics relate to educational effectiveness. Second, empirically, the study simultaneously examines four system-related dimensions and identifies their relative relationships with perceived usefulness and smart learning effectiveness using data from both students and faculty. The findings particularly highlight information quality as a central consideration in the investigated smart-campus context and provide evidence of heterogeneity between user groups in selected relationships. Third, from a design and practical perspective, the study translates the empirical findings into an evidence-informed smart-campus design framework. This approach provides a basis for prioritizing data quality, system efficiency, accessibility, and real-time service capabilities according to their observed relationships with user perceptions and learning effectiveness, thereby connecting empirical evaluation with smart-campus architecture and service-design decisions.

The remainder of the paper is organized as follows. Section 2 develops the theoretical background and reviews relevant literature on smart campuses, system quality, information-systems success, and technology acceptance. Section 3 develops the research hypotheses and conceptual model. Section 4 describes the research design, measurement instrument, data collection, and analytical procedures. Section 5 presents the measurement and structural model results. Section 6 discusses the findings in relation to theory and previous research. Section 7 translates the empirical findings into an evidence-

informed smart-campus design framework. The final sections discuss theoretical and practical implications, limitations and future research directions, and the conclusions of the study.

2. Literature Review and Theoretical Background

2.1 Smart Campuses and Smart Learning Environments

The digital transformation of higher education has produced several overlapping concepts, including digital campus, intelligent campus, technology-enhanced campus, smart learning environment, and smart campus. Although these terms are sometimes used interchangeably, they represent different levels of technological integration and educational functionality. A digital campus primarily refers to the digitization and integration of institutional information, administrative processes, learning resources, and communication services. Its emphasis is therefore largely on replacing or extending conventional processes through digital technologies. A technology-enhanced campus represents a broader setting in which digital technologies support teaching, learning, communication, and institutional activities, but the presence of such technologies does not necessarily imply context awareness, adaptive services, or integrated intelligence.

The notion of an intelligent campus extends this development by incorporating technologies capable of automated processing, sensing, decision support, and service optimization. A smart campus, however, represents a more integrated socio-technical ecosystem in which infrastructure, information systems, connected devices, data, and intelligent services interact to support multiple stakeholder needs. Dong et al. (2020) conceptualized the smart campus as an educational environment in which enabling technologies support smart services intended to enhance educational performance while responding to stakeholder interests. Their framework places stakeholders at the center and organizes smart-campus capabilities across infrastructure, technology, and service layers. Importantly, this perspective moves smart-campus development beyond technology deployment toward a human-centered and learning-oriented model in which technological capabilities are evaluated according to the value they create for users and educational processes.

Smart learning environments represent the educational dimension of this broader ecosystem. Spector (2014) conceptualized smart learning environments in terms of their capacity to make learning more effective, efficient, and engaging, with adaptability and personalization representing important characteristics. Similarly, Hwang (2014) argued that smart learning environments extend conventional technology-enhanced learning by using contextual information to provide appropriate learning resources, guidance, feedback, or tools at suitable times and locations. Such environments are therefore distinguished not simply by the availability of digital technologies but by their capacity to respond dynamically to learner needs and learning contexts. Koper (2014) likewise emphasized digitally enriched, context-aware, and adaptive environments designed to facilitate learning.

These distinctions are important because a technologically advanced campus cannot be considered educationally “smart” solely because it incorporates IoT devices, cloud infrastructure, wireless connectivity, artificial intelligence, or automated management systems. Smartness emerges from the ability of technological and informational resources to provide accessible, reliable, contextually appropriate, and educationally useful services. Dong et al. (2020), for example, identified context awareness, data-driven operation, forecasting, immersion, collaboration, and ubiquity as important characteristics of smart campuses while emphasizing that technological deployment should remain human-centered and learning-oriented. Consequently, the smart campus and smart learning environment are closely related but conceptually distinct. The former encompasses the wider institutional ecosystem of infrastructure, technologies, stakeholders, management, and services, whereas the latter focuses more specifically on how technology-rich environments facilitate and adapt to learning processes.

This distinction also reveals an important tension in the existing literature. A substantial stream of smart-campus research has concentrated on technological architectures and enabling technologies, including IoT, cloud computing, wireless sensing, LoRaWAN, data analytics, and interconnected campus services (Dong et al., 2020; Ali et al., 2020; Celdrán et al., 2020; Chen, 2021). These studies are valuable for establishing the technological feasibility and architectural foundations of smart campuses. However, technological capability alone provides limited evidence concerning whether users regard these systems as useful or whether their characteristics are associated with better learning experiences. A learning-oriented smart campus therefore requires attention not only to *what technologies are deployed* but also to *how users experience the resulting systems and information*. This shifts the analytical focus from technological availability toward system quality, user perception, and educational effectiveness.

2.2 System Quality in Smart-Campus Environments

System quality represents a multidimensional assessment of how effectively an information system performs its intended functions from the user's perspective. Within a smart-campus environment, this concept is particularly important because students and faculty interact with an interconnected portfolio of platforms, learning services, mobile applications, information resources, and digitally enabled physical environments. The educational value of these systems may therefore depend on whether users can access them when needed, whether they operate efficiently and reliably, whether they provide accurate and relevant information, and whether they respond to time-sensitive learning and teaching requirements.

In the present study, four system-related dimensions are examined: accessibility, system efficiency, information quality, and real-time capability. Although these dimensions are related, they represent conceptually distinct aspects of the smart-campus user experience.

Accessibility refers to the extent to which users can obtain access to smart-campus systems and services when and where they are needed. Accessibility is particularly relevant to smart learning because learning activities increasingly extend beyond fixed classrooms and scheduled instructional periods. Smart learning environments are expected to reduce

temporal and spatial constraints by enabling learners to interact with digital resources and services across locations and devices. Hwang (2014), for example, emphasized that smart learning environments should provide learners with appropriate support in relevant contexts and at appropriate times. Similarly, cloud-enabled and ubiquitous smart-campus services can facilitate access to learning resources beyond conventional classroom boundaries (Dong et al., 2020). From an educational perspective, greater accessibility may reduce barriers to participation, support continuity of learning, and enable students and faculty to integrate digital services more effectively into their academic activities. Accessibility, however, should not be equated simply with technical availability; meaningful accessibility also depends on whether systems remain usable and dependable across different contexts of use.

System efficiency refers to the responsiveness, stability, reliability, and operational performance of the smart-campus system. These characteristics influence the effort and time users must invest in completing technology-supported academic activities. Systems characterized by slow response times, interruptions, instability, or unreliable functionality may impose additional cognitive and procedural burdens on students and faculty, thereby reducing the perceived value of the technology. Conversely, reliable and responsive systems can reduce technological friction and allow users to focus on learning and teaching tasks rather than system operation. Within the Information Systems Success Model, system quality represents a fundamental dimension of information-system success because the technical performance of a system shapes how users interact with it and evaluate its benefits (DeLone & McLean, 2003). In smart-campus environments, where multiple academic and administrative services may depend on interconnected platforms, system efficiency becomes particularly important for maintaining continuity and confidence in technology-mediated activities.

Information quality concerns the accuracy, relevance, completeness, consistency, and timeliness of information delivered through a system. DeLone and McLean (2003) identify information quality as a central dimension of information-system success, reflecting the quality of the outputs generated by an information system. This dimension has particular significance in smart-campus environments because many services depend on the continuous integration and exchange of data across learning platforms, academic management systems, campus applications, and connected devices. Students and faculty rely on these systems for learning materials, academic schedules, assessment information, notifications, administrative information, and other forms of decision-relevant content. A technically sophisticated platform may therefore provide limited value when the information it supplies is inaccurate, outdated, inconsistent, or irrelevant. In contrast, high-quality information can improve users' confidence in the system, reduce uncertainty, and support more effective academic decision-making. Information quality consequently represents not merely a technical data-management issue but a potential educational resource.

Real-time capability refers to the system's ability to provide timely interaction, updates, notifications, feedback, and responses. This dimension is closely associated with the

context-aware and adaptive characteristics emphasized in smart-learning research. Hwang (2014) argues that smart learning environments should be capable of providing appropriate support according to learners' immediate needs and contextual conditions. In a smart-campus setting, real-time capability can support immediate access to updated information, timely academic notifications, interactive feedback, dynamic service adjustment, and rapid communication between users and systems. Such responsiveness may be particularly relevant to students, whose learning activities often require timely feedback and coordination across multiple academic tasks. Nevertheless, real-time capability should be understood in terms of meaningful responsiveness rather than technological immediacy alone. The educational value of instantaneous communication depends on whether the information or feedback delivered is accurate, relevant, and useful.

Taken together, these four dimensions capture complementary characteristics of smart-campus systems. Accessibility concerns whether services can be reached; system efficiency concerns how reliably and responsively they operate; information quality concerns the value of the information they provide; and real-time capability concerns whether relevant services and information are delivered at appropriate moments. Examining these dimensions simultaneously allows the study to move beyond a generic assessment of "system quality" and investigate which specific characteristics are most closely associated with users' perceptions and smart learning effectiveness.

2.3 Information Systems Success Model

The Information Systems Success Model provides the first theoretical foundation for examining how characteristics of smart-campus systems are associated with user evaluations and outcomes. DeLone and McLean initially developed the model to organize the multidimensional nature of information-system success and subsequently updated it to incorporate six interrelated dimensions: system quality, information quality, service quality, use/intention to use, user satisfaction, and net benefits (DeLone & McLean, 2003). Rather than evaluating information-system success solely through technical performance, the model proposes that technological and informational characteristics are connected to users' interactions with systems and the benefits derived from their use.

Two dimensions are particularly relevant to the present study. System quality captures the desirable technical characteristics of an information system, whereas information quality concerns the characteristics of the information generated or delivered by that system. These distinctions are useful in smart-campus research because technological performance and informational performance may contribute differently to users' evaluations. A platform can, for example, operate efficiently while delivering poor-quality information, or provide valuable information through an unreliable interface. Evaluating smart-campus effectiveness therefore requires attention to both technological and informational characteristics.

The Information Systems Success Model also provides an important conceptual bridge from system characteristics to outcomes. Its logic suggests that information-system success should ultimately be evaluated according to the benefits created through system

use rather than the presence of technology alone (DeLone & McLean, 2003). In an educational setting, such benefits can include improvements in access to learning resources, learning efficiency, engagement, comprehension, or other dimensions of learning effectiveness. This outcome-oriented perspective is consistent with the argument that smart-campus initiatives should be evaluated according to their contribution to educational performance rather than merely the sophistication of their infrastructure.

However, the Information Systems Success Model alone does not fully explain the psychological mechanism through which users translate technological characteristics into evaluations of educational value. Specifically, although system and information quality provide important antecedent conditions, users may not derive educational benefits simply because those conditions exist. Their perceptions regarding whether a system improves their academic performance may play an important explanatory role. This creates a theoretical rationale for complementing the Information Systems Success Model with a technology-acceptance perspective.

2.4 Technology Acceptance Model

The Technology Acceptance Model (TAM) provides a complementary theoretical perspective centered on users' beliefs about technology. Davis (1989) proposed two central beliefs perceived usefulness and perceived ease of use to explain user acceptance of information technology. Perceived usefulness refers to the degree to which an individual believes that using a particular system enhances his or her performance. Within educational settings, this concept can be interpreted as the extent to which students or faculty believe that a digital system contributes meaningfully to their learning or teaching activities.

Perceived usefulness is especially relevant to smart-campus research because the availability of advanced technological functions does not guarantee that users will regard those functions as valuable. Students and faculty evaluate technologies according to whether they help them complete tasks more efficiently, access relevant resources, improve communication, obtain timely feedback, or otherwise enhance academic performance. Consequently, two systems with similar technological capabilities may produce different user evaluations when their accessibility, reliability, information quality, or responsiveness differs.

The inclusion of perceived usefulness therefore shifts attention from the technological properties of a smart-campus system to the value attributed to those properties by users. This distinction is theoretically important. Accessibility, efficiency, high-quality information, and real-time functionality represent characteristics of the system or its outputs, whereas perceived usefulness represents an evaluative belief concerning what those characteristics enable users to accomplish. In this sense, perceived usefulness can provide a cognitive link between technological conditions and users' assessments of learning effectiveness.

The present study focuses on perceived usefulness rather than attempting to reproduce the complete TAM. This selective use requires theoretical justification. The purpose of the

study is not primarily to explain behavioral intention or adoption of a new technology; rather, it seeks to understand how smart-campus system characteristics relate to perceived educational value and learning effectiveness among users interacting with such systems. Perceived usefulness is therefore incorporated because it corresponds directly to the study's interest in whether users believe smart-campus services improve their learning or teaching performance.

2.5 Integrating the Information Systems Success Model and Technology Acceptance Model

Integrating the Information Systems Success Model and TAM provides greater explanatory value than applying either framework independently because the two perspectives operate at different but complementary levels. The Information Systems Success Model emphasizes the quality characteristics of the technological and informational environment, whereas TAM emphasizes users' cognitive evaluations of the value of technology. Their integration therefore makes it possible to connect what a system provides with how users interpret those characteristics and, subsequently, with the educational outcomes associated with its use.

The theoretical mechanism proposed in this study can be summarized as:

System characteristics → Perceived usefulness → Smart learning effectiveness

At the first stage, accessibility, system efficiency, information quality, and real-time capability represent technological and informational conditions that may shape users' evaluations of the smart-campus environment. Systems that are readily accessible, stable, responsive, informative, and timely are more likely to be regarded as useful because they enable students and faculty to perform academic activities with fewer technological barriers and better informational support. Perceived usefulness therefore captures an important user-level evaluation through which system characteristics can be connected conceptually to educational value.

At the second stage, users who perceive smart-campus systems as useful may report greater smart learning effectiveness because useful systems can facilitate access to resources, support task completion, improve learning efficiency, and strengthen interaction with educational services. This mechanism extends the conventional technology-acceptance perspective beyond the decision to adopt or continue using technology. In the present context, perceived usefulness is treated as an explanatory construct connecting system characteristics with users' evaluations of learning effectiveness.

Direct relationships between system characteristics and smart learning effectiveness are also theoretically plausible. Accessibility may directly reduce barriers to learning resources; efficient systems may reduce delays and interruptions; high-quality information may improve comprehension and decision-making; and real-time capability may provide timely feedback and interaction. Thus, system characteristics may be associated with smart learning effectiveness both through users' perceptions of usefulness and through their immediate functional contribution to technology-supported learning activities.

Importantly, the integrated framework should not be interpreted as establishing causality solely on the basis of cross-sectional survey evidence. Instead, it provides a theoretically grounded structure for examining associations among technological characteristics, users' cognitive evaluations, and perceived learning effectiveness. Similarly, although the proposed framework positions perceived usefulness between system characteristics and smart learning effectiveness, a formal claim of statistical mediation requires evidence from bootstrapped indirect-effect analyses. Such mediation should therefore be concluded only if the corresponding indirect effects are empirically tested and supported.

The integration also creates an important bridge between technology evaluation and smart-campus design. If particular system characteristics exhibit stronger relationships with perceived usefulness and smart learning effectiveness, they can provide empirically informed priorities for architecture and service design. The theoretical framework consequently serves two purposes: explaining users' evaluations of smart-campus systems and establishing an evidence base for translating those evaluations into design requirements.

2.6 Research Gap and Conceptual Framework

The literature reviewed above reveals three connected streams of knowledge. First, smart-campus research demonstrates that IoT, cloud computing, sensing technologies, data analytics, intelligent services, and integrated digital infrastructures can transform campus operations and learning environments. Second, smart-learning research emphasizes that technological environments should be adaptive, context-aware, accessible, and responsive to learners rather than being evaluated according to technological sophistication alone. Third, information-systems and technology-acceptance theories suggest that system and information characteristics are connected to user evaluations and that perceived usefulness represents an important cognitive assessment of technology's performance value.

Nevertheless, an unresolved issue lies at the intersection of these streams. Smart-campus architecture research has predominantly explained what technological capabilities can be implemented, whereas user-centered information-systems research explains how technological characteristics can be evaluated by users. A stronger connection is needed between these perspectives to determine which specific smart-campus system characteristics are associated with users' perceived usefulness and learning effectiveness and how such empirical evidence can subsequently inform campus-system design.

The present study addresses this issue by examining four system-related characteristics accessibility, system efficiency, information quality, and real-time capability together with perceived usefulness and smart learning effectiveness. The framework further considers whether selected relationships vary according to user role, recognizing that students and faculty may evaluate smart-campus characteristics differently because their academic activities, technological needs, and patterns of system interaction are not identical.

Accordingly, the conceptual framework positions accessibility, system efficiency, information quality, and real-time capability as antecedent system characteristics

associated with both perceived usefulness and smart learning effectiveness. Perceived usefulness is subsequently linked to smart learning effectiveness, while user role is examined as a potential source of heterogeneity in selected relationships. This framework provides the theoretical foundation for the hypotheses developed in the following section and subsequently informs the translation of empirical findings into smart-campus design priorities.

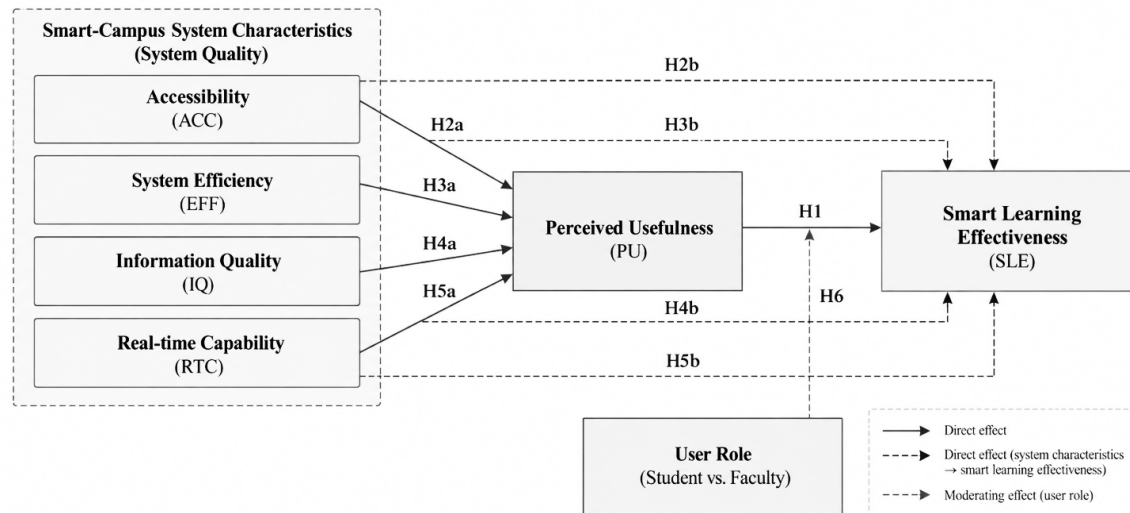


Figure 1. Conceptual framework linking smart-campus system characteristics, perceived usefulness, and smart learning effectiveness

This conceptualization establishes the progression from existing knowledge to the unresolved theoretical issue and, finally, to the empirical model examined in this study.

3. Hypothesis Development

Building on the integrated theoretical framework developed in the preceding section, this study proposes that the quality characteristics of smart-campus systems are associated with users' perceptions of usefulness and smart learning effectiveness. Accessibility, system efficiency, information quality, and real-time capability represent distinct characteristics of the technological and informational environment, whereas perceived usefulness captures users' evaluations of whether the system contributes meaningfully to their academic activities. The following subsections develop the theoretical rationale for each hypothesized relationship.

3.1 Perceived Usefulness and Smart Learning Effectiveness

Perceived usefulness represents a central construct in the Technology Acceptance Model and refers to the extent to which individuals believe that using a particular technology enhances their performance (Davis, 1989). In educational environments, perceived usefulness reflects users' judgments concerning whether a technological system facilitates learning or teaching activities, improves efficiency, supports access to relevant resources, or otherwise contributes to academic performance.

The relevance of perceived usefulness extends beyond users' willingness to adopt a technology. When students perceive a digital learning system as useful, they are more

likely to regard it as contributing meaningfully to their academic activities. Similarly, faculty members may perceive smart-campus systems as useful when they facilitate teaching, resource access, communication, feedback, or instructional management. Previous research on e-learning systems has consistently positioned perceived usefulness as an important mechanism connecting technological characteristics with users' acceptance and evaluations of system benefits. For example, Alkhawaja et al. (2022) found that perceived usefulness was significantly associated with subsequent acceptance-related outcomes in university e-learning environments.

Within a smart-campus environment, perceived usefulness should therefore be related not merely to whether users intend to use the system but also to how they evaluate its contribution to learning effectiveness. A system perceived as enhancing access to resources, supporting academic tasks, improving learning efficiency, and facilitating educational interactions should be associated with more favorable assessments of smart learning effectiveness. Accordingly, the following hypothesis is proposed:

H1. Perceived usefulness is positively associated with smart learning effectiveness.

3.2 Accessibility, Perceived Usefulness, and Smart Learning Effectiveness

Accessibility refers to the extent to which users can access smart-campus services and learning resources when and where they are needed. This characteristic is fundamental to smart learning because technology-mediated education increasingly extends beyond conventional classroom boundaries. Access across devices, locations, and times can enable students to engage with learning resources more flexibly and allow faculty to interact with educational services without being constrained by physical settings.

From a technology-acceptance perspective, accessibility can enhance perceived usefulness when it enables users to accomplish academic tasks more conveniently and efficiently. A system that provides valuable functions but is difficult to access may offer limited practical value. Conversely, readily available smart-campus services can enable users to retrieve information, communicate, complete academic tasks, and interact with learning resources under a broader range of circumstances. Research on e-learning systems similarly recognizes accessibility and availability among important characteristics of system quality and technology-enabled educational services.

Accessibility may also be directly associated with smart learning effectiveness. Greater access to academic resources and services can reduce spatial and temporal barriers to learning, support continuity of academic activities, and enable students to engage with resources according to their learning needs. Consequently, accessibility may contribute to learning effectiveness both through users' perceptions of the system's usefulness and through the functional benefits created by more flexible access.

Accordingly:

H2a. Accessibility is positively associated with smart learning effectiveness.

H2b. Accessibility is positively associated with perceived usefulness.

3.3 System Efficiency, Perceived Usefulness, and Smart Learning Effectiveness

System efficiency reflects the responsiveness, stability, reliability, and operational performance of a smart-campus system. These characteristics are important because users'

academic interactions with digital systems depend on their ability to perform required functions consistently and without unnecessary delay or disruption. From the Information Systems Success perspective, system quality captures desirable technical characteristics that influence users' experiences with information systems (DeLone & McLean, 2003).

In educational contexts, reliable and responsive systems can enhance perceived usefulness by reducing technological friction associated with learning and teaching tasks. When platforms operate efficiently, students and faculty can concentrate on their academic objectives rather than overcoming system delays, failures, or interruptions. Conversely, unstable or inefficient systems may reduce the practical value users attribute to otherwise beneficial technological functions. Empirical research in higher-education e-learning environments supports a positive relationship between system quality and perceived usefulness. Alkhawaja et al. (2022), for example, found that system quality significantly predicted perceived usefulness in an e-learning context. Other studies integrating information-system success and technology-acceptance perspectives have similarly identified system quality as an antecedent of perceived usefulness.

System efficiency may also be directly associated with smart learning effectiveness. Reliable system performance can reduce interruptions, shorten task-completion time, and maintain continuity in technology-supported learning activities. This relationship is particularly relevant in smart-campus environments, where academic processes may depend on multiple interconnected digital services.

Accordingly:

H3a. System efficiency is positively associated with smart learning effectiveness.

H3b. System efficiency is positively associated with perceived usefulness.

3.4 Information Quality, Perceived Usefulness, and Smart Learning Effectiveness

Information quality refers to the accuracy, relevance, completeness, consistency, and timeliness of information delivered through an information system. The Information Systems Success Model identifies information quality as a fundamental determinant of information-system success (DeLone & McLean, 2003). Its relevance is especially pronounced in educational environments because students and faculty rely on digital systems to obtain learning materials, schedules, assessment information, academic notifications, administrative information, and other resources that influence academic decisions.

High-quality information can strengthen perceived usefulness because a system is more likely to be considered valuable when the information it provides is accurate, relevant, understandable, and current. In contrast, outdated, incomplete, inconsistent, or inaccurate information can undermine users' confidence in a system even when its technical performance is satisfactory. Empirical research on e-learning supports this relationship. Extended information-system success models have found information quality to be associated with perceived usefulness, while studies integrating TAM and the DeLone–McLean framework similarly identify information quality as an important determinant of users' evaluations of educational technologies.

Information quality may also be directly associated with smart learning effectiveness because educational activities depend fundamentally on the quality of information available to learners and instructors. Accurate and relevant learning information can reduce uncertainty, support comprehension, facilitate academic decision-making, and improve the efficiency with which users complete learning-related tasks. Poor information quality, by contrast, may create confusion and increase the effort required to identify trustworthy or relevant content.

Accordingly:

H4a. Information quality is positively associated with smart learning effectiveness.

H4b. Information quality is positively associated with perceived usefulness.

3.5 Real-Time Capability, Perceived Usefulness, and Smart Learning Effectiveness

Real-time capability refers to the capacity of a smart-campus system to provide timely interactions, notifications, updates, responses, and feedback. This characteristic differentiates smart environments from conventional static information systems because context-aware educational technologies are expected to respond dynamically to changing user needs and environmental conditions.

The usefulness of smart-campus services can depend substantially on when information or support becomes available. Academic notifications, changes in schedules, learning feedback, resource availability, and other time-sensitive information may lose value when delivered too late. Real-time capability can therefore enhance perceived usefulness by allowing users to obtain relevant information and interact with campus services at the point of need.

Real-time functionality may also contribute directly to smart learning effectiveness. Timely feedback can enable learners to identify errors, adjust learning strategies, and respond to academic requirements more quickly, while immediate notifications and interactions can improve coordination and engagement. However, technological immediacy alone does not guarantee educational value. Real-time information must also be accurate and relevant. Real-time capability is therefore conceptualized as complementary to, rather than a substitute for, information quality.

Accordingly:

H5a. Real-time capability is positively associated with smart learning effectiveness.

H5b. Real-time capability is positively associated with perceived usefulness.

3.6 Mediating Role of Perceived Usefulness

The integration of the Information Systems Success Model and TAM suggests that perceived usefulness may provide an explanatory mechanism linking smart-campus system characteristics with smart learning effectiveness. Accessibility, system efficiency, information quality, and real-time capability describe what the system provides, whereas perceived usefulness captures users' cognitive evaluations of whether those characteristics enhance their academic performance. Prior research integrating system-quality and technology-acceptance perspectives demonstrates that perceived usefulness can transmit the effects of technological characteristics to subsequent user outcomes. For example,

Alkhawaja et al. (2022) identified an indirect mechanism involving system quality and perceived usefulness in explaining e-learning acceptance.

Conceptually, this suggests that system characteristics may be associated with smart learning effectiveness partly because they increase the extent to which users perceive smart-campus services as useful. An accessible platform may facilitate learning partly because students recognize that it allows them to perform academic activities more flexibly; efficient systems may contribute to effectiveness because users recognize their capacity to reduce technological barriers; high-quality information may generate educational value because users perceive the information as useful for learning and decision-making; and real-time capability may contribute because users recognize the value of timely information and interaction.

Accordingly, the theoretical model supports the following mediation hypotheses:

H6a. Perceived usefulness mediates the relationship between accessibility and smart learning effectiveness.

H6b. Perceived usefulness mediates the relationship between system efficiency and smart learning effectiveness.

H6c. Perceived usefulness mediates the relationship between information quality and smart learning effectiveness.

H6d. Perceived usefulness mediates the relationship between real-time capability and smart learning effectiveness.

3.7 Moderating Role of User Role

Students and faculty interact with smart-campus systems for different purposes and may consequently assign different importance to particular system characteristics. Students frequently use digital campus systems to access learning resources, receive academic notifications, communicate, complete learning activities, and obtain time-sensitive information. Faculty members, by contrast, may interact with the same ecosystem through teaching, course administration, assessment, resource management, and instructional communication. These differences in tasks and usage contexts suggest that identical technological characteristics may not generate equivalent evaluations of usefulness across the two groups.

Information quality and real-time capability may be particularly sensitive to these differences. Students often depend on current learning materials, schedules, assessment information, deadlines, and immediate academic notifications, potentially increasing the importance of accurate and timely information in their evaluations of system usefulness. Faculty members may have different informational and operational priorities. More generally, differences in user roles may create heterogeneity in the relationships between smart-campus system characteristics and perceived usefulness.

Accordingly:

H7. The relationships between smart-campus system characteristics and perceived usefulness differ between students and faculty members.

For greater theoretical precision, H7 can be decomposed into:

H7a. The relationship between accessibility and perceived usefulness differs between students and faculty members.

H7b. The relationship between system efficiency and perceived usefulness differs between students and faculty members.

H7c. The relationship between information quality and perceived usefulness differs between students and faculty members.

H7d. The relationship between real-time capability and perceived usefulness differs between students and faculty members.

Because these hypotheses involve comparisons between groups, measurement invariance should be established before interpreting differences in structural relationships. The Measurement Invariance of Composite Models (MICOM) procedure was specifically developed for this purpose in PLS-SEM; without measurement invariance, apparent group differences may reflect measurement artifacts rather than genuine differences in relationships (Henseler et al., 2016).

4. Methodology

4.1 Research Design and Context

This study employed a quantitative, cross-sectional survey design to examine the relationships among smart-campus system characteristics, perceived usefulness, and smart learning effectiveness. The unit of analysis was the individual user of the smart-campus environment, comprising students and faculty members who interacted with the institution's digital systems and services.

The empirical study was conducted at the School of Light Industry, North China University of Science and Technology. This institutional context provided an appropriate setting because the school had established digital infrastructure and smart-campus services while continuing to experience challenges related to system integration, information sharing, and service experience. The setting therefore enabled examination of how users evaluated different characteristics of an operational smart-campus environment and how those evaluations were associated with perceived usefulness and smart learning effectiveness.

The research model contained six principal constructs: accessibility (ACC), system efficiency (EFF), information quality (IQ), real-time capability (RTC), perceived usefulness (PU), and smart learning effectiveness (SLE). User role student or faculty member was additionally considered in the multigroup analysis.

Because the research design was cross-sectional and observational, the structural relationships estimated in the study should be interpreted as theoretically specified associations rather than definitive evidence of temporal causality.

4.2 Participants and Data Collection

Data were collected through an online questionnaire administered to students and faculty members at the School of Light Industry, North China University of Science and Technology. The study focused on these two groups because they represent the principal

academic users of the smart-campus environment and interact with its digital services in learning, teaching, communication, and related academic activities.

A total of 420 valid questionnaires were included in the final dataset. Of these, 330 respondents were students (78.6%) and 90 were faculty members (21.4%). The unequal group sizes were taken into consideration when interpreting comparisons between students and faculty.

Table 1. Distribution of respondents by user role

User role	Frequency (n)	Percentage (%)
Students	330	78.6
Faculty members	90	21.4
Total	420	100.0

The original survey documentation indicates that demographic information on gender, age, and frequency of system use was collected and describes these characteristics as balanced. However, the corresponding category frequencies are not reported in the available manuscript. Consequently, no unsupported claim of statistical representativeness is made here.

4.3 Measurement Instrument

The survey instrument consisted of demographic questions and measurement items representing six constructs: accessibility (ACC), system efficiency (EFF), information quality (IQ), real-time capability (RTC), perceived usefulness (PU), and smart learning effectiveness (SLE). The questionnaire primarily used a six-point response scale.

Accessibility represents the extent to which smart-campus services can be accessed when and where required. System efficiency captures the responsiveness, stability, and reliability of the system. Information quality concerns the accuracy, relevance, and timeliness of information provided by the system, whereas real-time capability reflects support for timely interaction, notifications, and feedback. Perceived usefulness represents users' beliefs concerning the extent to which smart-campus services improve their learning or teaching performance. Smart learning effectiveness captures perceived improvements in learning-related dimensions such as comprehension, achievement, engagement, and efficiency. These definitions correspond to the six constructs specified in the original research model.

The available manuscript provides examples of two questionnaire items: an information-quality item assessing whether the learning or teaching information supplied by the system is accurate and a perceived-usefulness item assessing whether use of the system improves learning or teaching efficiency. The manuscript does not contain the complete item-level instrument. Therefore, a complete measurement-item table should not be reconstructed from assumed or newly created items.

Table 2. Operationalization of the study constructs

Construct	Code	Operational focus	Example item available in manuscript	Response scale
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Accessibility	ACC	Access anytime and anywhere	Complete item wording not	Six-point reported
System efficiency	EFF	Responsiveness, stability, reliability	Complete item wording not	Six-point reported
Information quality	IQ	Accuracy, relevance, timeliness	"The learning/teaching information provided by this system is accurate."	Six-point
Real-time capability	RTC	Timely interaction, notifications, feedback	Complete item wording not	Six-point reported
Perceived usefulness	PU	Improvement in learning/teaching performance	"Using this system can improve my learning/teaching efficiency."	Six-point
Smart learning effectiveness	SLE	Comprehension, achievement, engagement, efficiency	Complete item wording not	Six-point reported

4.4 Instrument Development and Measurement Specification

The questionnaire was structured around the six constructs specified in the conceptual framework. Its content was designed to capture users' evaluations of smart-campus system characteristics, perceived usefulness, and smart learning effectiveness. The construct definitions were theoretically aligned with the study's integration of information-systems-success and technology-acceptance perspectives.

Similarly, the manuscript does not explicitly state whether the six constructs were specified as reflective or formative/composite measurement models. Because this distinction determines the appropriate measurement-model evaluation criteria, the specification used in the original PLS-SEM model should be reported explicitly.

For a submission-ready manuscript, add one short factual paragraph once the original survey and analysis file are available:

4.5 Data-Analysis Strategy

Partial least squares structural equation modeling (PLS-SEM) was employed to examine the proposed relationships among accessibility, system efficiency, information quality, real-time capability, perceived usefulness, and smart learning effectiveness. PLS-SEM enabled the simultaneous estimation of relationships among the latent constructs in the proposed research framework. Statistical significance was evaluated using bootstrapping with 5,000 resamples.

The analysis should be reported in two sequential stages. First, the measurement model should be evaluated to establish the quality of the construct measures before interpretation of the structural relationships. For constructs specified as reflective, the assessment should examine indicator loadings, internal-consistency reliability, convergent validity, and discriminant validity. Accordingly, the final results should report outer loadings, Cronbach's α , rho_A, composite reliability (CR), average variance extracted (AVE), and the heterotrait-monotrait ratio (HTMT), where appropriate to the actual measurement specification.

Second, the structural model should be evaluated by examining collinearity among predictors and the magnitude and statistical significance of the hypothesized paths. The analysis should report standardized path coefficients (β), bootstrap t -values, p -values, and 95% bootstrap confidence intervals. Explanatory performance should additionally be assessed using R^2 for the endogenous constructs and f^2 for individual predictor contributions. Q^2 or an appropriate out-of-sample predictive assessment may be reported if it was performed and is relevant to the study's analytical objective.

The manuscript confirms nine statistically significant direct paths. For example, perceived usefulness was positively associated with smart learning effectiveness ($\beta = .255$), while information quality showed the largest reported coefficient with perceived usefulness ($\beta = .569$). These direct-path results do not, however, establish mediation.

The proposed mediating role of perceived usefulness should therefore be examined separately using bootstrapped specific indirect effects for $ACC \rightarrow PU \rightarrow SLE$, $EFF \rightarrow PU \rightarrow SLE$, $IQ \rightarrow PU \rightarrow SLE$, and $RTC \rightarrow PU \rightarrow SLE$. An indirect relationship should be interpreted from its bootstrapped estimate and confidence interval rather than inferred solely from the significance of its component paths.

Differences between students and faculty members should be evaluated using multigroup analysis. The current manuscript reports that the relationships of information quality and real-time capability with perceived usefulness were significantly stronger among students than faculty members. Before these differences are interpreted substantively, measurement invariance should be assessed. For PLS-SEM, the MICOM procedure can be used to determine whether the composite measures operate equivalently across groups (Henseler et al., 2016).

Accordingly, the analytical procedure is organized as follows:

Data screening $\rightarrow$ measurement-model assessment $\rightarrow$ structural-model assessment $\rightarrow$ direct hypothesis testing $\rightarrow$ mediation analysis $\rightarrow$ measurement invariance assessment $\rightarrow$ multigroup analysis.

5. Results

5.1 Participant Characteristics

A total of 420 usable responses were included in the analysis. The sample comprised 330 students (78.6%) and 90 faculty members (21.4%) from the School of Light Industry, North China University of Science and Technology. Students therefore constituted the majority of respondents. This unequal group distribution should be considered when interpreting the subsequent student–faculty multigroup analysis.

Table 3. Participant characteristics

Characteristic	Category	Frequency (n)	Percentage (%)
User role	Student	330	78.6
	Faculty member	90	21.4
Total		420	100.0

Although the original manuscript states that respondents were balanced with respect to gender, age, and frequency of system use, the corresponding frequencies and percentages

are not reported in the available document. Accordingly, this claim should not be retained unless the original demographic dataset is available.

5.2 Preliminary Analysis

Prior to assessment of the measurement and structural models, the dataset should be examined for data quality. The available manuscript identifies 420 questionnaires as valid, but it does not document the number of responses screened or the procedures used to identify missing, incomplete, duplicate, patterned, or otherwise invalid responses. Consequently, no additional data-screening procedure should be claimed without supporting records.

Descriptive statistics should be reported for the six constructs to characterize respondents' evaluations of the smart-campus system. Means, standard deviations, and observed ranges should be calculated from the original dataset rather than inferred from structural-model estimates.

Because the predictor and outcome constructs were obtained from the same questionnaire, common-method bias is a potential methodological concern. However, the available manuscript does not report a statistical assessment of common-method bias. Therefore, no such test should be claimed retrospectively unless it was actually conducted. If the original dataset remains available, an appropriate assessment can be performed and reported transparently.

5.3 Measurement Model

Assessment of the measurement model should precede interpretation of the structural relationships. The appropriate evaluation criteria depend on whether the constructs were modeled reflectively or formatively. The available manuscript does not explicitly state the measurement specification. Accordingly, the specification used in the original PLS-SEM model should first be confirmed.

If ACC, EFF, IQ, RTC, PU, and SLE were specified as reflective constructs, measurement quality should be assessed through indicator reliability, internal-consistency reliability, convergent validity, and discriminant validity. Indicator reliability should be examined using outer loadings. Internal consistency should be evaluated using Cronbach's α , ρ_A , and composite reliability (CR), while convergent validity should be evaluated using average variance extracted (AVE). Discriminant validity should preferably be examined using the heterotrait-monotrait ratio (HTMT).

The current manuscript states that the measurement model was considered adequate before structural-model testing, but it does not provide the underlying measurement statistics. Thus, adequacy of reliability and validity cannot presently be independently evaluated.

5.4 Structural Model

Following measurement-model assessment, the structural model was evaluated to test the proposed relationships among accessibility, system efficiency, information quality, real-

time capability, perceived usefulness, and smart learning effectiveness. Statistical significance was assessed using 5,000 bootstrap resamples.

All nine direct relationships reported in the original model were statistically significant. Among the predictors of perceived usefulness, information quality exhibited the largest standardized path coefficient ($\beta = .569$, $t = 13.264$, $p < .001$), followed by system efficiency ($\beta = .230$, $t = 5.954$, $p < .001$), accessibility ($\beta = .134$, $t = 3.555$, $p < .001$), and real-time capability ($\beta = .080$, $t = 2.295$, $p = .022$).

A similar pattern was observed for smart learning effectiveness. Information quality showed the largest direct coefficient ($\beta = .342$, $t = 5.287$, $p < .001$). Perceived usefulness was also positively associated with smart learning effectiveness ($\beta = .255$, $t = 3.723$, $p < .001$). Positive relationships were additionally observed for real-time capability ($\beta = .135$, $t = 3.484$, $p = .001$), system efficiency ($\beta = .122$, $t = 2.652$, $p = .010$), and accessibility ($\beta = .105$, $t = 2.635$, $p = .010$).

These results establish the direction and statistical significance of the reported structural relationships. They do not, however, establish the magnitude of each predictor's substantive contribution. Effect sizes (f^2), coefficients of determination (R^2), and predictive-relevance measures should therefore be reported separately where available.

5.5 Hypothesis Testing

All nine direct relationships specified in the original research model were statistically significant and were therefore supported.

The coefficients and significance statistics above reproduce the values in the original hypothesis-testing table. Actual bootstrap confidence intervals should be exported from the PLS-SEM output rather than approximated from the reported t -statistics.

5.6 Mediation Analysis

The conceptual framework positions perceived usefulness as a potential explanatory mechanism linking smart-campus system characteristics with smart learning effectiveness. Although the direct results show that ACC, EFF, IQ, and RTC are each positively related to perceived usefulness, and perceived usefulness is positively related to smart learning effectiveness, significance of these component paths is not sufficient to demonstrate statistical mediation.

Mediation should instead be assessed through the bootstrapped specific indirect effects of each system characteristic on smart learning effectiveness through perceived usefulness. Accordingly, four indirect relationships require evaluation:

ACC $\rightarrow$ PU $\rightarrow$ SLE; EFF $\rightarrow$ PU $\rightarrow$ SLE; IQ $\rightarrow$ PU $\rightarrow$ SLE; and RTC $\rightarrow$ PU $\rightarrow$ SLE.

5.7 Multigroup Analysis

The study also examined whether relationships in the structural model differed between students and faculty members. According to the existing manuscript, the relationships of information quality with perceived usefulness and real-time capability with perceived usefulness were significantly stronger among students than among faculty members.

This finding is potentially important because it suggests that the value users derive from smart-campus characteristics may depend on their academic role. Nevertheless, the available manuscript does not report the student-specific and faculty-specific path coefficients, the differences between coefficients, exact multigroup p -values, or measurement-invariance statistics. The magnitude of the reported group differences therefore cannot yet be independently evaluated.

Before structural coefficients are compared across groups, measurement invariance should be established using an appropriate procedure. In a PLS-SEM context, the measurement invariance of composite models (MICOM) procedure provides a systematic basis for determining whether constructs are measured sufficiently similarly across groups to permit meaningful comparison. The assessment should address configural invariance, compositional invariance, and, where relevant, equality of composite means and variances.

6. Discussion

The findings demonstrate that the perceived educational value of a smart-campus environment is associated not merely with the availability of digital infrastructure but with the quality of the systems and information experienced by users. Accessibility, system efficiency, information quality, and real-time capability were positively associated with both perceived usefulness and smart learning effectiveness. However, the magnitude of these relationships differed considerably, suggesting that statistically significant smart-campus characteristics should not automatically receive equal priority in system design.

The findings therefore support a shift from a technology-centered understanding of smart campuses toward a user- and learning-centered perspective. The contribution of smart-campus technologies appears to depend on whether the underlying systems provide reliable access, efficient operation, high-quality information, and timely services that users perceive as useful for academic activities.

6.1 System Characteristics and Smart Learning Effectiveness

The first major finding is the consistent positive relationship between the four examined smart-campus characteristics and smart learning effectiveness. Information quality showed the largest direct relationship with SLE ($\beta = .342$), followed by real-time capability ($\beta = .135$), system efficiency ($\beta = .122$), and accessibility ($\beta = .105$). All four relationships were statistically significant.

This pattern is broadly consistent with the Information Systems Success Model (ISSM), which distinguishes characteristics of information systems and information from the benefits users derive from them (DeLone & McLean, 2003). In the smart-campus context, the results suggest that learning effectiveness is associated with multiple dimensions of the digital environment rather than with technological availability alone. Students and faculty require systems that are accessible and reliable, but they also require information and services that support their academic activities.

The relatively smaller coefficients for accessibility and system efficiency should not be interpreted as indicating that these dimensions are unimportant. One plausible interpretation is that they function partly as enabling conditions. Reliable access and acceptable system performance may represent basic expectations in a digitally supported university environment. Once these conditions are established, differences in the informational and functional value of the system may become more salient to users' evaluations of learning effectiveness. This interpretation was not directly tested and should therefore be treated as a theoretical explanation rather than an empirical conclusion.

The findings consequently suggest a useful distinction between infrastructural prerequisites and educational value-generating characteristics. Infrastructure enables smart-campus services to function, but technological availability alone does not guarantee that users will perceive those services as contributing meaningfully to learning.

6.2 The Central Role of Information Quality

Information quality emerged as the most prominent system characteristic in the structural model. It exhibited the largest reported relationship with perceived usefulness ($\beta = .569$) and the largest direct relationship with smart learning effectiveness ($\beta = .342$). This finding places the quality of information not simply the technological infrastructure carrying that information at the center of the smart-campus value proposition.

The result is consistent with DeLone and McLean's (2003) distinction between system quality and information quality. A technically reliable platform may still provide limited educational value when its information is inaccurate, outdated, fragmented, inconsistent, or irrelevant. Conversely, accurate, relevant, and timely information can support academic decision-making and improve users' ability to perform learning and teaching activities.

The strong relationship between information quality and perceived usefulness is also theoretically consistent with TAM. Perceived usefulness concerns the extent to which users believe that a technology enhances their performance (Davis, 1989). In a smart-campus environment, information constitutes an important part of that performance value. Students may depend on accurate learning resources, assessment information, schedules, deadlines, and academic notifications, while faculty members require reliable instructional, course, and administrative information.

This result has implications for how smart campuses are conceptualized. Expanding the number of connected devices, applications, sensors, or automated services should not be considered an objective in itself. The value of these technologies depends partly on the quality of the information they generate, integrate, and deliver.

Nevertheless, the coefficient of .569 should not be interpreted as demonstrating that information quality is universally the "most important" smart-campus characteristic. Such a conclusion would extend beyond the evidence available from this sample and would require consideration of effect sizes, collinearity, construct relationships, and replication across settings. The more defensible conclusion is that information quality exhibited the

strongest reported structural relationship with perceived usefulness among the predictors examined in this study.

6.3 Perceived Usefulness as an Explanatory Mechanism

Perceived usefulness was positively associated with smart learning effectiveness ($\beta = .255$, $t = 3.723$, $p < .001$). This finding provides an important link between the information-systems-success and technology-acceptance perspectives employed in the study.

In TAM, perceived usefulness traditionally represents users' beliefs that using a technology will enhance their performance and is commonly examined as an antecedent of technology acceptance or behavioral intention (Davis, 1989). The present framework applies this construct to an established smart-campus environment and relates it to perceived learning effectiveness. The result suggests that users' evaluations of the practical value of smart-campus services remain relevant beyond the initial decision to adopt or use a technology.

The four system characteristics were also positively related to perceived usefulness. Information quality showed the largest coefficient ($\beta = .569$), followed by system efficiency ($\beta = .230$), accessibility ($\beta = .134$), and real-time capability ($\beta = .080$). Taken together, these findings support the conceptual logic that characteristics of the technological environment are related to how useful users perceive that environment to be, and that perceived usefulness is in turn associated with smart learning effectiveness.

However, these results do not yet establish statistical mediation. Although the original manuscript describes perceived usefulness as a mediating variable, it does not report the specific indirect effects or corresponding bootstrap confidence intervals required to test mediation. Until these analyses are available, perceived usefulness should be described as a theoretically relevant explanatory mechanism, rather than as a statistically confirmed mediator.

If the specific indirect effects are subsequently shown to be significant, the theoretical interpretation can be strengthened accordingly. Such evidence would indicate that system characteristics are associated with smart learning effectiveness both directly and indirectly through users' evaluations of their usefulness.

6.4 Potential Differences Between Students and Faculty

The existing manuscript reports that the relationships of information quality and real-time capability with perceived usefulness were significantly stronger among students than among faculty members.

A plausible explanation concerns differences in academic roles and tasks. Students frequently interact with time-sensitive information concerning learning materials, assessments, schedules, deadlines, feedback, and academic activities. Information accuracy and timely communication may therefore be particularly relevant to their judgments of system usefulness. Faculty members interact with the same digital environment through teaching, assessment, course management, resource provision, and

administrative activities, potentially producing different evaluations of particular system characteristics.

These interpretations require caution. The groups differ substantially in size, with 330 students and 90 faculty members. Moreover, the current manuscript does not provide the group-specific coefficients, exact between-group significance tests, or measurement-invariance results necessary for a complete assessment. The reported differences should therefore presently be interpreted as evidence of potential user-role heterogeneity, rather than definitive moderation.

If measurement invariance is established and the reported differences remain significant, the findings would provide empirical support for designing smart-campus services that recognize differences between student and faculty requirements rather than assuming a uniform user experience.

6.5 Implications for Smart-Campus Design

The findings have an important implication for the relationship between empirical research and smart-campus architecture. System design should not begin with a catalogue of available technologies. Instead, the empirical findings can be translated into requirements that guide architectural decisions.

Information quality suggests a requirement for accurate, relevant, consistent, and timely information across smart-campus services. This points toward integrated data management, interoperability, data-quality controls, synchronization, and appropriate data governance. System efficiency suggests the need for reliable and responsive services supported by scalable infrastructure, performance monitoring, and availability management. Accessibility emphasizes convenient and inclusive access across relevant devices and contexts, while real-time capability supports timely notifications, feedback, and information exchange where immediacy contributes to academic activities.

The positive relationship between perceived usefulness and smart learning effectiveness adds a cross-cutting requirement: technological functions should be evaluated according to whether they support meaningful academic tasks. Consequently, user-centered design, usability assessment, and stakeholder feedback should accompany technological development.

The empirical evidence therefore provides a clear transition to the proposed architecture: Empirical evidence → design requirement → architectural response → educational benefit

This logic forms the basis of the framework presented in Section 7.

7. Empirically Informed Smart-Campus Design Framework

The empirical findings provide a basis for translating user evaluations into smart-campus design priorities. The purpose of the proposed framework is not to enumerate every technology that could be deployed on a university campus. Rather, it identifies architectural capabilities that correspond to the system characteristics associated with perceived usefulness and smart learning effectiveness.

Importantly, the architecture itself was not empirically tested as a technological artifact. The PLS-SEM analysis evaluates relationships among users' perceptions of system characteristics, perceived usefulness, and smart learning effectiveness. The framework should therefore be understood as an empirically informed design proposal derived from those findings.

7.1 Design Principles Derived from the Empirical Findings

The empirical findings can be translated into a small set of design principles. Information quality receives particular attention because it exhibited the strongest reported relationships with perceived usefulness and smart learning effectiveness. System efficiency and accessibility represent important enabling characteristics, while real-time capability provides additional value where timely information and interaction are relevant to academic activities.

Table 4. Empirically informed smart-campus design principles

Empirical evidence	Design principle	Architectural response	Expected educational benefit
IQ $\rightarrow$ PU $\beta = .569$; IQ $\rightarrow$ SLE $\beta = .342$	Ensure high-quality information	Data integration, quality controls, governance	Reliable and consistent academic information
EFF $\rightarrow$ PU $\beta = .230$; EFF $\rightarrow$ SLE $\beta = .122$	Ensure reliable performance	Scalable services, monitoring, availability management	Reduced disruption to learning and teaching
ACC $\rightarrow$ PU $\beta = .134$; ACC $\rightarrow$ SLE $\beta = .105$	Enable convenient access	Cross-device access, identity management, accessible interfaces	Flexible access to learning resources
RTC $\rightarrow$ PU $\beta = .080$; RTC $\rightarrow$ SLE $\beta = .135$	Support timely interaction	Notifications, event services, data synchronization	Timely feedback and academic updates
PU $\rightarrow$ SLE $\beta = .255$	Design for useful academic tasks	User-centered and task-oriented services	Better alignment between technology and academic needs
Potential role differences	Recognize heterogeneous users	Role-sensitive services and interfaces	Better fit for student and faculty requirements

This translation prevents the architecture from becoming a generic technology inventory. Each major design principle can instead be traced to either an empirical relationship or, where necessary, an explicitly identified cross-cutting system requirement.

7.2 Proposed Smart-Campus Architecture

The proposed architecture is organized into five layers: user and experience, smart-learning applications, intelligent services, data and integration, and smart infrastructure. Governance, security, privacy, and interoperability operate across the architecture.

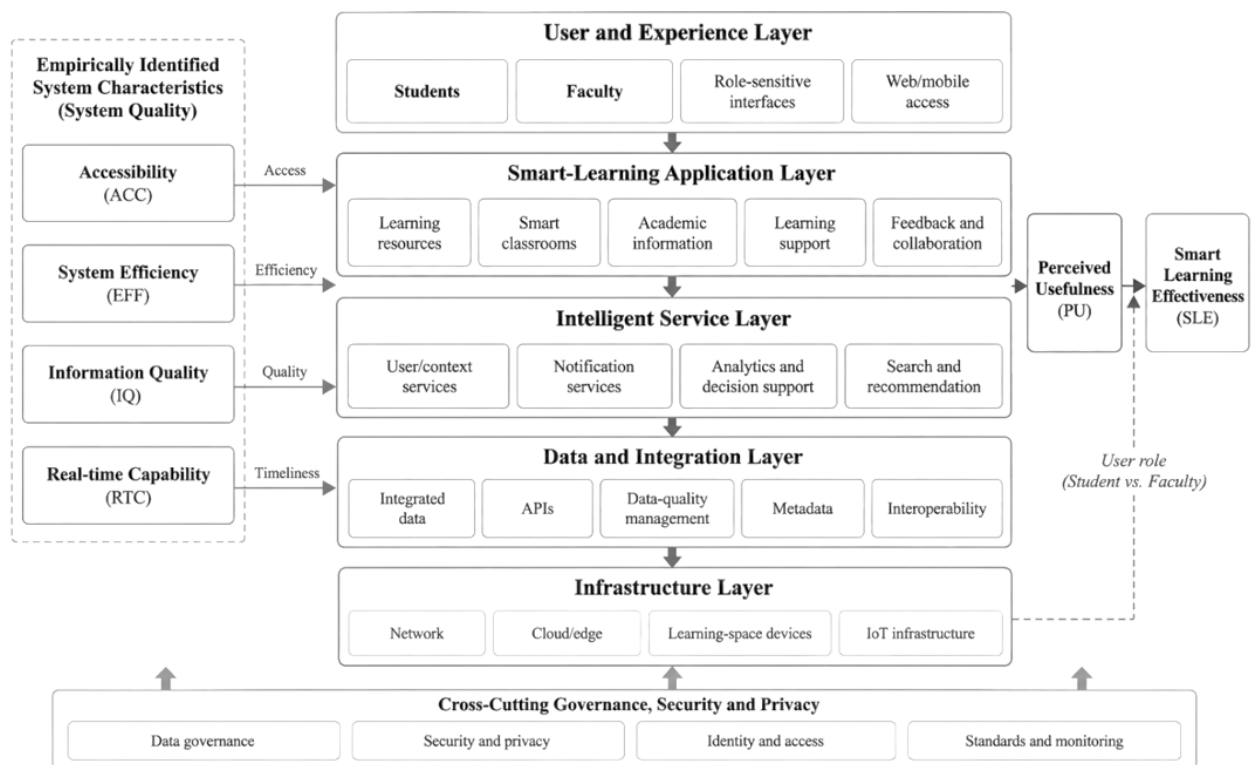


Figure 2. Empirically informed smart-campus architecture

The empirical constructs should be mapped visibly onto this architecture. Information quality is primarily supported by the data and integration layer but extends upward into information-delivery services. System efficiency depends on reliable infrastructure, integration, and service performance. Accessibility is supported through connectivity, identity management, and user-facing services. Real-time capability is enabled through event and notification services and timely synchronization. Perceived usefulness, by contrast, should not be represented as a technological layer. It represents a user evaluation emerging from interaction with the system and therefore belongs at the interface between system capabilities and smart learning effectiveness.

This layered structure replaces the current manuscript's extensive descriptions of individual technologies and operational applications. Detailed explanations of RFID mechanisms, canteen management, bathhouse water control, lighting control, and similar applications should be removed unless a target journal specifically requires them. Such technologies may be implementation examples, but they are not central to the theoretical contribution demonstrated by the empirical model.

7.3 Key Smart-Learning Services

The revised framework should retain only services that have a clear connection with learning and teaching. First, integrated learning-resource services should enable students and faculty to access accurate and current learning materials and academic information through consistent interfaces. This directly responds to the importance of information quality and accessibility identified in the empirical model.

Second, smart-classroom services can integrate instructional resources, classroom technologies, digital learning platforms, and appropriate context-sensitive functions. The

objective should not be classroom automation for its own sake but reduction of technological barriers to teaching and learning.

Third, academic notification and feedback services can support time-sensitive communication concerning learning activities, schedules, assessments, feedback, and relevant academic events. These services translate real-time capability into educationally meaningful functionality.

Fourth, personalized user services can differentiate interfaces and information delivery according to user roles and relevant academic requirements. Such differentiation is particularly relevant if subsequent invariance and multigroup analyses confirm meaningful differences between student and faculty relationships.

Finally, learning-support and analytics services may provide information that assists students, instructors, and institutional decision makers. However, such functionality should be presented as a proposed architectural capability rather than as an empirically evaluated outcome of the present study.

7.4 Data Governance, Interoperability, Security, and Privacy

The prominence of information quality in the empirical findings has implications beyond interface design. Accurate and consistent information depends on how institutional data are generated, integrated, maintained, governed, and exchanged. Consequently, data governance should constitute a central component of smart-campus architecture rather than an administrative activity separated from system design.

A governance framework should establish responsibilities for data ownership, quality assurance, updating, metadata, access, retention, and correction. Where multiple academic and administrative systems exchange information, interoperability mechanisms should reduce fragmentation and inconsistent representations of the same information. Standardized interfaces and appropriately governed APIs can support such integration while avoiding excessive dependence on isolated applications.

Security and privacy are similarly cross-cutting requirements. Smart-campus systems may process academic, identity, behavioral, and contextual data. Access to these data should therefore follow appropriate authentication, authorization, least-privilege, confidentiality, and data-protection principles. The proposed architecture should also minimize unnecessary collection and use of personal data.

These governance, interoperability, security, and privacy requirements were not directly measured as constructs in the present SEM model. Their inclusion in the architecture represents design requirements logically associated with maintaining trustworthy, integrated smart-campus information and services, rather than additional empirical findings of this study.

7.5 Design Implications

The findings suggest that universities should avoid approaching smart-campus development as a procurement exercise centered on the number of intelligent devices or

applications deployed. Investment decisions should instead begin by identifying which system deficiencies most strongly constrain educational value.

In the investigated setting, the results suggest particular attention to information quality. Universities should therefore examine whether learning and academic information is accurate, consistent, relevant, timely, and integrated before expanding technologically sophisticated functions. The next priority is ensuring that systems operate reliably and efficiently, followed by maintaining convenient access and deploying real-time functionality where immediate information or feedback provides educational value.

The architecture should consequently be developed incrementally. Universities can first establish trustworthy data and reliable integration, then strengthen system performance and accessibility, and subsequently expand intelligent, context-aware, and real-time services according to demonstrated user needs. Such prioritization provides a stronger connection between technological expenditure and educational objectives than a technology-first strategy.

8. Theoretical Contributions

This study contributes to the smart-campus literature by integrating information-systems and technology-acceptance perspectives to explain how characteristics of a smart-campus environment are associated with perceived usefulness and smart learning effectiveness.

First, the study contextualizes the Information Systems Success Model (ISSM) within a smart-campus learning environment. DeLone and McLean (2003) distinguish system quality and information quality as important dimensions of information-system success. Building on this logic, the present study examines accessibility, system efficiency, information quality, and real-time capability as characteristics relevant to users' experiences of smart-campus systems. The findings show that these characteristics are positively associated with perceived usefulness and smart learning effectiveness but differ substantially in the magnitude of their relationships. In particular, information quality exhibited the strongest reported relationship with perceived usefulness ($\beta = .569$) and the strongest direct relationship with smart learning effectiveness ($\beta = .342$). These results suggest that distinguishing among specific technological and informational characteristics can provide greater explanatory specificity than treating smart-campus quality as a single undifferentiated concept.

Second, the study extends the application of the Technology Acceptance Model (TAM) from technology acceptance toward the evaluation of educational value within an established smart-campus environment. In TAM, perceived usefulness represents the extent to which users believe that a technology enhances their performance (Davis, 1989). Rather than positioning perceived usefulness solely as an antecedent of behavioral intention, the present framework relates it to smart learning effectiveness. The positive relationship between perceived usefulness and smart learning effectiveness ($\beta = .255$, $p < .001$) indicates that users' evaluations of the practical value of smart-campus services are associated with their perceptions of learning effectiveness.

Third, the study brings the two theoretical perspectives together within a unified explanatory framework. ISSM provides a basis for understanding the technological and informational characteristics of the smart-campus environment, whereas TAM contributes a user-centered evaluation through perceived usefulness. Smart learning effectiveness represents the educationally relevant outcome considered in the model. The resulting theoretical logic can be summarized as:

Smart-campus system and information characteristics → perceived usefulness → smart learning effectiveness

This integration connects characteristics of the technological environment with users' cognitive evaluations and an educationally relevant outcome. Importantly, however, the present direct-effect results do not establish the middle component as a statistical mediating mechanism. Formal mediation requires evidence from bootstrapped specific indirect effects. Until those results are available, perceived usefulness should be characterized as a theoretically relevant explanatory mechanism rather than a statistically confirmed mediator.

Finally, the reported student–faculty differences raise the possibility that user role represents a boundary condition in the proposed framework. The original analysis reports stronger relationships of information quality and real-time capability with perceived usefulness among students than among faculty members. However, because complete measurement-invariance and multigroup statistics are not currently reported, this contribution should remain provisional. If MICOM and subsequent multigroup analysis confirm these differences, the findings would indicate that relationships between smart-campus characteristics and perceived usefulness vary across academic stakeholder groups.

Taken together, these contributions position smart-campus effectiveness as a relationship among technological and informational characteristics, user evaluations, and perceived educational value, rather than as a consequence of technological deployment alone.

9. Practical and Design Implications

The findings provide several implications for universities seeking to develop or improve smart-campus environments. Most importantly, smart-campus performance should not be evaluated primarily by infrastructure expenditure, technological sophistication, or the number of connected applications and devices. Evaluation should also consider whether systems provide high-quality information, operate reliably, remain accessible, support timely interaction, and are perceived as useful for academic activities.

For university administrators, the comparatively strong relationship of information quality with both perceived usefulness and smart learning effectiveness suggests that institutional information management should receive strategic attention alongside physical and digital infrastructure investment. Universities should therefore consider data accuracy, consistency, relevance, timeliness, and integration when evaluating smart-campus initiatives. Investment decisions should be linked to identifiable improvements in teaching, learning, and academic service delivery rather than technological novelty alone.

For CIOs and university IT departments, the findings emphasize the importance of combining reliable infrastructure with effective information management. Priorities include reducing information silos, defining responsibilities for data quality, improving interoperability among academic systems, monitoring service performance, and maintaining secure and reliable access. Real-time functionality should be implemented where timely information or interaction provides identifiable academic value rather than added indiscriminately to every service.

For educational technology managers, perceived usefulness provides an important criterion for evaluating digital services. A technically functional system may still have limited educational value when users do not perceive its functions as relevant to their academic tasks. User testing, stakeholder feedback, usage analysis, and iterative service improvement can therefore help distinguish genuinely useful functions from features that increase technological complexity without corresponding educational benefit.

For faculty members, the findings highlight their role in the informational quality of digital learning environments. Accurate learning resources, current course information, timely feedback, and reliable communication contribute to the information students encounter through institutional systems. Information quality should therefore be understood not only as an IT responsibility but also as a shared institutional responsibility involving those who create, manage, and communicate academic information.

For smart-campus designers and system architects, the principal implication is the need for traceability between user requirements and technological components. Data integration and governance address information-quality requirements; resilient and scalable services support system efficiency; cross-device and appropriately accessible interfaces support accessibility; and event-driven or notification services support real-time requirements. This requirement-driven approach can reduce the risk of developing technologically sophisticated but educationally marginal services.

More broadly, the findings support a user-centered investment logic: technological capability should be justified by the academic tasks it enables and the value users derive from it. This principle provides the practical link between the empirical model and the architecture proposed in Section 7.

10. Limitations and Future Research

The findings should be interpreted in light of several limitations.

First, the study was conducted among students and faculty members in the School of Light Industry at North China University of Science and Technology. Institutional infrastructure, disciplinary practices, digital maturity, and organizational arrangements may influence users' evaluations of smart-campus systems. The findings should therefore not be generalized automatically to other universities or higher-education contexts. Future studies should test the proposed framework across multiple institutions, academic disciplines, university types, regions, and countries.

Second, the study employed a cross-sectional survey design. Consequently, the structural relationships represent associations among constructs measured at a particular point in

time and do not establish temporal precedence or causality. Longitudinal studies could examine whether changes in smart-campus characteristics are followed by changes in perceived usefulness and learning effectiveness. Experimental or quasi-experimental studies could provide stronger evidence regarding the consequences of particular smart-campus interventions.

Third, the study relies predominantly on self-reported questionnaire measures. Measuring predictors and outcomes using the same survey can introduce common-method concerns, while respondents' perceptions of learning effectiveness may not correspond directly to objectively measured academic performance. Future research should combine perceptual measures with additional evidence such as system logs, actual usage behavior, learning analytics, course performance, retention measures, or other independently observed outcomes.

Fourth, the sample comprised 330 students and 90 faculty members, resulting in substantially unequal group sizes. This imbalance warrants caution when interpreting multigroup findings, particularly for the smaller faculty subgroup. Future studies should seek larger and more balanced stakeholder samples and establish measurement invariance before interpreting differences in structural relationships.

Fifth, the study is embedded within a specific institutional and cultural setting. Expectations concerning digital technology, teaching practices, information services, privacy, and institutional systems may differ across higher-education environments. Cross-cultural and cross-institutional research could therefore determine whether the relative relationships of information quality, system efficiency, accessibility, and real-time capability remain stable across contexts.

Sixth, smart learning effectiveness is operationalized as a perceptual construct and should not be equated with objectively demonstrated academic achievement. Perceptions of improved comprehension, engagement, efficiency, or performance are educationally relevant, but they do not independently demonstrate improvements in examination scores, knowledge retention, course completion, or other objective learning outcomes. Future research should connect the proposed framework with independently measured indicators of educational performance.

Seventh, the proposed smart-campus architecture is empirically informed rather than empirically validated as a complete technical artifact. The PLS-SEM results provide evidence concerning relationships among user perceptions of smart-campus characteristics, perceived usefulness, and smart learning effectiveness; they do not test the effectiveness of every architectural component proposed in Section 7. Future design-science research could implement the framework and evaluate it iteratively to determine whether architecture changes based on the identified priorities improve user experience and educational outcomes.

Finally, the present manuscript does not yet report all measurement-model, mediation, measurement-invariance, and multigroup statistics required for a complete assessment of the proposed model. These analyses should be completed before submission. Future

replication should additionally examine whether the model remains stable across alternative samples and measurement contexts.

11. Conclusion

Smart-campus development increasingly requires universities to demonstrate not only technological capability but also educational value. This study examined the relationships among accessibility, system efficiency, information quality, real-time capability, perceived usefulness, and smart learning effectiveness by integrating insights from the Information Systems Success Model and the Technology Acceptance Model. Using questionnaire data from 420 students and faculty members and PLS-SEM, the study found positive and statistically significant relationships across the nine direct paths examined. Among the smart-campus characteristics, information quality exhibited the strongest reported relationship with perceived usefulness ($\beta = .569$) and the strongest direct relationship with smart learning effectiveness ($\beta = .342$). Perceived usefulness was also positively associated with smart learning effectiveness ($\beta = .255$). These findings highlight the importance of considering not only whether smart-campus technologies are available and functional, but also whether they provide information and services that users regard as valuable for their academic activities. The study contributes theoretically by connecting technological and informational characteristics with users' evaluations of usefulness and perceived educational effectiveness. Rather than conceptualizing smart-campus development primarily in terms of infrastructure, connectivity, or automation, the findings emphasize the importance of the quality and usefulness of the services delivered through that infrastructure.

Building on these findings, the study proposes an empirically informed smart-campus design framework organized around trustworthy information, reliable system performance, accessible services, timely interaction, and user-centered functionality. The framework provides a structured means of translating empirical evidence into architectural and investment priorities while avoiding the assumption that technological sophistication automatically produces educational value. Overall, the study supports a shift from technology-centered smart-campus development toward evidence-informed and learning-oriented system design. For universities, the central challenge is not simply to create more connected or automated campuses, but to develop digital environments in which technological infrastructure, information, and services work together to support meaningful teaching and learning activities.

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