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Adopting Smart Campus in Iraqi HEIs: a UTAUT and KM perspective

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Abstract

Smart campus initiatives connect teaching, research and administrative services, but Iraqi academics' acceptance remains underexplored. This study examines how technology acceptance and knowledge management relate to teaching staff members' behavioural intention to adopt smart campus technologies. An integrated model combines four constructs from the unified theory of acceptance and use of technology - performance expectancy, effort expectancy, social influence and facilitating conditions - with knowledge generation, knowledge storage and sharing, and knowledge application. Data were collected between March and July 2024 through an emailed Google Forms questionnaire completed by a convenience sample of professors, assistant professors and lecturers at the public Universities of Baghdad, Mosul and Basrah. The proposed relationships were assessed using partial least squares structural equation modelling in SmartPLS 3.9. All seven paths to behavioural intention were positive and statistically significant ($p < 0.001$). Knowledge application had the largest estimated coefficient ($\beta = 0.370$), followed by knowledge storage and sharing ($\beta = 0.323$). Among the technology acceptance factors, facilitating conditions had the largest coefficient ($\beta = 0.265$). Together, the predictors explained 52.6% of the variance in behavioural intention; Q^2_predict (0.498) indicated improvement over a naïve mean-prediction benchmark. The findings suggest that academics assess smart campus technologies partly through their expected contribution to using and exchanging knowledge, alongside usability and institutional support. Universities can use these insights to design services around academic tasks and strengthen practical support.

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1. Introduction

Universities increasingly rely on connected digital services to support teaching, research, administration and campus operations. In this study, *smart-campus adoption* refers to teaching staff members' willingness to use integrated digital campus services, rather than a single application. These services may connect learning platforms, information systems and communication tools across academic activities. Their value depends on whether staff see them as useful, can use them with reasonable effort and receive adequate support. Technology acceptance offers one part of the explanation; the university's ability to generate, retain, share and apply knowledge offers another (Alsulami et al., 2022; Venkatesh et al., 2003).

The Iraqi higher education setting makes these questions especially relevant. Studies of e-learning and learning management systems (LMS) have identified the importance of perceived usefulness, usability, information quality and technical support (Ameen et al., 2018; Sulaiman et al., 2023; Zwain, 2019). Their findings nevertheless vary across users and applications. At the University of Kufa, the factors associated with faculty members' acceptance of Moodle differed from those associated with students' acceptance (Zwain, 2019). Among academics in three Iraqi private universities, performance expectancy, effort expectancy and facilitating conditions were positively associated with intention to use e-learning, whereas social influence was not (Jameel et al., 2022). Findings from students, private institutions or an individual LMS therefore cannot be assumed to describe teaching staff members' intentions towards a wider range of smart-campus services.

Direct research on Iraqi smart campuses has addressed other aspects of adoption. Sneesl, Jusoh, Jabar, Abdullah, et al. (2022) used an analytic hierarchy process to *prioritise* factors relevant to Internet of Things (IoT) smart campuses. Their ranking does not estimate behavioural effects among Iraqi teaching staff. Subsequently, Sneesl et al. (2023) surveyed 442 Iraqi university stakeholders and examined an IoT-based adoption model using structural equation modelling and an artificial neural network. They reported the importance of factors spanning perceived usefulness, facilitating conditions, social influence, government support and domain-specific knowledge. This work establishes the relevance of smart-campus adoption in Iraq, while its broad stakeholder sample and IoT focus leave room to examine how teaching staff evaluate integrated campus services.

The unified theory of acceptance and use of technology (UTAUT) provides a starting point. Its four central constructs are performance expectancy, effort expectancy, social influence and facilitating conditions (Venkatesh et al., 2003). Iraqi university studies demonstrate their relevance, although the reported relationships differ by setting (Jameel et al., 2022; Zwain, 2019). For an institutional smart-campus initiative, intention may also be associated with how knowledge is generated, stored, shared and applied. A study of 209 academic staff across five Iraqi public universities linked knowledge-

management processes and infrastructure to smart-university development (Al-Sulami et al., 2023). Other studies identified limited integration between knowledge processes and information technology at the University of Basrah (Hashim & Alsulami, 2018) and associated knowledge-management processes with educational service quality at the University of Thi-Qar (Yusuf & Altabtabae, 2019). These studies examined institutional development or service outcomes; they did not establish how specific knowledge practices relate to an individual lecturer's intention to adopt smart-campus services.

Table 1 brings together the most relevant earlier studies. The evidence points to two related lines of inquiry: acceptance of particular educational technologies and the contribution of knowledge management to university activities. This study examines their intersection by asking: *How are UTAUT determinants and knowledge-management practices associated with teaching staff members' behavioural intention to adopt smart-campus services in Iraqi public universities?* It considers performance expectancy, effort expectancy, social influence and facilitating conditions alongside knowledge generation, knowledge storage and sharing, and knowledge application. Treating facilitating conditions as a direct predictor of *intention* extends the original UTAUT specification, in which this construct chiefly predicts use behaviour (Venkatesh et al., 2003).

Table 1. Selected previous studies relevant to smart-campus adoption in Iraqi higher education

Study	Setting and approach	Relevant finding	Remaining gap
Venkatesh et al. (2003)	Development and organisational validation of UTAUT	Identified performance expectancy, effort expectancy and social influence as determinants of intention; facilitating conditions chiefly relate to use.	Did not examine Iraqi higher education or knowledge management.
Hashim and Alsulami (2018)	217 technical employees, University of Basrah; questionnaire	Found weak knowledge-management processes and limited integration with IT.	Did not test teaching staff members' smart-campus intention.
Ameen et al. (2018)	300 Iraqi university students; e-learning survey and PLS-SEM	Usefulness, ease of use, norms, system and information quality, support and self-efficacy related to intention.	Examined student e-learning rather than integrated smart-campus services.
Zwain (2019)	228 faculty and 553 students, University of Kufa; Moodle survey and PLS-SEM	Facilitating conditions mattered for both groups; other significant factors differed.	Focused on one LMS at one university.
Yusuf and Altabtabae (2019)	120 teaching staff, University of Thi-Qar; survey	Knowledge acquisition, storage, transfer and application related to educational service quality.	Examined service quality rather than adoption intention.

Alsulami et al. (2022)	415 academics and students, University of Basrah; Web 2.0 survey	Technological, organisational and peer factors related to knowledge sharing, which was associated with academic performance.	Examined a specific practice using a mixed academic and student sample.
Jameel et al. (2022)	187 academics in three Iraqi private universities; UTAUT e-learning survey	Performance expectancy, effort expectancy and facilitating conditions related positively to intention; social influence was insignificant.	Examined e-learning during COVID-19 without knowledge-management constructs.
Sneesl, Jusoh, Jabar, Abdullah, et al. (2022)	IoT smart-campus factor prioritisation; analytic hierarchy process	Ranked government support, privacy, social influence, facilitating conditions and service collaboration highly.	Ranked factors rather than testing behavioural effects among Iraqi teaching staff.
Sulaiman et al. (2023)	393 lecturers, Kurdistan Region of Iraq; TAM–TOE survey	Usefulness and ease of use related to LMS usage; quality and policy factors shaped these perceptions.	Examined regional LMS usage rather than integrated campus services.
Sneesl et al. (2023)	442 Iraqi university stakeholders; IoT smart-campus SEM and neural-network analysis	Supported several technology, organisational, environmental and user factors.	Used a broad stakeholder group and an IoT-specific model.
Al-Sulami et al. (2023)	209 academic staff across five Iraqi public universities; survey	Knowledge-management processes and infrastructure related to smart-university development.	Examined institutional development rather than individual adoption intention.

Source: *Author's own work*

The study uses an electronic questionnaire distributed by email to professors, assistant professors and lecturers at the Universities of Baghdad, Mosul and Basrah between March and July 2024. Respondents were recruited through convenience sampling, and the proposed relationships were examined using partial least squares structural equation modelling in SmartPLS 3.9. The unit of analysis is the individual teaching staff member, and the outcome is *behavioural intention*, rather than observed use or institution-wide transformation. The study contributes evidence from three major Iraqi public universities and assesses whether knowledge-related perceptions warrant consideration alongside established technology-acceptance factors.

The remainder of this paper is organised as follows. Sections 2 and 3 review the theoretical foundations and develop the research hypotheses, Section 4 presents the research methodology, Section 5 reports the empirical results, Section 6 discusses and concludes the findings. Finally, Section 7 present the study's limitations, and recommendations for future research.

2. Literature review

2.1 The Smart Campus Concept

The smart campus adapts the principles of the smart city to the purposes of a higher education institution (HEI). It connects physical infrastructure, digital systems and institutional services to support teaching, learning, research and campus life. Dong et al. (2020) propose a human-centred, learning-oriented conception in which technologies serve stakeholders' needs rather than define the campus by themselves. Similarly, Min-Allah and Alrashed (2020) describe the smart campus as a combination of intelligent technologies and physical infrastructure that can improve services, decision-making and sustainability. These accounts suggest that installing connected devices is only one part of becoming a smart campus.

The concept is broader than a digital campus understood primarily as a collection of online systems. Smart campus services can use information from different sources to respond to changing needs, while linking academic, administrative and operational activities. The boundary is nevertheless difficult to draw consistently: universities vary in their priorities, resources and definitions of "smartness" (Min-Allah & Alrashed, 2020). Polin et al. (2023) organise the concept around society, economy, environment and governance, showing why an assessment confined to technology would be incomplete. For the present study, a smart campus is therefore understood as an integrated, knowledge-enabled university environment that uses connected technologies and institutional processes to improve academic work and campus services.

2.2 Importance of the Smart Campus

The importance of a smart campus lies first in its potential to improve the academic experience. Connected learning environments can give lecturers and students more flexible access to resources, support interaction and enable learning across locations (Atif et al., 2014; Zhang et al., 2022). Their educational value depends on how they are incorporated into teaching, rather than on connectivity alone. For faculty, the relevant question is whether a service helps them prepare courses, communicate, obtain information or collaborate on academic work. A smart campus can also support knowledge creation and exchange when its systems make expertise and resources accessible across departments (Hidayat & Sensuse, 2022).

Administrative and operational benefits extend this case for adoption. Integrated services may simplify recurring processes and give institutional managers more timely information. Monitoring and analytics can help identify patterns in resource use and guide decisions about campus facilities (Villegas-Ch et al., 2019). In the sustainability domain, smart energy systems offer possibilities for

monitoring consumption, improving control and supporting renewable energy integration; Kifor et al. (2023) also emphasise the need for indicators that assess whether these systems achieve their intended outcomes. A smart campus thus has potential value for both its users and the institution, although the benefits of a particular implementation must be evaluated rather than assumed.

2.3 Characteristics and Features

Connectivity is a foundational characteristic: networks link users, buildings, devices and applications so that information can move across the campus. Internet of Things (IoT) sensors, wireless networks and mobile interfaces can support services such as environmental monitoring, access to learning resources and facilities management (Baba et al., 2024; Fraga-Lamas et al., 2019). Integration is equally important. A university with several isolated applications may have extensive digital provision without allowing information or services to work together. Interoperable platforms can connect academic and administrative functions while reducing repeated tasks for users (Dong et al., 2020).

A further characteristic is responsiveness: data can be analysed and presented in ways that help people act on current conditions. Cloud services, analytics and, where appropriate, artificial intelligence can support this capability (Baba et al., 2024). Smart campus services may also be tailored to different users, since a lecturer, student and facilities officer require different information. These features require careful governance. Collecting and combining campus data raises questions about access, privacy and security, particularly where information relates to individuals' learning or work (Amo-Filva et al., 2024; Zhang et al., 2022). Finally, knowledge management is a distinguishing feature of the model used here: a campus is more useful to faculty when its systems help generate, retain, share and apply knowledge, as well as deliver routine services (Hidayat & Sensuse, 2022).

2.4 Smart Campus Adoption

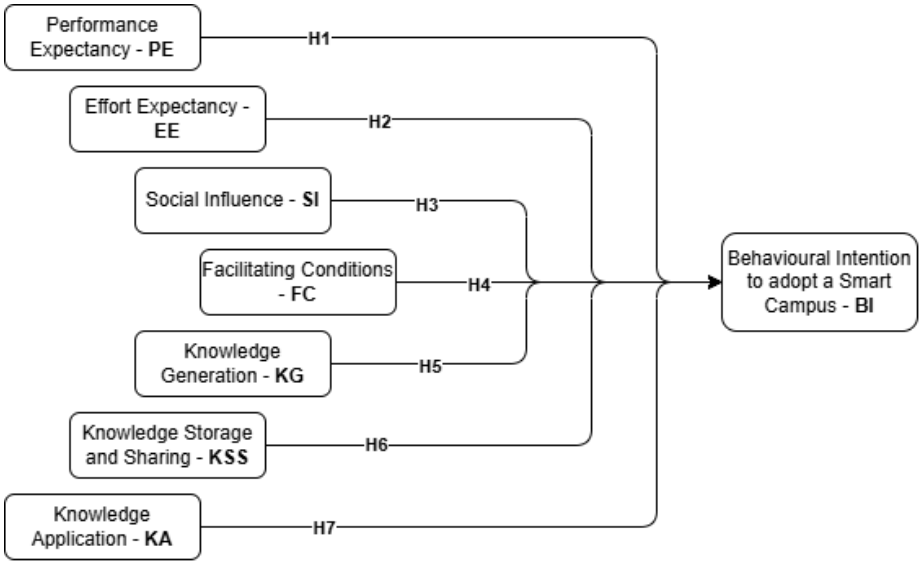
Adoption concerns whether intended users are willing and able to incorporate smart campus services into their work. It therefore requires attention to faculty perceptions alongside institutional readiness. Reviews identify technological reliability, privacy, trust, cost and implementation capability among the factors that can shape smart campus adoption (Sneesl, Jusoh, Jabar, & Abdullah, 2022). From a stakeholder perspective, Agbehadji et al. (2022) highlight experience, ICT infrastructure, user capability, support capacity and data practices as elements of a campus transition. These factors help explain why providing a platform does not guarantee that it will become part of everyday academic practice.

Institutional adoption also requires planning across services. Polin et al. (2023) found limited evidence of comprehensive implementation across all four domains of their smart campus framework, suggesting that individual projects should not automatically be treated as campus-wide transformation. Readiness assessments can help universities identify what users and infrastructure need before extending an initiative (Hidayat et al., 2021). In Iraqi HEIs, this makes faculty members' behavioural intention a pertinent starting point for examining adoption. The present study uses UTAUT to consider expected performance, ease of use, social influence and facilitating conditions (Venkatesh et al., 2003), and adds knowledge generation, storage and sharing, and application to reflect faculty members' knowledge-intensive work. Together, these perspectives examine whether prospective users see a smart campus as both usable and valuable to their academic activities.

3. Conceptual Model and Hypotheses Development

The proposed model combines the Unified Theory of Acceptance and Use of Technology (UTAUT) with a knowledge management (KM) perspective to explain faculty members' behavioural intention to adopt smart campus technologies. Its four UTAUT predictors are performance expectancy (PE), effort expectancy (EE), social influence (SI) and facilitating conditions (FC). Three KM predictors - knowledge generation (KG), knowledge storage and sharing (KSS), and knowledge application (KA) - capture whether faculty expect a smart campus to support their academic knowledge work. All seven constructs have direct paths to behavioural intention, as shown in the Figure 1.

Figure 1. The conceptual model of study



Source: *Author's own work*

3.1 Performance Expectancy

Performance expectancy refers to the extent to which an individual believes that using a technology will improve their task performance. It is a central predictor of behavioural intention in UTAUT because prospective users assess whether a system offers a worthwhile return for the time and attention required to adopt it (Venkatesh et al., 2003). For university faculty, that assessment concerns teaching, research and administrative work. A smart campus may make academic resources easier to find, speed up communication, improve access to learning materials and support more timely decisions. Faculty who anticipate these benefits should be more willing to adopt its technologies. The educational setting gives performance expectancy a particular meaning. Instructors may value a smart campus when it helps them retrieve course information, coordinate with colleagues, monitor learning activities or complete routine tasks more efficiently. Aqlan et al. (2021) examine behavioural intention to use learning management systems among university instructors, while Al-Mamary (2022) applies UTAUT to learning management system use in higher education. These studies place perceived work benefits within the academic technology context. Smart campus research also describes connected services that can support learning and campus activities (Ahmed et al., 2020; Atif et al., 2014). In Iraqi and Syrian HEIs, the anticipated benefit must be credible in relation to faculty members' actual responsibilities. A platform that connects information and services may appear valuable, but its breadth alone does not establish usefulness. Intention should be stronger when faculty can see how specific functions save time, improve the quality of academic work or provide information they could not previously obtain as readily. Performance expectancy therefore captures the expected academic value of adoption, alongside the other conditions in the model. This reasoning leads to the following hypothesis:

H1: Performance expectancy positively influences faculty members' behavioural intention to adopt smart campus technologies in Iraqi and Syrian HEIs.

3.2 Effort Expectancy

Effort expectancy is the perceived ease associated with learning and using a technology (Venkatesh et al., 2003). Even a potentially useful smart campus service may attract limited interest if faculty expect it to be difficult to navigate, require repeated data entry or disrupt established academic routines. Conversely, clear interfaces, straightforward access and familiar workflows can make adoption appear manageable. Research applying UTAUT to university learning management systems illustrates the relevance of perceived ease in educational technology acceptance (Al-Mamary, 2022). Smart campus adoption may involve several connected tools rather than one application. Faculty may

need to use digital learning environments, mobile services, knowledge repositories and administrative systems during the same working day. The perceived effort of adoption thus depends partly on how easily they can move between these services and find what they need. If systems use inconsistent procedures or require substantial technical learning, the cumulative burden may discourage use. Donmez-Turan (2020) considers the relationship between UTAUT factors and resistance or anxiety towards a new system, reinforcing the need to account for the experience of learning it. For faculty in Iraqi HEIs, effort expectancy can be understood through ordinary academic tasks: obtaining teaching materials, sharing a document, locating a policy or accessing a service. When these actions seem simple, faculty can devote more attention to teaching and research. When they seem cumbersome, the expected effort may outweigh the anticipated benefit, even if the technology has useful capabilities. Ease of use is therefore relevant at the point when faculty form an intention, before they have necessarily developed extensive experience with the system. The model proposes a positive relationship: greater perceived ease should correspond to stronger intention to adopt smart campus technologies. This reasoning leads to the following hypothesis:

H2: Effort expectancy positively influences faculty members' behavioural intention to adopt smart campus technologies in Iraqi HEIs.

3.3 Social Influence

Social influence denotes the degree to which an individual believes that important others think they should use a technology (Venkatesh et al., 2003). Within a university, those others may include departmental colleagues, academic leaders and faculty members whose judgement is respected. Their views can make a new system appear professionally relevant and can shape whether using it becomes a normal part of academic work. UTAUT identifies social influence as a predictor of intention, although its strength can depend on the setting in which adoption occurs (Venkatesh et al., 2003). Applications of UTAUT in other organisational contexts likewise show why the social environment belongs in an acceptance model (Kijsanayotin et al., 2009). A smart campus depends in part on participation across the institution. Shared platforms for learning, communication and knowledge exchange become more useful when colleagues contribute and use them consistently. Faculty may therefore pay attention to whether peers recommend a service, whether department leaders encourage its use and whether participation helps them collaborate. For example, a colleague's account of finding or sharing academic materials through a campus platform may make its value easier to judge. Conversely, limited participation within a department could weaken the practical appeal of joining. Social influence in this model concerns perceived expectations and endorsement. Technical help from colleagues may also be valuable, but the availability of help is represented primarily by facilitating

conditions. Keeping these concepts distinct makes the proposed relationship clearer: social influence addresses who supports adoption, while facilitating conditions address whether the means to adopt are available. In Iraqi HEIs, where faculty work within departments and academic networks, endorsement by relevant peers and leaders may encourage an intention to use shared smart campus services. This is a proposed relationship requiring empirical assessment rather than an assumption that all faculty will respond equally to social expectations. This reasoning leads to the following hypothesis:

H3: Social influence positively influences faculty members' behavioural intention to adopt smart campus technologies in Iraqi HEIs.

3.4 Facilitating Conditions

Facilitating conditions describe an individual's belief that the organisational and technical resources needed to use a system are available (Venkatesh et al., 2003). For a smart campus, these conditions may include dependable connectivity, accessible devices, compatible platforms, user guidance and responsive technical support. They matter because faculty can intend to use a service with greater confidence when they believe they will be able to access it and resolve problems that arise. Studies of smart campus criteria and readiness similarly draw attention to the infrastructure and institutional arrangements needed to support connected campus services (Ahmed et al., 2020; Hidayat et al., 2021). The proposed path requires a theoretical distinction. In the original UTAUT model, facilitating conditions principally predict use behaviour, whereas performance expectancy, effort expectancy and social influence predict behavioural intention (Venkatesh et al., 2003). The present model tests a direct path from facilitating conditions to intention because faculty are considering adoption in a setting where the availability of resources and support may influence whether adoption seems feasible. This extension should be identified explicitly and assessed empirically. In an Iraqi HEI, a faculty member might recognise the value of a digital repository or connected teaching service yet hesitate to adopt it if access is unreliable, training is unavailable or the service does not work with tools already in use. Conversely, visible support and workable infrastructure can reduce uncertainty about starting to use the technology. Facilitating conditions are therefore distinct from perceived ease: a system may be simple to operate but inaccessible without suitable resources, while a technically supported system may still be difficult to learn. Both perceptions can contribute independently to intention. On this basis, the model proposes that stronger perceived facilitating conditions are associated with a greater willingness to adopt smart campus technologies. This reasoning leads to the following hypothesis:

H4: Facilitating conditions positively influence faculty members' behavioural intention to adopt smart campus technologies in Iraqi HEIs.

3.5 Knowledge Generation

Knowledge generation is the creation or acquisition of ideas, insights and understandings that can inform future work. It may arise through research, interaction, reflection and the combination of existing knowledge. Nonaka et al. (2000) describe knowledge creation as a dynamic process involving interactions between tacit and explicit knowledge. In HEIs, such interactions occur when faculty exchange expertise, develop teaching approaches or interpret research and institutional information. Knowledge generation is consequently a core academic activity, making it a relevant consideration when faculty evaluate smart campus technologies. A smart campus can offer digital spaces and connected information sources through which faculty encounter new material and collaborate. Its value for knowledge generation lies in whether those features help academics develop insights they can use, rather than simply increasing the amount of information available. Hidayat and Sensuse (2022) place knowledge management within a smart campus model, while Alblaihed et al. (2022) link smart campus technologies and knowledge management. Research on knowledge management in higher education also identifies knowledge practices as relevant to institutional work (Govender et al., 2018). Together, these sources provide a basis for examining knowledge generation as a perceived reason to adopt. The proposed mechanism is that faculty who expect smart campus services to help them discover relevant expertise, connect ideas or develop new teaching and research knowledge will have a stronger intention to use them. This argument differs from general performance expectancy. Performance expectancy concerns anticipated improvement in completing academic tasks; knowledge generation concerns the creation of knowledge through those activities. A faculty member might therefore see a platform as efficient without expecting it to contribute much to intellectual exchange, or value its collaborative possibilities even before immediate efficiency gains are clear. Including both constructs allows the model to test whether the knowledge creating potential of a smart campus adds to its perceived practical benefits. This reasoning leads to the following hypothesis:

H5: Knowledge generation positively influences faculty members' behavioural intention to adopt smart campus technologies in Iraqi HEIs.

3.6 Knowledge Storage and Sharing

Knowledge storage concerns retaining and organising knowledge so that it can be retrieved, while knowledge sharing concerns making knowledge available to others through formal or informal exchange. Both processes are relevant to universities, where teaching resources, research outputs, procedures and professional experience are produced across departments and over time. Knowledge management systems can support the organisation and movement of such knowledge (Alavi &

Leidner, 2001). Studies of higher education also describe the importance of making academic knowledge accessible to members of an institution (Jamil & Lodhi, 2015; Ramachandran et al., 2009). In a smart campus, repositories, learning platforms and collaboration tools may allow faculty to store materials and locate colleagues' contributions. Yet storage and sharing are connected without being identical. A repository has limited value if its contents are difficult to find; a communication tool has limited long term value if useful exchanges are not retained. The combined construct in this model captures the expectation that smart campus technologies will help faculty preserve knowledge and circulate it to people who can use it. Digital systems can support knowledge exchange, although effective sharing still depends on people's willingness to contribute and on the relevance of what is shared (Al-Busaidi & Olfman, 2017; Deng et al., 2022). Faculty may be more willing to adopt a smart campus when they expect easier access to teaching materials, documented experience and colleagues' expertise. These possibilities can reduce the need to recreate existing work and can make participation in a shared platform more valuable. The proposed relationship should nevertheless be tested separately from performance expectancy and knowledge generation: storage and sharing concern the availability and exchange of existing knowledge, whereas generation concerns developing new knowledge. If faculty regard the platform as a dependable means of retaining and exchanging useful academic knowledge, their behavioural intention to adopt it should increase. This reasoning leads to the following hypothesis:

H6: Knowledge storage and sharing positively influence faculty members' behavioural intention to adopt smart campus technologies in Iraqi HEIs.

3.7 Knowledge Application

Knowledge application is the use of available knowledge to perform tasks, solve problems or make decisions. It is particularly important in HEIs because the value of generated and shared knowledge depends partly on whether faculty can put it to work in teaching, research and academic administration. Knowledge management research treats application as a substantive process through which knowledge contributes to organisational activity (Al-Emran et al., 2018; Mahdi et al., 2019). Within higher education, applying knowledge to a new situation may also reveal gaps and prompt further learning (Ramachandran et al., 2009). Smart campus technologies may support application by helping faculty locate relevant information when a decision or task arises. A connected service could, for example, make teaching resources available during course preparation or bring together information needed to coordinate an academic activity. Decision support and other knowledge oriented systems are among the smart campus mechanisms discussed by Hidayat and Sensuse (2022). The proposed benefit lies in the faculty member's ability to use accessible knowledge in practice, rather

than in the mere presence of data within a platform. For the present hypothesis, knowledge application should be interpreted as a perceived capability of the proposed smart campus environment. This avoids treating extensive prior use of a smart campus as a prerequisite for intending to adopt it. Faculty can form an expectation, based on available functions or demonstrations, that a system will help them apply academic knowledge to their work. If they anticipate that support, adopting the system becomes more attractive. Knowledge application is distinct from the other KM constructs: generation produces insights, storage and sharing preserve and circulate them, and application puts them to use. Testing each path allows the study to examine which knowledge related expectations contribute to behavioural intention alongside the established UTAUT predictors. This reasoning leads to the following hypothesis:

H7: Knowledge application positively influences faculty members' behavioural intention to adopt smart campus technologies in Iraqi HEIs.

4. Methodology

This study used a quantitative survey to examine the behavioural intention of academic staff to adopt smart campus technologies in Iraqi higher education institutions (HEIs). The unit of analysis was the individual academic. The model integrated four predictors from the Unified Theory of Acceptance and Use of Technology (UTAUT) - performance expectancy (PE), effort expectancy (EE), social influence (SI) and facilitating conditions (FC) - with three knowledge management (KM) constructs: knowledge generation (KG), knowledge storage and sharing (KSS), and knowledge application (KA). All seven constructs were specified as direct predictors of behavioural intention (BI). A structured survey enabled consistent collection of academics' assessments of the smart campus across three universities.

4.1 Measurement Scales and Questionnaire Design

The questionnaire comprised measures of the eight study constructs and respondent characteristics. The UTAUT measures were adapted to the smart campus context from Venkatesh et al. (2003) and Venkatesh et al. (2012). PE captured the extent to which faculty expected smart campus services to improve the efficiency and effectiveness of their academic work. EE addressed the perceived ease of learning and using those services. SI reflected perceived expectations and encouragement from colleagues and academic leaders, whereas FC concerned the resources, compatibility and assistance available to support use. BI captured respondents' intention to use smart campus technologies in their work. The proposed direct path from FC to BI extends the original UTAUT formulation, in which facilitating conditions principally predict use behaviour (Venkatesh et

al., 2003). The KM measures were informed by prior work on knowledge processes. KG captured the expected contribution of smart campus services to developing new academic ideas and insights (Akhavan et al., 2012; Ramachandran et al., 2009). KSS addressed the retention, retrieval and exchange of academic knowledge (Ramachandran et al., 2009; Sangari et al., 2015). KA captured the expected use of available knowledge in teaching, research and academic decisions (Ramachandran et al., 2009; Sangari et al., 2015). The measures were contextualised to academics' knowledge-intensive responsibilities. The constructs were specified as reflective in the PLS-SEM model - see Appendix A. Their empirical reliability and validity were examined before interpreting the hypothesised relationships. Particular attention was paid to the combined KSS construct, since retaining knowledge and sharing it are related yet conceptually distinct activities.

4.2 Sampling and data collection

The target respondents were teaching staff holding the ranks of Professor, Assistant Professor and Lecturer at the Universities of Baghdad, Mosul and Basrah. These academics were relevant to the research question because their work involves teaching, research, collaboration and the creation and application of knowledge. Data were collected from March to July 2024 using an electronic questionnaire hosted on Google Forms. The questionnaire link was distributed by email to accessible teaching staff at the three universities. The study used convenience sampling, with participation determined by access to the invitation and the recipient's decision to respond. This non-probability approach facilitated recruitment across institutions but did not give every eligible academic a known probability of selection. Academics more interested in digital services may have been more inclined to participate, the final analytical sample size was 278 respondents.

4.3 Data analysis

The data were analysed with partial least squares structural equation modelling (PLS-SEM) using SmartPLS version 3.9. This approach allowed the seven theorised relationships with BI to be estimated simultaneously while evaluating the adapted measures. The assessment proceeded from the measurement model to the structural model. For the reflective measures, indicator loadings, Cronbach's alpha, composite reliability, rho_A and average variance extracted (AVE) were used to evaluate indicator reliability, internal consistency and convergent validity. Discriminant validity was considered primarily through the heterotrait-monotrait ratio (HTMT), with the Fornell-Larcker criterion and cross-loadings serving as supplementary information (Henseler et al., 2015). The distinction among PE, KG and KA was examined carefully because anticipated academic effectiveness and knowledge-related benefits may overlap conceptually. The structural assessment examined

collinearity among predictors using variance inflation factors (VIF), followed by the standardised coefficients for H1-H7. The coefficient of determination (R^2) for BI indicated the explanatory power of the model in the analysed sample, and local effect sizes (f^2) indicated each predictor's contribution. Bootstrap-based confidence intervals and significance statistics were used to assess uncertainty in the path estimates.

5. Results

The PLS-SEM results are reported in the sequence recommended for reflective models: assessment of measurement quality, discriminant validity, structural relationships, and predictive performance (Hair et al., 2019). The supplied outputs concern eight constructs and seven direct paths to behavioural intention (BI).

5.1 Reflective Measurement Model

The 24 indicators loaded on their designated constructs at values between 0.868 (EE_item3) and 0.963 (SI_item3), exceeding the commonly used 0.708 benchmark for indicator reliability. Table 2 reports the three loadings for each construct together with internal-consistency and convergent-validity statistics. Cronbach's alpha ranged from 0.900 (PE) to 0.951 (SI), rho_A from 0.930 (FC and KA) to 0.972 (SI), and composite reliability from 0.937 (PE) to 0.968 (SI). All eight constructs exceeded 0.70 on these measures. Average variance extracted (AVE) ranged from 0.831 (PE) to 0.910 (SI), exceeding 0.50 for every construct. These results support indicator reliability, internal consistency and convergent validity for the specified reflective measures (Hair et al., 2019).

Table 2. Indicator loadings, reliability and convergent validity

Construct	Item 1	Item 2	Item 3	Cronbach's α	rho_A	CR	AVE
BI	0.934	0.948	0.954	0.940	0.941	0.962	0.893
EE	0.949	0.940	0.868	0.910	0.952	0.943	0.846
FC	0.944	0.919	0.940	0.927	0.930	0.954	0.873
KA	0.938	0.912	0.945	0.924	0.930	0.952	0.868
KG	0.956	0.940	0.951	0.945	0.948	0.964	0.900
KSS	0.940	0.935	0.946	0.935	0.938	0.958	0.885
PE	0.939	0.912	0.883	0.900	0.937	0.937	0.831
SI	0.962	0.936	0.963	0.951	0.972	0.968	0.910

Notes: Item 1–3 correspond to the SmartPLS labels [construct]_item1 to [construct]_item3. CR = composite reliability; AVE = average variance extracted.
***Source**: Author's own work*

5.2 Discriminant Validity

Discriminant validity was assessed with the heterotrait-monotrait ratio (HTMT; Henseler et al., 2015). As shown in Table 3, the HTMT values ranged from 0.020 (EE-KG) to 0.387 (BI-KA). The largest ratios involving BI were 0.387 with KA, 0.335 with KG and 0.278 with FC. Every pair was below the conservative 0.85 threshold, supporting empirical distinctiveness among the eight reflective constructs. The relatively larger BI-KA ratio remains well below that threshold.

Table 3. Heterotrait–monotrait ratios (HTMT)

Construct	BI	EE	FC	KA	KG	KSS	PE	SI
BI	—							
EE	0.233	—						
FC	0.278	0.021	—					
KA	0.387	0.035	0.038	—				
KG	0.335	0.020	0.101	0.029	—			
KSS	0.276	0.099	0.042	0.134	0.035	—		
PE	0.222	0.073	0.066	0.078	0.021	0.068	—	
SI	0.250	0.046	0.036	0.034	0.057	0.047	0.044	—

Note: The table shows HTMT ratios below the diagonal. The dash denotes comparison of a construct with itself.
***Source**: Author's own work*

5.3 Structural Model and Hypothesis Tests

The inner-model variance inflation factors (VIFs) for the seven predictors of BI ranged from 1.007 (SI) to 1.025 (KSS), indicating no material predictor-collinearity concern. The model explained 52.6% of the variance in BI ($R^2 = 0.526$; adjusted $R^2 = 0.514$). Table 4 presents the standardised paths, their bootstrapped standard errors and t statistics, and local effect sizes. All seven estimated coefficients were positive, with $p < 0.001$. Among the UTAUT variables, FC had the largest coefficient ($\beta = 0.265$, $t = 5.968$, $f^2 = 0.146$), followed by EE ($\beta = 0.253$, $t = 6.506$, $f^2 = 0.134$). SI ($\beta = 0.221$, $t = 4.854$, $f^2 = 0.102$) and PE ($\beta = 0.220$, $t = 5.557$, $f^2 = 0.101$) were also positively associated with BI. Thus, H1-H4 were supported in the estimated model. The direct FC-BI result concerns the extension proposed in this study; it should not be described as the original UTAUT use-behaviour path. All three KM variables were positively associated with BI. KA had the largest coefficient in the full model ($\beta = 0.370$, $t = 8.300$, $f^2 = 0.283$), followed by KSS ($\beta = 0.323$, $t = 7.176$, $f^2 = 0.214$) and KG ($\beta = 0.264$, $t = 6.419$, $f^2 = 0.145$). H5-H7 were therefore supported. The f^2 values indicate that KA and KSS made the largest individual contributions to explained variance among the seven predictors.

Table 4. Structural paths, collinearity and hypothesis tests

Hypothesis	Path	β	Bootstrap mean	SE	*t*	*p*	VIF	f^2	Decision
H1	PE → BI	0.220	0.223	0.040	5.557	<0.001	1.014	0.101	Supported
H2	EE → BI	0.253	0.255	0.039	6.506	<0.001	1.014	0.134	Supported
H3	SI → BI	0.221	0.225	0.046	4.854	<0.001	1.007	0.102	Supported
H4	FC → BI	0.265	0.267	0.044	5.968	<0.001	1.016	0.146	Supported
H5	KG → BI	0.264	0.262	0.041	6.419	<0.001	1.014	0.145	Supported
H6	KSS → BI	0.323	0.322	0.045	7.176	<0.001	1.025	0.214	Supported
H7	KA → BI	0.370	0.370	0.045	8.300	<0.001	1.022	0.283	Supported

Notes: β = original-sample standardised path coefficient; SE = bootstrap standard error; VIF = inner-model variance inflation factor; f^2 = local effect size.
***Source**: Author's own work*

5.4 Model Fit and Predictive Assessment

The saturated and estimated models both returned an SRMR of 0.035. The remaining reported fit statistics were d_ULS = 0.359, d_G = 0.395, χ^2 = 691.965 and NFI = 0.885 (Table 5). All value are a favourable descriptive diagnostic. For BI, the PLSpredict output reported Q^2_predict = 0.498, root mean square error (RMSE) = 0.714 and mean absolute error (MAE) = 0.578. A positive Q^2_predict indicates lower prediction error than the naïve training-sample mean benchmark.

Table 5. Model fit, explanatory power and prediction summary

Assessment	Statistic	Value
Model fit	SRMR	0.035
Model fit	d_ULS	0.359
Model fit	d_G	0.395
Model fit	χ^2	691.965
Model fit	NFI	0.885
Explanatory power	BI R^2; adjusted R^2	0.526; 0.514
PLSpredict for BI	Q^2_predict	0.498
PLSpredict for BI	RMSE; MAE	0.714; 0.578

***Source**: Author's own work*

6. Discussion and Conclusion

This study examined how four UTAUT beliefs and three knowledge management (KM) expectations relate to Iraqi academics' behavioural intention to adopt smart campus technologies. All seven hypothesised paths were positive and statistically significant in the pooled model. The predictors explained 52.6% of the variance in intention, while the positive Q^2_predict value (0.498) indicates that

the model performed better than a naïve mean-prediction benchmark for BI. These findings support the relevance of both technology-acceptance and knowledge-work perspectives to intended adoption.

6.1 Interpreting the UTAUT relationships

Within the UTAUT group, facilitating conditions (FC; $\beta = 0.265$) and effort expectancy (EE; $\beta = 0.253$) had somewhat larger estimated associations with intention than social influence (SI; $\beta = 0.221$) and performance expectancy (PE; $\beta = 0.220$). The positive PE relationship is consistent with UTAUT's proposition that expected gains in task performance motivate technology acceptance (Venkatesh et al., 2003). For lecturers and professors, such gains could include timely access to learning resources, easier coordination of courses and more efficient retrieval of academic information. Research on university instructors' intentions to use learning management systems likewise indicates the relevance of task-related technology beliefs in an educational setting (Aqlan et al., 2021). The EE result suggests that intended adoption is related to the anticipated ease of learning and navigating connected services. A smart campus brings several tools into the same working environment; even if individual applications offer benefits, inconsistent interfaces or repeated administrative steps may increase the perceived effort of using them. Technology-acceptance research distinguishes ease of use from expected performance gains because a valuable tool can still appear costly to learn (Venkatesh et al., 2003).

SI was also positively associated with intention. Academic leaders and colleagues can signal that a platform is legitimate, useful and worth incorporating into established routines. This aligns with the social component of UTAUT (Venkatesh et al., 2003) and may be pertinent to shared repositories and collaboration tools, whose value depends partly on others' participation. The result should not be read as evidence that managerial pressure is effective or desirable. Encouragement may coincide with access to resources, local training or enthusiasm within a department. This study extends the framework by treating anticipated access, compatibility and support as factors in forming intention. The positive coefficient is compatible with that extension: a faculty member may be unwilling to plan to use a service if connectivity, devices or technical help seem uncertain. Smart campus research emphasises that infrastructure and organisational readiness underpin connected services (Ahmed et al., 2020; Hidayat et al., 2021). Nonetheless, this result concerns perceived conditions, not an audit of actual infrastructure. A subsequent study could compare staff perceptions with documented service availability and test whether FC predicts observed use after intention is formed.

6.2 The role of Knowledge Management

Knowledge application (KA) had the largest path coefficient in the full model ($\beta = 0.370$; $f^2 = 0.283$). Academics who expect smart campus technologies to help them put knowledge to work were especially likely to express an intention to use them. KM theory distinguishes the existence of information from its productive use in decisions and tasks (Alavi & Leidner, 2001). In a university, an integrated platform becomes practically meaningful when a lecturer can apply retrieved resources to course design, use colleagues' experience to resolve a teaching problem or bring evidence into an academic decision. Hidayat and Sensuse (2022) place KM processes within the smart campus concept. The present result adds an adoption perspective: expected support for using knowledge is associated with willingness to engage with campus technologies.

Knowledge storage and sharing (KSS; $\beta = 0.323$; $f^2 = 0.214$) also showed a sizeable positive association. Academics may see value in a system that preserves teaching materials and experience while making them accessible to colleagues. This interpretation is consistent with the role of knowledge repositories and exchange in information-systems research (Alavi & Leidner, 2001) and the importance of KM processes in HEIs (Ramachandran et al., 2009). Yet storage and sharing should not be conflated. A repository can preserve documents without encouraging contribution, whereas active exchange may occur through informal networks without leaving reusable records. The combined three-item KSS measure produced strong reliability, but reliability cannot demonstrate that both activities are adequately represented or operate identically. Future work could assess them separately and examine whether trust, recognition or retrieval quality shapes the value faculty attach to sharing.

Knowledge generation (KG; $\beta = 0.264$; $f^2 = 0.145$) was associated with intention, although its estimated coefficient was smaller than those of KA and KSS. The finding is consistent with accounts of knowledge creation as a social and iterative process in which people combine existing ideas and experience to develop new understanding (Nonaka et al., 2000). Connected services might help academics locate expertise and collaborate across departments; however, a digital platform cannot generate insight simply by accumulating information. Its contribution depends on meaningful interaction, interpretation and the ability to revisit and apply emerging ideas. Thus, the findings suggest that faculty evaluate smart campus services in relation to knowledge-intensive work as well as technical usability.

6.3 Implications for Universities

For the participating universities, the results support designing smart campus initiatives around concrete academic workflows. A repository should make relevant material easy to retrieve and reuse;

collaborative services should help staff share expertise across departments; and information systems should enable academics to apply that expertise when preparing courses and making decisions. This emphasis follows the relatively large KA and KSS associations, while remaining an implementation proposition that requires evaluation. Hidayat and Sensuse (2022) describe KM as part of a smart campus model, whereas human-centred accounts stress that technology should serve educational and organisational purposes (Dong et al., 2020). An institution could test these ideas through bounded pilots that collect evidence on task completion, user experience and actual uptake.

The positive FC and EE paths also suggest attention to access, interoperability, training and responsive support. Academic staff cannot readily judge a system's value if they expect access to fail or regard the learning burden as excessive. Faculty demonstrations and collegial exchange may complement support services, consistent with the SI result. The seven coefficients are not a budget allocation formula. Spending priorities should also reflect costs, security, privacy, accessibility and differences among campuses. Reviews of smart campus adoption identify such organisational and technical conditions as part of the transition (Sneesl, Jusoh, Jabar, Abdullah, et al., 2022). Wider deployment should therefore assess whether academic benefits are realised in use, rather than treating favourable intention scores as sufficient evidence of success.

7. Limitations and further research

The evidence comes from an emailed, convenience-sampled survey of Professors, Assistant Professors and Lecturers at three Iraqi universities. Academics with stronger digital interests or greater access to the invitation may be over-represented; the results should not be extended uncritically to all faculty, other Iraqi HEIs, students, or administrative and technical staff. Simultaneous measurement of predictors and intention prevents a temporal test of the proposed direction of effects. Common-source self-reports may inflate or otherwise alter associations, and no statistical diagnostic can by itself eliminate that possibility. The study measures intention, rather than subsequent platform use, teaching outcomes, the quality of knowledge application or institutional transformation.

Future research could follow academics over time, link initial perceptions with consented usage records, and evaluate whether actual engagement improves academic tasks. A more systematic sampling frame would help assess generalisability. Multigroup comparisons across universities or academic ranks should first establish measurement invariance and adequate group sizes. A UTAUT-only comparison would test the incremental value of KM expectations, while separate storage and sharing scales could clarify their distinct roles. Such designs would move from evidence about what academics expect towards evidence about how specific smart campus services are used, which knowledge practices they support and under what institutional conditions those benefits occur.

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Conflict of Interest

The author declare that there is no conflict of interest regarding the publication of this manuscript.

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Data availability

The datasets analysed during the current study are available from the corresponding author on reasonable request.

Appendix A. Study Questionnaire Items

Performance expectancy (PE; Venkatesh et al. (2003); Venkatesh et al. (2012)): *PE1 Using smart campus technologies would help me complete my academic tasks more efficiently. PE2 Using smart campus technologies would help me accomplish teaching or research tasks more quickly. PE3 Using smart campus technologies would improve my effectiveness as a faculty member*.

Effort expectancy (EE; Venkatesh et al. (2003); Venkatesh et al. (2012)): *EE1 Learning to use smart campus technologies would be easy for me. EE2 Interacting with smart campus technologies would be clear and understandable. EE3 I could become proficient in using smart campus technologies without much effort*.

Social influence (SI; Venkatesh et al. (2003); Venkatesh et al. (2012)): *SI1 Colleagues whose opinions I value would think that I should use smart campus technologies. SI2 Academic leaders whose opinions matter to me would encourage me to use smart campus technologies. SI3 People who influence my academic work would expect me to use smart campus technologies*.

Facilitating conditions (FC; Venkatesh et al. (2003); Venkatesh et al. (2012)): *FC1 I would have access to the resources needed to use smart campus technologies. FC2 Smart campus technologies*

would be compatible with the digital systems I use for my work. FC3 I would be able to obtain assistance if I encountered problems using smart campus technologies.

Knowledge generation (KG; Akhavan et al. (2012); Ramachandran et al. (2009)): *KG1 Smart campus technologies would help me develop new academic ideas by combining knowledge from different sources. KG2 Smart campus technologies would support interactions with colleagues that generate new teaching or research insights. KG3 Smart campus technologies would help me create new knowledge from academic information and experience*.

Knowledge storage and sharing (KSS; Ramachandran et al. (2009); Sangari et al. (2015)): *KSS1 Smart campus technologies would allow me to store and organise academic materials for later retrieval. KSS2 Smart campus technologies would help me share academic knowledge and experience with colleagues. KSS3 Smart campus technologies would make stored academic knowledge accessible to colleagues when they need it*.

Knowledge application (KA; Ramachandran et al. (2009); Sangari et al. (2015)): *KA1 Smart campus technologies would help me apply relevant knowledge when carrying out academic tasks. KA2 Smart campus technologies would help me use existing academic knowledge to solve work-related problems. KA3 Smart campus technologies would help me put available knowledge into practice when making academic decisions*.

Behavioural intention (BI; Venkatesh et al. (2003); Venkatesh et al. (2012)): *BI1 I intend to use smart campus technologies when they are available at my university. BI2 I plan to incorporate available smart campus technologies into my academic work. BI3 I expect to use smart campus technologies regularly when I have access to them*.

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