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Exploring Faculty and Student Perceptions and Use of Smart Learning Systems in Computing Education

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Abstract. Smart learning systems are increasingly used in higher education to facilitate student learning. However, there is little empirical evidence on how they are utilized by faculty members and students in computing courses at Saudi universities. This cross-sectional quantitative study examined perceptions of smart learning systems among 50 faculty members and 200 students using structured surveys. Faculty members at public universities reported significantly higher usage frequency but significantly lower perceived teaching effectiveness and training adequacy than those at private universities. Usage frequency correlated negatively with teaching effectiveness and training adequacy, whereas teaching effectiveness correlated strongly and positively with training adequacy. Students at private universities reported significantly higher usability, engagement, and feedback quality than students at public universities. Correlations among student constructs were positive but mostly weak. Overall, faculty and student perceptions were neutral. The findings suggest that, where use is institutionally required, frequent use does not necessarily reflect genuine acceptance, and that facilitating conditions, especially training, are strongly related to perceived usefulness. Ease of use appears necessary but not a sufficient condition for engagement, whereas feedback quality is more closely associated with it. Further research is needed to understand how smart learning systems can be meaningfully integrated.

Keywords: Smart Learning Systems; Computing Education; Faculty Development; Student Engagement; Higher Education.

1. Introduction

Smart learning systems extend conventional e-learning by using artificial intelligence, learning analytics, and adaptive technologies to create data-driven, learner-centered environments that respond to each student's context, needs, and progress (Chen et al., 2021; García-Sigüenza et al., 2026). They are expected to personalize learning, support interaction, and provide timely feedback (Čep et al., 2026; du Plooy et al., 2024; Khalifeh et al., 2026; Parusheva et al., 2023). Broadly, a smart learning system is knowledge-based software that acts as an intelligent tutor for teaching and training (Voskoglou & Salem, 2020); in the present study, the term refers to the digital learning platforms and related smart features that participants used in computing courses. The COVID-19 pandemic accelerated the adoption of such platforms (Bond et al., 2021), and in Saudi Arabia, emergency remote learning exposed weaknesses in faculty–student interaction, technical reliability, and platform usability and engagement (Almusharraf, 2024; Shaiba et al., 2023).

This study is motivated by the gap between the scale of investment in these systems and what is known about how they are actually used for teaching and learning. In line with Saudi Vision 2030, universities have invested heavily in digital infrastructure and intelligent educational technologies (Alenezi & Akour, 2023; Government of Saudi Arabia, 2016; Khan et al., 2025; Ryan, 2023), and

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institutions often require platform use. However, pedagogical use varies across institutions and programs (Sirate et al., 2026); instructors frequently use platforms for access, compliance, and content delivery rather than for their interactive and adaptive capabilities (Ramdana et al., 2026; Ubaidah et al., 2026); and Saudi faculty report insufficient training, heavy workloads, and limited pedagogical support (Aldogiher et al., 2025). International evidence likewise indicates that technology alone does not improve teaching and that its benefits depend on how instructors integrate it (Amemasor et al., 2025; Kirkwood & Price, 2014). Consequently, high levels of platform use cannot be assumed to indicate effective teaching or engaged learning. However, most studies examine faculty (Alshaie et al., 2026) or students (Abubakar et al., 2024; Kim et al., 2025) separately, so evidence on instructor adoption and on student experience is rarely available for the same systems, courses, and institutions (Simon et al., 2024). Therefore, collecting both perspectives in one design allows us to see whether faculty acceptance patterns and student experiences converge or diverge across institutions, something neither perspective can reveal alone.

This study draws on two complementary perspectives: technology acceptance theory, which explains why users adopt a technology, and student engagement theory, which explains its educational consequences. The Technology Acceptance Model (TAM) proposes that acceptance depends mainly on perceived usefulness and perceived ease of use (Davis, 1989). The Unified Theory of Acceptance and Use of Technology (UTAUT) combined previous models into four determinants: performance expectancy, effort expectancy, social influence, and facilitating conditions. It was moderated by gender, age, experience, and voluntariness of use (Venkatesh et al., 2003).

The two models have been extensively applied in higher education in areas that include learning management systems, online and mobile learning, and AI-based and smart learning platforms (Li et al., 2025; Ribeirinha et al., 2025; Xue et al., 2024; Xue et al., 2026). Performance expectancy and perceived usefulness strongly predict intention, but reviews report heterogeneity across contexts and user types, with most studies relying on student samples (Xue et al., 2024; Xue et al., 2026). Acceptance is also context-specific: habit and hedonic motivation predicted Portuguese students' intention to use generative AI (Ribeirinha et al., 2025), whereas enjoyment, usefulness, and expectation confirmation predicted Chinese students' continued use of smart learning platforms (Li et al., 2025). However, researchers often treat adoption as the endpoint of analysis rather than as a condition with consequences for learning (Sulaiman, 2024; Xue et al., 2024).

In this study, TAM and UTAUT underpin the adoption-related constructs (Table 2), and each measured construct is treated as a context-specific indicator of a theoretical concept rather than as the concept itself. For faculty, usage frequency operationalizes use behavior, the outcome variable in both models (Davis, 1989; Venkatesh et al., 2003), and was measured as how often faculty members use smart learning systems in their computing courses. Perceived teaching effectiveness refers to faculty members' judgment that smart learning systems improve their teaching (Chen et al., 2024). It is narrower than perceived usefulness, which concerns improved job performance in general (Davis, 1989), and than performance expectancy, which concerns the gains a user expects from using a system (Venkatesh et al., 2003); it is therefore used as a teaching-specific indicator of these beliefs, not as a direct measure of either. Training adequacy refers to faculty members' evaluation of whether the training they have received is sufficient for using the systems (Panda & Mishra, 2007). It represents one component of facilitating conditions, the organizational and technical resources that support use (Venkatesh et al., 2003), and does not cover other resources such as infrastructure or technical support. For students, usability refers to the perceived ease and efficiency of interacting with the system (Brooke, 1996, 2013) and corresponds to perceived ease of

use and effort expectancy. Because platform use in Saudi universities is often institutionally required, voluntariness of use matters when judging whether frequent use reflects acceptance or compliance (Ramdana et al., 2026; Sirate et al., 2026; Venkatesh et al., 2003).

Acceptance models explain why a system is adopted but not how its use relates to learning. Building on Astin's (1984) theory of student involvement, engagement is conceptualized as behavioral (participation and effort), emotional (interest and affective reactions), and cognitive (self-regulation and investment in understanding) (Fredricks et al., 2004; Wang, 2025). In this study, engagement was measured as students' composite self-reported course engagement using items adapted from Handelsman et al. (2005); the three dimensions inform interpretation but were not measured separately. Feedback quality refers to students' perceptions of the quality and usefulness of the feedback they receive through the system (Ituma, 2011). The three student constructs are conceptually ordered rather than interchangeable. Usability is an enabling condition: a difficult-to-use system limits interaction, but ease of use alone gives students no particular reason to invest effort. Feedback quality is a pedagogical feature of use that is expected to support cognitive and emotional engagement by guiding self-regulation and sustaining motivation (Fu et al., 2025; Long et al., 2026). Engagement is the learning-related outcome. Usability is therefore expected to be positively but modestly associated with engagement, and feedback quality is expected to be more closely associated. Because the educational value of AI-supported tools depends on how instructors embed them in interactive pedagogy (Long et al., 2026), and evidence for cognitive engagement remains mixed (Lo et al., 2024), the faculty constructs provide context for interpreting student perceptions; however, this study does not test a link between faculty and student constructs.

Research has established that perceived usefulness or performance expectancy, perceived ease of use or effort expectancy, and facilitating conditions predict students' intention to use learning management systems and AI-based tools (Abubakar et al., 2024; Xue et al., 2024; Xue et al., 2026). In addition, AI tools can affect behavioral, emotional, and cognitive engagement (Lo et al., 2024; Long et al., 2026). There are still three limitations. First, acceptance research usually ends at intention or use and does not examine whether use aligns with perceived teaching value or student engagement; Gulf learning management system research has focused on initial adoption rather than actual use (Sulaiman, 2024; Xue et al., 2024). Second, most studies rely on student samples, and few studies examine faculty and student experiences of the same systems within a single design, especially in computing education (Simon et al., 2024; Sulaiman, 2024). Third, while acceptance relationships differ across contexts (Xue et al., 2026), few studies from Saudi universities, where use is often mandated, provide empirical evidence (Taha, 2026). Therefore, it is unclear whether high faculty usage reflects acceptance or compliance, and how students' perceptions of usability and feedback relate to their engagement. This study addresses this gap by examining faculty usage frequency, perceived teaching effectiveness, and training adequacy alongside student-perceived usability, feedback quality, and engagement in computing courses at Saudi public and private universities.

The study aimed to achieve four specific objectives. The first objective was to describe faculty members' use of smart learning systems in computing courses. The second objective was to describe students' perceptions of these systems. The third objective was to examine differences in perceptions by demographic variables. The last objective was to examine the relationships among the constructs within each group. To achieve these objectives, the study addresses the following questions: (1) How do faculty members use and perceive smart learning systems in computing courses with respect to usage frequency, perceived teaching effectiveness, and training adequacy? (2) How do students perceive smart learning systems in computing courses with respect to usability, engagement, and feedback quality? (3) Are there significant differences in faculty and student perceptions by

demographic variables? (4) What are the relationships among the faculty constructs and among the student constructs?

2. Method

The study used a cross-sectional quantitative approach to analyze faculty and student perceptions of using smart learning systems in computing courses (Creswell, 2012). The data were collected quantitatively using a structured survey. This study was conducted at four Saudi universities (two public and two private) that had used learning management systems for more than a decade. The sample included 50 faculty members teaching computing-related courses and 200 students registered for computing-related courses during the data-gathering period. The purposive sampling method was adopted to include as many respondents as possible, with equal representation across public and private universities and computing disciplines. Table 1 shows the participants' characteristics.

Table 1. Participants Profile

Faculty			Student		
Variable	**Category**	**N (%)**	**Variable**	**Category**	**N (%)**
University Type	Public	25 (50.0)	University Type	Public	100 (50.0)
	Private	25 (50.0)		Private	100 (50.0)
Gender	Male	32 (64.0)	Gender	Male	110 (55.0)
	Female	18 (36.0)		Female	90 (45.0)
Age Group	30–39 years	20 (40.0)	Age Group	18–21 years	85 (42.5)
	40–49 years	22 (44.0)		22–25 years	95 (47.5)
	50+ years	8 (16.0)		26+ years	20 (10.0)
Academic Rank	Lecturer	13 (26.0)	Level of Study	Undergraduate	180 (90.0)
	Assistant Professor	10 (20.0)		Postgraduate	20 (10.0)
	Associate Professor	13 (26.0)	Field of Study	Computer Science	90 (45.0)
	Full Professor	14 (28.0)		Information Technology	68 (34.0)
Highest Qualification	Master's	13 (26.0)		Computer Engineering	42 (21.0)
	PhD	37 (74.0)	Mode of Learning	Face to Face	60 (30.0)
Teaching Experience	1–5 years	12 (24.0)		Blended	140 (70.0)
	6–10 years	22 (44.0)	Prior E-learning Experience	No	40 (20.0)
	>10 years	16 (32.0)		Yes	160 (80.0)
Field of Specialization	Computer Science	20 (40.0)			
	Information Technology	15 (30.0)			
	Computer Engineering	15 (30.0)			

Two structured surveys were developed for faculty members and students with three different constructs for each group. Each construct comprised five items adapted from established instruments (Table 2). Participants rated usage frequency on a five-point scale (1 = Never to 5 = Always), and rated all other items on a five-point agreement scale (1 = Strongly Disagree to 5 = Strongly Agree).

Two experts in computing education reviewed the items for alignment with the constructs and clarity of wording. The surveys were piloted with 17 faculty members and 31 students from public and private universities, who were excluded from the final samples. Cronbach's alpha exceeded .80 for all constructs (Table 2), indicating good internal consistency (Bryman, 2021; Pallant, 2020). We administered the surveys online during the first semester of the 2025 academic year. Faculty members and students in the targeted departments and programs received an invitation through their university email containing the survey link. Participation was voluntary and anonymous; respondents were informed that their responses would be used for academic research and that they could withdraw at any time.

Table 2. Reliability of the Survey

Survey	Construct	Cronbach's alpha	Source
Faculty	Usage Frequency	.89	(Venkatesh et al., 2003)
	Teaching effectiveness	.84	(Chen et al., 2024; Davis, 1989)
	Training adequacy	.85	(Panda & Mishra, 2007)
Student	Usability	.86	(Brooke,1996, 2013; Thamilarasan et al., 2023)
	Student engagement	.88	(Handelsman et al., 2005)
	Quality of feedback	.90	(Ituma, 2011)

The data were analyzed using SPSS (version 20). Descriptive statistics were used to obtain frequencies, means, and standard deviations. Pearson correlation was used to examine correlations between the study constructs. Before applying inferential statistical tests, we evaluated the assumptions of parametric analysis and found them to be met (Field, 2024; Pallant, 2020). Therefore, we used independent-samples t-tests and one-way analyses of variance to examine differences between faculty members and students across demographic variables.

3. Results

Descriptive analysis of the faculty survey responses showed that faculty generally used smart learning systems sometimes when teaching computing courses (M = 3.00, SD = .84), but reported more frequent use at public universities (Table 3). The results indicated that faculty members perceived neutral teaching effectiveness (M= 3.30, SD= .77), but positive teaching effectiveness was reported at private universities. Faculty members perceived neutral training adequacy (M = 2.88, SD = .81); although faculty members at private universities perceived higher training adequacy than those at public universities, it was still neutral. Faculty members at public universities reported using smart learning systems more frequently than those at private universities. However, faculty members at public universities reported lower mean values for perceived teaching effectiveness and training adequacy than those at private universities. Notably, professors reported using smart learning systems less frequently than faculty at other ranks. Overall, descriptive statistics indicated similar perceptions across faculty members for the study's constructs, after accounting for other demographic variables.

The descriptive analysis of student survey responses showed that students generally had neutral perceptions of the usability of smart learning systems (M = 3.28, SD = .61). However, students at private universities had more positive perceptions of usability (Table 3). Similarly, students had neutral perceptions regarding engagement (M= 3.00, SD= .57) and feedback quality (M= 3.05, SD= .63). Further, private university students had a higher level of overall perception of smart learning systems usability, engagement, and feedback quality than public university students, whose perceptions were lower for usability, engagement, and feedback quality. Generally, descriptive statistics indicated similar student perceptions of the study's constructs across demographic variables.

A series of independent samples t-tests and one-way analyses of variance were conducted to measure the difference between faculty perceptions as well as the difference between student perceptions regarding the study's constructs (Table 3) and (Table 4).

Table 3. Comparison Results of Independent Samples T-Test

Sample	Category	Construct	t	df	Sig. (2-tailed)
Faculty	University Type	Usage Frequency	5.35	48	.000

		Teaching Effectiveness	-4.35	48	.000
		Training Adequacy	-5.09	48	.000
		Usage Frequency	-.29	26.01	.774
	Gender	Teaching Effectiveness	1.08	48	.287
		Training Adequacy	.06	48	.952
		Usage Frequency	1.46	48	.152
	Highest Qualification	Teaching Effectiveness	-.88	48	.383
		Training Adequacy	-.95	48	.348
		Usability	-4.24	198	.000
	University Type	Engagement	-3.84	198	.000
		Feedback Quality	-7.64	198	.000
		Usability	-.99	198	.322
	Gender	Engagement	-1.05	198	.297
		Feedback Quality	-1.84	198	.068
		Usability	.12	198	.908
Student	Level of Study	Engagement	-.74	198	.459
		Feedback Quality	.30	198	.766
		Usability	.08	198	.940
	Mode of Learning	Engagement	-.27	198	.788
		Feedback Quality	1.37	198	.171
		Usability	-1.99	198	.048
	Prior E-learning Experience	Engagement	-.12	198	.902
		Feedback Quality	-1.09	50.38	.282

According to Table 3, the independent-samples t-test revealed p-values below .001 for the study's constructs by university type, confirming statistical differences between faculty members and indicating that faculty members at public universities reported significantly higher usage frequency. In contrast, faculty members at private universities reported higher perceptions of teaching effectiveness and training adequacy. However, Tables 3 and 4 showed no statistically significant differences in faculty members' perceptions by gender, qualification, age, academic rank, teaching experience, or specialization.

According to Table 3, the independent-samples t-test revealed p-values below .001 for the study's constructs, indicating that students in private universities reported significantly higher perceptions of smart learning system usability, engagement, and feedback quality than those in public universities. In addition, students with prior e-learning experience reported significantly higher perceptions of smart learning system usability than those with no prior e-learning experience. However, Table 3 and Table 4 revealed that no statistically significant difference was detected for student perceptions based on gender, level of study, mode of learning, and field of study.

In addition, a series of one-way analyses of variance were conducted to measure the difference between faculty members' perceptions regarding the study's constructs based on age, academic rank, teaching experience, and specialization, as well as the difference between student perceptions regarding the study's constructs based on field of study (Table 4).

Table 4. Comparison Results of One-Way Analysis of Variance

Sample	Category	Construct	F	df (B.G, W.G)	Sig.
		Usage Frequency	.72	(2, 47)	.490
	Age (Years	Teaching Effectiveness	.91	(2, 47)	.410
		Training Adequacy	.77	(2, 47)	.469
Faculty		Usage Frequency	2.51	(3, 46)	.070
	Academic Rank	Teaching Effectiveness	1.27	(3, 46)	.295
		Training Adequacy	.59	(3, 46)	.626
	Teaching Experience by Years	Usage Frequency	1.68	(2, 47)	.197

		Teaching Effectiveness	1.89	(2, 47)	.162
		Training Adequacy	2.77	(2, 47)	.073
		Usage Frequency	.75	(2, 47)	.479
	Field of Specialization	Teaching Effectiveness	.96	(2, 47)	.390
		Training Adequacy	.27	(2, 47)	.761
		Usability	1.60	(2, 197)	.205
Student	Field of Study	Engagement	.02	(2, 197)	.979
		Feedback Quality	.18	(2, 197)	.832

A correlation analysis of the relationships between the faculty survey constructs and between the student survey constructs was conducted. For faculty, the results indicated a negative, significant relationship between frequency of use and perceived teaching effectiveness ($r = -.46$, $p < .01$), suggesting a moderate relationship. Frequency of use was negatively and significantly related to training adequacy ($r = -.55$, $p < .01$), suggesting a strong relationship. However, perceived teaching effectiveness was positively and significantly related to training adequacy ($r = .70$, $p < .01$), suggesting a strong relationship. For students, the results indicated positive and significant relationships among the three major variables. Remarkably, the correlation between usability and engagement was $r = .25$, $p < .01$. The correlation between usability and feedback was $r = .23$, $p < .01$. The correlation between engagement and feedback was $r = .30$, $p < .01$. These relationships were considered weak and moderate based on Cohen's (1988) criteria.

4. Discussion

Faculty Usage of Smart Learning Systems

Faculty perceptions were neutral overall, but university type produced an inverse pattern: faculty at public universities reported more frequent use yet lower perceived teaching effectiveness and training adequacy than their private-university counterparts. The data establish this pattern but not its causes. One plausible explanation is that institutional requirements drive use more strongly at public universities, so frequency reflects compliance rather than perceived value. However, the study did not measure institutional requirements or voluntariness. Hence, this explanation remains a hypothesis, and unmeasured differences such as class size, workload, platform type, or training content could produce the same pattern. The data do show that, in this sample, the group that used the systems most also valued them least and felt least prepared to use them.

This pattern is inconsistent with the positive usefulness-use relationship predicted by acceptance models, and generally supported by meta-analytic evidence (Xue et al., 2026). The departure is informative rather than anomalous. Most acceptance studies have examined voluntary student use (Xue et al., 2024), but our sample consisted of faculty members at institutions where platform use is often expected. Under these conditions, usage frequency may no longer indicate acceptance, a situation UTAUT recognizes but rarely explores in Gulf research (Sulaiman, 2024). The pattern of private universities- less frequent use but higher perceived teaching effectiveness and training adequacy- is consistent with selective, purpose-driven use. However, frequency data cannot tell how the systems were actually used.

Regarding the relationship among the faculty constructs, training adequacy was strongly and positively associated with perceived teaching effectiveness, whereas usage frequency was negatively associated with both. This positive association aligns with Long et al.'s (2026) review, which concluded that the benefits of AI-supported tools depend on instructors' competence in active pedagogies, and with Amemasor et al.'s (2025) review, which linked professional development to digital instructional integration. However, unlike the intervention and longitudinal evidence summarised in those reviews, the present data come from a single time point, so the direction of the

relationship cannot be determined: adequately trained faculty may perceive greater teaching value, or faculty who value the systems may seek more training and rate it more favorably. Mekheimer (2025) found that training focused on operational skills had little effect on instructional quality; because training content was not measured, it cannot be determined whether faculty in this sample received similarly technical training. The negative associations with usage frequency largely reflect the university-type difference and should not be interpreted as evidence that more use harms teaching.

Taken together, the faculty findings suggest that usage frequency alone is a weak indicator of pedagogically meaningful adoption where use may be expected, and that perceived training adequacy is closely tied to faculty members' judgments of the value of teaching. These conclusions concern perceptions and associations; whether they correspond to differences in actual teaching practice requires evidence from observation or analytics.

Student Usage of Smart Learning Systems

Student perceptions of usability, engagement, and feedback quality were neutral, with engagement and feedback quality rated slightly lower than usability. Students found the systems reasonably usable but not strongly engaging or particularly useful for feedback. Unlike acceptance studies of smart and AI-supported platforms (Kim et al., 2025; Li et al., 2025), this profile highlights perceptions of the learning experience in required courses rather than adoption intention or continued use. It is more similar to Almusharraf's (2024) study of Saudi students, which identified shortcomings in learning management system usability and engagement. Because engagement was measured as a composite, the interpretation that the systems support behavioral participation more than emotional or cognitive engagement (Lo et al., 2024) remains tentative.

Private university students rated usability, engagement, and feedback quality significantly higher than public university students, with the largest difference in feedback quality. The data do not explain why. Possible reasons may include differences in platforms or features adopted, the way instructors configured and used feedback tools, or class size, none of which were measured. Faculty at private universities also reported higher perceived teaching effectiveness and training adequacy. This correspondence reflects a pattern at the university-type level; because faculty and student responses were not linked and only two universities of each type were included, it cannot be interpreted as evidence that faculty training or teaching effectiveness caused higher student engagement. It is consistent with reviews proposing that teaching methods shape the effect of AI tools on engagement (Long et al., 2026), and it identifies a relationship that linked, multilevel designs should test.

Students with prior e-learning experience rated usability significantly higher than those without such experience, although the difference was marginal ($p = .048$) and should be interpreted cautiously. This finding aligns with Chen and Senatorova (2024), who found that prior online learning experience shaped students' learning under emergency remote teaching, and with Alanoglu et al. (2026), who found that digital literacy predicted online learning readiness; it is also consistent with the moderating role of experience in UTAUT. However, compared with those studies, this finding applied only to perceived ease of use; prior experience was not related to engagement or feedback quality. Thus, familiarity appears to facilitate use but does not necessarily promote engagement in learning.

Among the student constructs, they were positively correlated, ranging from weak to moderate. Feedback quality was most strongly related to engagement ($r = .30$), and usability was less strongly related ($r = .25$); the difference between these coefficients is small and was not tested, so it should not be overstated. Nevertheless, the pattern is consistent with the ordering proposed in

the theoretical framework, where usability enables interaction and feedback quality is more closely related to engagement. This finding aligns with Abubakar et al. (2024), who found that perceived ease of use did not predict Saudi students' intention to use a learning management system, and Martin and Bolliger (2018), whose students reported that instructor-to-student engagement strategies were particularly important. The weak correlations also suggest that perceptions of the system explain little variation in engagement.

Integrating TAM/UTAUT and student engagement theory helps clarify each perspective's unique contributions. Acceptance constructs describe whether systems are usable and adopted, while engagement theory asks if use is associated with students' investment in learning. Here, the two do not quite coincide, as reasonably usable systems were accompanied only by neutral engagement. Because these relationships are bivariate correlations of self-reported perceptions, this combined reading generates hypotheses, not a confirmed model.

The survey results have some direct implications. First, because usage frequency was negatively associated with perceived teaching effectiveness and training adequacy, universities should not use platform use frequency as their main indicator of successful digital transformation; indicators of pedagogical use, such as feedback and interactive features, would be more informative. Second, because training adequacy strongly correlated with perceived teaching effectiveness and was rated lowest in public universities, it is justified to prioritize reviewing faculty training adequacy, particularly in public universities. Third, feedback quality was most closely related to engagement and showed the largest public-private difference; thus, instructors and course designers should pay special attention to the feedback functions of smart learning systems.

Other recommendations require further investigation. The data do not show which training type is effective, whether pedagogically oriented training would raise student engagement, or why public and private universities differ. Therefore, redesigning training around active learning and feedback design (Amemasor et al., 2025; Long et al., 2026) is a reasonable proposal to test, not a conclusion of this study.

Future research should (a) use longitudinal or intervention designs to establish the direction of relationships among training, perceived effectiveness, and use; (b) link faculty and student records, where ethically possible, and apply multilevel or structural equation modeling to test the institutional pattern observed here; (c) measure the behavioral, emotional, and cognitive dimensions of engagement separately; (d) include objective indicators such as learning analytics and performance data; and (e) use probability sampling across more institutions, compare specific platforms, and measure voluntariness of use and training content directly.

Several limitations should be considered when interpreting the findings. First, the cross-sectional design captured perceptions at a single point in one semester, so the direction of relationships and change over time cannot be established. Second, all measures were self-reported; the findings reflect perceptions rather than objective teaching performance or learning outcomes and may be affected by social desirability and common-method bias. Third, purposive sampling was used, and no a priori sample size calculation was performed; the samples, particularly the faculty members, are small and not representative, which limits statistical power and generalizability. Fourth, institutional coverage was limited to four universities and computing-related courses so that university-type differences may reflect institutional characteristics, such as platforms, policies, and implementation practices, rather than general public-versus-private differences. Fifth, faculty and student data were not linked at the individual or course level, so we could describe correspondence between faculty and student patterns only at the university-type level and could not test it as a causal or mediating relationship. Finally, engagement was measured

as a single composite construct, so interpretations concerning its dimensions are tentative. Despite these limitations, the study provides baseline evidence on smart learning systems use in Saudi computing education and a basis for longitudinal and linked research.

5. Conclusion

This study examined faculty and student perceptions and use of smart learning systems in computing courses at four Saudi universities. Three findings are particularly notable. First, public university faculty reported higher usage frequency of these systems but lower perceived teaching effectiveness and training adequacy than private university faculty, and usage frequency was negatively associated with both constructs. Second, perceived training adequacy was strongly and positively associated with perceived teaching effectiveness. Third, students' perceptions of usability, engagement, and feedback quality were, on average, neutral and higher at private universities, and the student constructs were only weakly to moderately interrelated.

The study's contribution is primarily empirical and contextual: it provides dual-perspective evidence from faculty and students in an under-researched setting where platform use is often institutionally required, and it shows that frequency of use and perceived teaching value need not coincide. Because the study measured perceptions and associations, it cannot establish that smart learning systems, training, or teaching practices improve student engagement. Instead, the findings suggest that frequency of use alone does not capture meaningful adoption and that training and feedback warrant closer investigation using causal designs.

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