

FROM PERCEPTIONS to INTENTIONS: THE MEDIATING ROLE of ATTITUDE in E-LEARNING TECHNOLOGY ACCEPTANCE among UNIVERSITY EMPLOYEES in LIBYA

Emhemad Alarabi Ibrahim Altaher^{1*}, Nahg A. Alawi², Khairi Ahmed R. Masaud³

¹IQRA Business School, Universiti Geomatika Malaysia, Kuala Lumpur, Malaysia, emhemadalarabi34@gmail.com

²IQRA Business School, Universiti Geomatika Malaysia, Kuala Lumpur, Malaysia, dr.nahg@geomatika.edu.my

*Corresponding Author's E-mail: emhemadalarabi34@gmail.com

Abstract: *E-learning in Libyan universities has expanded since the COVID-19 disruption, yet little is known about why staff accept or resist it. This study tests whether the two core beliefs of the Technology Acceptance Model (TAM), perceived usefulness (PU) and perceived ease of use (PEOU), shape employees' intention to use e-learning technology directly, or indirectly through their attitude. A cross-sectional survey was completed by 365 academic and administrative employees of the University of Tripoli between January and June 2026. The model was estimated with partial least squares structural equation modelling (PLS-SEM) and bootstrapping in SmartPLS. PEOU ($\beta = 0.410$) had a stronger effect on attitude than PU ($\beta = 0.241$), and together they explained 37.8% of the variance in attitude. Attitude was the strongest predictor of intention ($\beta = 0.486$; $f^2 = 0.264$). PU ($\beta = 0.182$) and PEOU ($\beta = 0.157$) also affected intention directly. Attitude partially mediated both relationships, with a larger indirect effect for PEOU (0.199) than for PU (0.117). The model explained 59.2% of the variance in intention. The study examines university employees rather than students in a fragile, post-conflict North African setting. It shows that ease of use, not usefulness, is the main route to favourable attitudes in a low-infrastructure context, and that attitude remains a necessary construct in TAM when adoption is institutionally encouraged but not yet routine.*

Keywords: technology acceptance model; perceived ease of use; attitude; e-learning; higher education employees; Libya.

1. Introduction

E-learning has moved from the margins of higher education to its core. The COVID-19 closures of 2020 forced universities worldwide into emergency remote teaching, and many institutions have since tried to turn that improvised response into planned, sustained online and blended provision (Dhawan, 2020; Hodges et al., 2020). For universities in developing and conflict-affected countries, the shift carries particular weight. E-learning promises continuity when campuses close, wider access to scarce teaching expertise, and more efficient administration. It also depends on people who must decide, day after day, whether to use the systems their institutions provide. Libya illustrates both the promise and the difficulty. Its public university system, concentrated in Tripoli, Benghazi, Misrata, Ajdabiya and Al-Bayda, has operated through more than a decade of political division, intermittent armed conflict, power cuts and weak internet infrastructure (Rhema & Miliszewska, 2012; Ghawail et al., 2021). Earlier studies argued that e-learning could help post-crisis countries rebuild their higher education

systems (Rhema & Miliszewska, 2012). Yet the same studies, and more recent reviews, report low readiness, limited training and uneven institutional support as persistent barriers (Ghawail et al., 2021; Awgheda & Radwan, 2022; Badi & Noor, 2024). Technology alone has not produced adoption; the human side of acceptance remains poorly understood.

The Technology Acceptance Model (TAM) offers a parsimonious account of that human side (Davis, 1989; Davis et al., 1989). It proposes that two beliefs, perceived usefulness (PU) and perceived ease of use (PEOU), shape a person's attitude toward a technology, and that attitude and usefulness together drive the intention to use it. TAM has been tested in thousands of studies and remains the most frequently used framework in educational technology research (King & He, 2006; Granić & Marangunić, 2019; Scherer et al., 2019). Two features of that literature, however, motivate the present study. First, the attitude construct has had an uneven history. Davis et al. (1989) found that attitude only partially mediated the effect of usefulness on intention, and later versions of the model, including TAM2 and the Unified Theory of Acceptance and Use of Technology (UTAUT), dropped attitude altogether (Venkatesh & Davis, 2000; Venkatesh et al., 2003). Other scholars have argued that this omission was premature, especially in voluntary or early-stage adoption settings where affective evaluations still guide behaviour (Yang & Yoo, 2004; Kim & Malhotra, 2005). Whether attitude matters therefore appears to depend on context, and the contexts in which it has been tested are overwhelmingly high-income or upper-middle-income ones. Second, most e-learning acceptance studies examine students (Šumak et al., 2011; Abdullah & Ward, 2016; Salloum et al., 2019). Faculty and administrative staff receive far less attention, even though they design courses, operate learning platforms, process records and set the example students follow. In Libya the few available studies focus on students or on specific groups such as English-language lecturers (Rhema & Miliszewska, 2014; Badi & Noor, 2024). No study, to our knowledge, has tested TAM's full attitudinal pathway among both academic and administrative employees of a Libyan public university. This study addresses these gaps. Using survey data from 365 employees of the University of Tripoli, Libya's largest and oldest public university, it asks three questions:

How strongly do perceived usefulness and perceived ease of use shape employees' attitude toward e-learning technology? Do perceived usefulness and perceived ease of use influence the intention to use e-learning technology directly? Does attitude mediate the effects of perceived usefulness and perceived ease of use on intention, and which of the two beliefs travels more strongly through attitude? The study makes three contributions. Theoretically, it shows that attitude is not redundant in TAM when adoption is institutionally encouraged but still discretionary: attitude carried the largest single effect on intention and transmitted a substantial share of both beliefs' influence. Contextually, it finds that ease of use rather than usefulness is the dominant route to favourable attitudes, a reversal of the pattern common in high-infrastructure settings that we attribute to the effort costs of using technology in a fragile environment. Practically, it gives Libyan university leaders an evidence-based order of priorities: make systems easy to use first, and build positive attitudes through experience and demonstration rather than through claims of usefulness alone. The remainder of the paper is organised as follows. Section 2 reviews the literature and develops the hypotheses. Section 3 describes the method. Section 4 reports the results. Section 5 discusses the findings, and Section 6 concludes with implications, limitations and directions for future research.

1.1 Literature review and hypotheses development

1.2 E-learning in Libyan higher education

E-learning refers to the use of digital technologies, typically learning management systems, video platforms and online assessment tools, to deliver, support and administer teaching and learning. For university employees it covers two overlapping activities: academic staff use it to teach and assess,

while administrative staff use the same platforms to register students, manage records, communicate and process examinations. Both groups therefore shape whether e-learning becomes part of institutional routine. Libya's 29 public universities entered the pandemic with limited digital foundations. Studies describe unreliable electricity and connectivity, shortages of devices, little formal training and an absence of clear national policy for online education (Rhema & Miliszewska, 2012; Ghawail et al., 2021). Political division has further weakened central coordination and investment in academic infrastructure (Awgheda & Radwan, 2022). A recent systematic review of e-learning acceptance among Libyan university lecturers concluded that most available studies were descriptive, relied on small samples and rarely tested established acceptance models (Badi & Noor, 2024). These conditions make Libya a demanding test of whether TAM's relationships hold where the effort of using technology is unusually high.

1.3 The Technology Acceptance Model

TAM was adapted from the Theory of Reasoned Action (Fishbein & Ajzen, 1975) to explain information system use (Davis, 1989; Davis et al., 1989). It holds that behavioural intention is the proximal cause of use, and that intention is determined by attitude toward using the system and by perceived usefulness. Attitude, in turn, is determined by perceived usefulness and perceived ease of use, and ease of use also increases perceived usefulness. Perceived usefulness is the degree to which a person believes that using a system would enhance his or her job performance (Davis, 1989). For university employees it captures whether e-learning helps them teach, process work faster or serve students better. Perceived ease of use is the degree to which a person believes that using a system would be free of effort (Davis, 1989). It reflects the clarity of the interface, the ease of learning the system and the flexibility with which it fits daily tasks. Attitude is the person's overall positive or negative evaluation of using the technology (Fishbein & Ajzen, 1975). Behavioural intention is the person's stated readiness to use the technology in the future (Davis et al., 1989). Meta-analyses confirm that the core TAM relationships are robust across technologies and user groups, although their strength varies with context (King & He, 2006; Schepers & Wetzels, 2007). In education specifically, a meta-analytic structural equation model of 114 studies of teachers found that usefulness and ease of use both predicted attitude and intention, and that attitude mediated a meaningful part of their effects (Scherer et al., 2019). Teo (2009) reported a similar structure among pre-service teachers.

1.4 The contested role of attitude

Attitude was part of the original TAM but was removed in later work. Davis et al. (1989) observed that usefulness influenced intention partly independently of attitude, which suggested that people might use a useful system even without liking it. Venkatesh and Davis (2000) omitted attitude from TAM2, and UTAUT did not include it among its core determinants (Venkatesh et al., 2003). The resulting parsimony came at a cost. Several studies have shown that attitude carries unique explanatory power, particularly when use is voluntary, when users have limited experience or when affective reactions to technology are strong (Taylor & Todd, 1995; Yang & Yoo, 2004; Kim & Malhotra, 2005). Theory from social psychology supports this view. Attitudes summarise beliefs into a single evaluative judgement that guides intention, particularly when a behaviour is new and people rely on general evaluations rather than habit (Ajzen, 1991; Glasman & Albarracín, 2006). In a setting such as Libyan universities, where e-learning is encouraged but not yet embedded in routine, employees' overall evaluation of the technology is likely to remain an important link between what they believe about the system and what they intend to do.

1.5 Hypotheses development

Perceived usefulness and attitude. Employees who believe e-learning improves their performance, productivity and effectiveness should evaluate it more favourably. This expectancy-value logic is central to TAM (Davis et al., 1989) and has been supported for teachers and university staff (Teo, 2009; Scherer et al., 2019). In Libya, where teaching and administrative workloads have been disrupted by closures, systems that save time or keep work moving are likely to be valued. H1. Perceived usefulness has a positive effect on employees' attitude toward e-learning technology. Perceived ease of use and attitude. Effort is a cost. When a system is easy to learn, clear to navigate and flexible, employees experience fewer frustrations and more sense of control, which should translate into a more favourable evaluation (Davis, 1989). Ease of use may matter even more where infrastructure is weak, because each additional difficulty with the system adds to difficulties that already exist with power and connectivity. Studies of e-learning users in developing countries report that ease of use is a strong predictor of attitude (Tarhini et al., 2014; Abdullah & Ward, 2016).

H2. Perceived ease of use has a positive effect on employees' attitude toward e-learning technology. Direct effects on intention. TAM predicts that usefulness also affects intention directly, because people form intentions toward behaviours they believe will improve their performance, even without strong positive affect (Davis et al., 1989; Venkatesh & Davis, 2000). UTAUT's equivalent construct, performance expectancy, is the strongest predictor of intention across its validation studies (Venkatesh et al., 2003). Ease of use may also influence intention directly: effort expectancy is a core UTAUT determinant, and its effect is typically strongest in early stages of adoption (Venkatesh et al., 2003). Meta-analyses of e-learning acceptance confirm direct effects of both beliefs on intention (Šumak et al., 2011). H3. Perceived usefulness has a positive effect on employees' intention to use e-learning technology. H4. Perceived ease of use has a positive effect on employees' intention to use e-learning technology. Attitude and intention. Attitude is the most proximal antecedent of intention in the Theory of Reasoned Action and in the original TAM (Fishbein & Ajzen, 1975; Davis et al., 1989). Employees who view e-learning as a good, enjoyable and desirable way of working should be more willing to use it regularly and recommend it to colleagues. Evidence from educational settings consistently shows a strong attitude-intention link (Teo, 2009; Scherer et al., 2019).

H5. Attitude toward e-learning technology has a positive effect on employees' intention to use it. The mediating role of attitude. If usefulness and ease of use shape attitude (H1, H2), and attitude shapes intention (H5), then part of each belief's influence on intention should travel through attitude. Beliefs about a system produce an evaluative response, and it is this evaluation that motivates a behavioural commitment (Fishbein & Ajzen, 1975; Yang & Yoo, 2004). Because direct effects are also expected (H3, H4), mediation is expected to be partial rather than full. H6a. Attitude toward e-learning technology mediates the relationship between perceived usefulness and intention to use. H6b. Attitude toward e-learning technology mediates the relationship between perceived ease of use and intention to use. Figure 1 summarises the research model. Employees' experience with e-learning technology was included in the estimated model as a predictor of intention to control for differences in familiarity; its role as a moderator is examined in a companion study and is not hypothesised here.

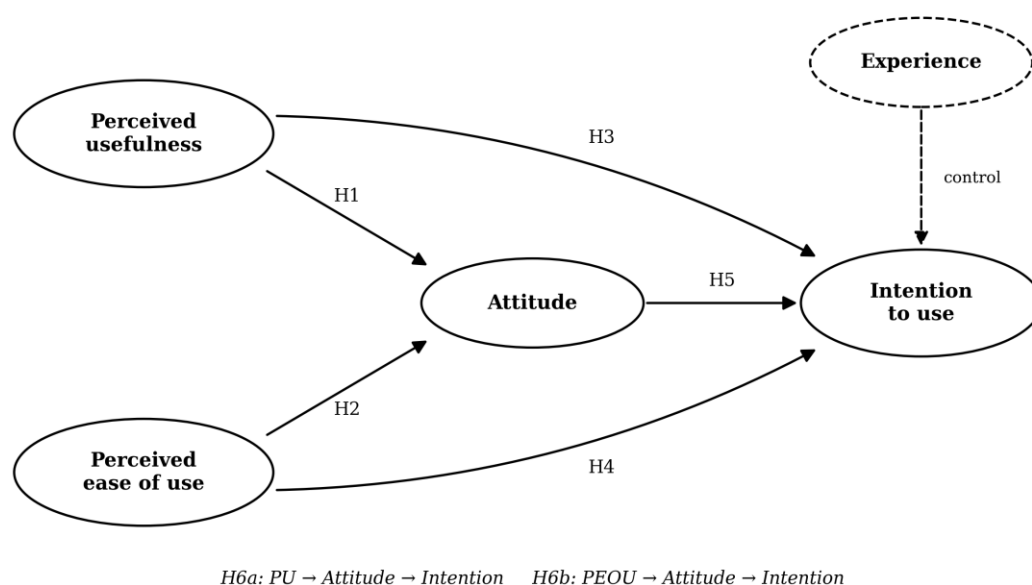


Figure 1. Research model. Solid arrows show the hypothesised direct paths (H1–H5); H6a and H6b are the indirect paths through attitude. The dashed arrow shows experience entered as a control variable.

2. Methodology

2.1 Research design and setting

The study followed a positivist, deductive design and used a cross-sectional survey to test the hypothesised relationships. The unit of analysis was the individual university employee. The research was conducted at the University of Tripoli, selected from Libya's public universities on three criteria: size, measured by student enrolment; stability of the political situation and continuity of teaching in the host city over at least the preceding three years; and age, taken as a proxy for the depth of academic, digital and financial infrastructure. Focusing on a single institution produced a more homogeneous sample and reduced confounding from differences in platforms and policies across universities (Sekaran & Bougie, 2016).

2.2 Population and sample

According to records obtained from the university, the target population comprised 9,314 employees: 3,634 faculty members and 5,680 administrative staff. Using the table of Krejcie and Morgan (1970), the required sample for a population of this size is 365. Because no complete list of employees was available to the researcher, convenience sampling was used. Employees who agreed to participate received an email containing a link to the online questionnaire. The form accepted only one response per respondent and required every item to be answered, so there were no missing values. Data were collected between January and June 2026, and 365 usable responses were obtained.

2.3 Measures

All constructs were measured with multi-item scales adapted from prior studies and worded for the e-learning context of university employees. Responses were recorded on a five-point Likert scale from 1 (strongly disagree) to 5 (strongly agree). Perceived usefulness and perceived ease of use were

each measured with five items adapted from Asif (2024), building on Davis (1989) and Natarajan et al. (2018). Attitude toward e-learning technology and intention to use were each measured with five items adapted from Xu et al. (2024). Experience, used as a control variable in this paper, was measured with five items capturing the extent, frequency and confidence of prior e-learning use, adapted from Lwoga et al. (2013). Table 1 lists the items.

Table 1. Measurement items

Construct	Code	Item
Perceived usefulness (PU)	PU1	Using the e-learning system improves my job performance.
	PU2	The e-learning system increases my work productivity.
	PU3	The e-learning system enhances my effectiveness in professional tasks.
	PU4	Using the system saves me the time needed to complete my duties.
	PU5	The system provides useful functions that fulfil my responsibilities.
Perceived ease of use (PEOU)	PEOU1	It is easy for me to learn how to use the e-learning platform.
	PEOU2	Interaction with the system is clear and easy to understand.
	PEOU3	I find the system flexible to use according to my needs.
	PEOU4	I can quickly develop my skills to use the system effectively.
	PEOU5	Navigating the system is easy and straightforward.
Attitude (ATT)	ATT1	I have a positive attitude toward using e-learning in my work.
	ATT2	Using e-learning is useful and effective for my professional tasks.
	ATT3	I like the idea of integrating e-learning into my daily routine.
	ATT4	E-learning represents a good approach to my workplace activities.
	ATT5	I find using e-learning systems an enjoyable experience.
Intention to use (INT)	INT1	I intend to use e-learning regularly in my professional role.
	INT2	I plan to continue using e-learning systems in the future.
	INT3	I want to adopt new features and updates of e-learning tools.
	INT4	I recommend my colleagues to use e-learning.
	INT5	I expect to use e-learning platforms frequently in my tasks.
Experience (EXP)	EXP1	I have extensive experience in using e-learning systems in my work.
	EXP2	I frequently use digital learning platforms in professional tasks.
	EXP3	I am confident in my ability to use e-learning technologies effectively.
	EXP4	My previous experience helps me to deal efficiently with e-learning systems.
	EXP5	I have sufficient experience in using e-learning tools to handle new tasks easily.

2.4 Content validity and pilot test

The questionnaire was reviewed in two stages. First, a panel of five academics judged whether each item matched the definition of its construct and was free of ambiguity and redundancy. Wording was revised in line with their comments. Second, the revised instrument was piloted with 20 employees of Libyan public universities, who were excluded from the main sample. Cronbach's alpha values in the pilot were 0.905 for perceived usefulness, 0.860 for perceived ease of use, 0.885 for attitude, 0.900 for intention and 0.799 for experience, all above the 0.70 threshold (Hair et al., 2017).

2.5 Data screening

No cases were missing. Standardised z-scores for all 25 items fell within ± 3.29 , indicating no univariate outliers (Tabachnick & Fidell, 2007). Item means ranged from 3.54 to 4.07 on the five-point scale. Skewness exceeded ± 2 for one item and kurtosis exceeded ± 2 for three items, so the data departed from multivariate normality. This supported the choice of a non-parametric, variance-based estimation method.

2.6 Analytical approach

The model was estimated using partial least squares structural equation modelling (PLS-SEM) in SmartPLS 3 (Ringle et al., 2015). PLS-SEM was appropriate because the study's aim was to explain and predict variance in key target constructs, the data were non-normal, and the model included mediating relationships (Hair et al., 2019). Following Hair et al. (2017), the analysis proceeded in two stages. The measurement model was assessed for indicator reliability, internal consistency, convergent validity and discriminant validity. The structural model was then assessed for collinearity, explanatory power (R^2), effect size (f^2), predictive relevance (Q^2) and the significance of path coefficients, obtained through bootstrapping. Indirect effects were tested by bootstrapping the product of the component paths, and mediation was classified following Zhao et al. (2010).

3. Results

3.1 Respondent profile

Of the 365 respondents, 54.0% were women and 46.0% men. Most were aged 31 to 40 (52.3%). Administrative staff made up 60.0% of the sample and faculty members 40.0%, roughly matching their shares in the university workforce (61.0% and 39.0%). Most respondents were regular users: 54.8% used e-learning platforms four or more times a month, and 73.7% reported four or more years of experience with e-learning technology. Table 2 gives the full profile.

Table 2. Respondent profile (N = 365)

Characteristic	Category	n	%
Gender	Female	197	54.0
	Male	168	46.0
Age	26–30	62	17.0
	31–35	98	26.8
	36–40	93	25.5
	41–45	58	15.9
	46–50	39	10.7
	Over 50	15	4.1
Position	Administrative staff	219	60.0
	Faculty member	146	40.0
Monthly use of e-learning platforms	Once	31	8.5
	Twice	54	14.8
	Three times	80	21.9
	Four times	88	24.1
	Five times	65	17.8

Characteristic	Category	n	%
	More than five times	47	12.9
Experience with e-learning	Less than 1 year	25	6.8
	1–3 years	71	19.5
	4–7 years	135	37.0
	8–10 years	84	23.0
	More than 10 years	50	13.7

3.2 Measurement model

All indicator loadings exceeded 0.70, ranging from 0.703 to 0.815 (Table 3). Cronbach's alpha ranged from 0.733 to 0.847 and composite reliability from 0.823 to 0.891, above the 0.70 threshold for internal consistency. Average variance extracted (AVE) ranged from 0.532 to 0.620, above 0.50, confirming convergent validity (Fornell & Larcker, 1981; Hair et al., 2019).

Table 3. Reliability and convergent validity

Construct	Loadings (range)	Cronbach's α	Composite reliability	AVE
Perceived usefulness	0.758–0.811	0.847	0.891	0.620
Perceived ease of use	0.706–0.815	0.828	0.879	0.592
Attitude	0.719–0.737	0.780	0.850	0.532
Intention to use	0.703–0.798	0.733	0.823	0.583
Experience	0.714–0.790	0.790	0.856	0.544

Discriminant validity was assessed with three criteria. Under the Fornell-Larcker criterion, the square root of each construct's AVE exceeded its correlations with the other constructs. Every item loaded more highly on its own construct than on any other. Finally, all heterotrait-monotrait (HTMT) ratios were below the conservative 0.85 threshold, the highest being 0.745 between ease of use and intention (Table 4; Henseler et al., 2015). The measurement model was therefore reliable and valid.

Table 4. Discriminant validity: heterotrait-monotrait ratios (HTMT)

Construct	PU	PEOU	ATT	INT	EXP
Perceived usefulness (PU)	—				
Perceived ease of use (PEOU)	0.517	—			
Attitude (ATT)	0.679	0.737	—		
Intention to use (INT)	0.643	0.745	0.643	—	
Experience (EXP)	0.528	0.617	0.658	0.564	—

3.3 Structural model

Inner variance inflation factors ranged from 2.190 to 2.953, below the threshold of 3.3 to 5, so collinearity among predictors was not a concern (Hair et al., 2019). The standardised root mean square residual (SRMR) was 0.077 for the estimated model, below the 0.08 threshold commonly used in PLS-SEM (Hu & Bentler, 1999; Henseler et al., 2015). The model explained 37.8% of the variance in attitude (adjusted $R^2 = 0.375$) and 59.2% of the variance in intention (adjusted $R^2 = 0.586$).

Following Hair et al. (2019), these represent weak-to-moderate and moderate explanatory power respectively; by Cohen's (1988) criteria for the behavioural sciences, both are large. Blindfolding produced cross-validated redundancy (Q^2) values of 0.420 for attitude and 0.209 for intention, both above zero, indicating predictive relevance (Stone, 1974; Geisser, 1974).

Table 5 reports the direct paths. All five hypothesised direct effects were positive and significant. Perceived ease of use had a stronger effect on attitude ($\beta = 0.410$, $t = 5.502$, $p < 0.001$) than perceived usefulness ($\beta = 0.241$, $t = 3.482$, $p = 0.001$), supporting H1 and H2. Perceived usefulness ($\beta = 0.182$, $t = 2.515$, $p = 0.021$) and perceived ease of use ($\beta = 0.157$, $t = 2.178$, $p = 0.029$) had smaller direct effects on intention, supporting H3 and H4. Attitude had the strongest effect in the model ($\beta = 0.486$, $t = 7.444$, $p < 0.001$), supporting H5.

Table 5. Direct effects

Hypothesis	Path	β	SD	t	p	f^2	Decision
H1	PU $\rightarrow$ ATT	0.241	0.069	3.482	0.001	0.038	Supported
H2	PEOU $\rightarrow$ ATT	0.410	0.075	5.502	< 0.001	0.111	Supported
H3	PU $\rightarrow$ INT	0.182	0.072	2.515	0.021	0.001	Supported
H4	PEOU $\rightarrow$ INT	0.157	0.072	2.178	0.029	0.020	Supported
H5	ATT $\rightarrow$ INT	0.486	0.065	7.444	< 0.001	0.264	Supported

Note: SD = bootstrap standard deviation. f^2 values of 0.02, 0.15 and 0.35 indicate small, medium and large effects (Cohen, 1988). Experience was included as a control predictor of intention ($f^2 = 0.066$). Figure 2 summarises the estimated structural model.

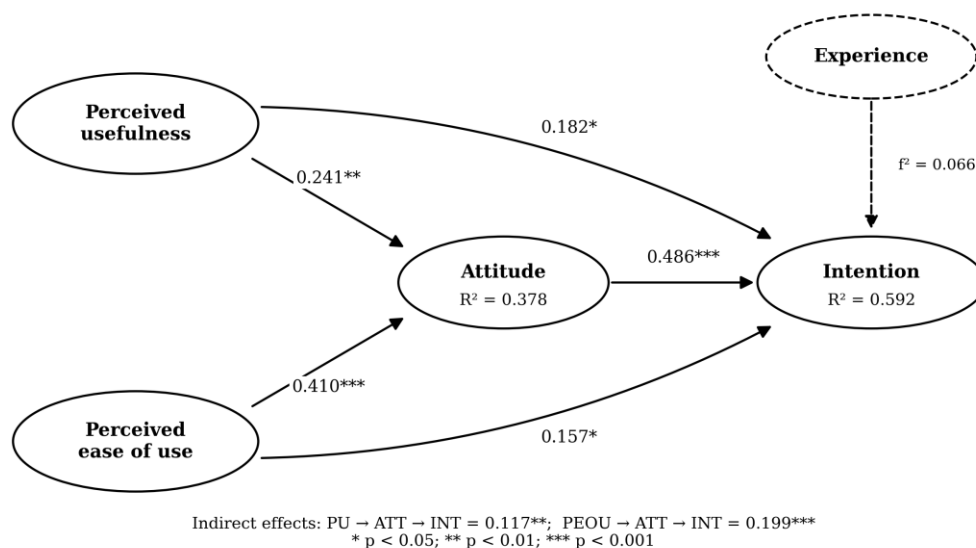


Figure 2. Structural model results: standardised path coefficients and explained variance (R^2). $p < 0.05$; $p < 0.01$; $p < 0.001$.

Effect sizes showed a clear ordering. Attitude made a medium contribution to intention ($f^2 = 0.264$), while ease of use made a small-to-medium contribution to attitude ($f^2 = 0.111$), roughly three times that of usefulness ($f^2 = 0.038$). The unique direct contributions of ease of use ($f^2 = 0.020$) and

usefulness ($f^2 = 0.001$) to intention were small or negligible once attitude was in the model, suggesting that most of their influence on intention is carried through attitude.

3.4 Mediation analysis

Both indirect effects were positive and significant (Table 6). The indirect effect of ease of use on intention through attitude was 0.199 ($t = 4.591$, $p < 0.001$), and that of usefulness was 0.117 ($t = 3.149$, $p = 0.002$). Because the corresponding direct effects were also significant and of the same sign, attitude acted as a complementary, partial mediator in both relationships (Zhao et al., 2010). H6a and H6b were supported.

Table 6. Indirect effects through attitude

Hypothesis	Indirect path	β	SD	t	p	Direct effect	Mediation type
H6a	PU $\rightarrow$ ATT $\rightarrow$ INT	0.117	0.037	3.149	0.002	0.182	Complementary (partial)
H6b	PEOU $\rightarrow$ ATT $\rightarrow$ INT	0.199	0.043	4.591	< 0.001	0.157	Complementary (partial)

Note: $p < 0.05$. The relative size of the paths is informative. For ease of use, the indirect effect through attitude (0.199) was larger than the direct effect (0.157), so attitude carried more than half of its total influence on intention. For usefulness, the indirect effect (0.117) was smaller than the direct effect (0.182), so usefulness worked more through a direct, instrumental route.

4. Discussion

The results support all hypothesised relationships and confirm that TAM's core structure holds among university employees in Libya. Three findings, however, qualify the usual reading of the model and deserve closer attention. Ease of use, not usefulness, is the main route to favourable attitudes. Perceived ease of use had a markedly stronger effect on attitude than perceived usefulness, both in path strength (0.410 against 0.241) and in unique contribution (f^2 of 0.111 against 0.038). This reverses the pattern commonly reported in high-income settings, where usefulness usually dominates and ease of use is expected to lose importance as users gain experience (Davis et al., 1989; Venkatesh & Davis, 2000; King & He, 2006). We interpret the reversal as a consequence of context. In Libyan universities, using an e-learning system often means working around unstable electricity, slow connections, shared devices and limited technical support (Rhema & Miliszewska, 2012; Ghawail et al., 2021). Each additional difficulty created by the system itself compounds those external costs. Under these conditions, a system that is clear, flexible and quick to learn is valued not only because it saves effort but because it makes use feasible at all. Employees' overall evaluation of e-learning therefore depends heavily on whether the system reduces, rather than adds to, the burdens they already face. The finding is consistent with studies in other developing countries that identify ease of use as the strongest determinant of attitude among e-learning users (Tarhini et al., 2014; Abdullah & Ward, 2016).

A second, complementary explanation concerns the nature of the respondents' work. Sixty per cent of the sample were administrative staff, whose use of e-learning platforms is largely procedural: registering students, uploading records, processing examinations. For such tasks, usefulness is partly defined by the institution, while ease of use is what the individual experiences directly. It is therefore plausible that ease of use weighs more heavily in their personal evaluation of the technology.

4.1 Attitude is not redundant

Attitude was the strongest predictor of intention ($\beta = 0.486$) and the only predictor with a medium effect size ($f^2 = 0.264$). Once attitude was in the model, the unique contribution of usefulness to intention fell to a negligible level and that of ease of use to a small one. These results support the view that attitude was removed from later acceptance models too early (Yang & Yoo, 2004; Kim & Malhotra, 2005). The importance of attitude is theoretically expected where adoption is institutionally encouraged but not yet habitual. Social psychological research shows that general evaluations guide intentions most strongly when behaviour is not yet automatic and when people must decide repeatedly whether to engage (Ajzen, 1991; Glasman & Albarracín, 2006). Libyan universities fit this description: e-learning expanded rapidly after 2020, but its use remains uneven and often depends on individual initiative rather than binding policy. In such settings, what employees believe about a system is filtered through how they feel about using it, and this evaluation then drives their commitment. Researchers who study acceptance in early-stage or discretionary contexts should therefore retain attitude in their models rather than defaulting to UTAUT's attitude-free structure.

4.2 Two different routes to intention

The mediation results show that the two beliefs reach intention in different ways. For ease of use, the indirect effect through attitude (0.199) exceeded the direct effect (0.157): ease of use mainly works by making employees feel more positive about e-learning. For usefulness, the direct effect (0.182) exceeded the indirect effect (0.117): usefulness works more through an instrumental calculation that employees make somewhat independently of how much they like the technology. This pattern echoes Davis et al.'s (1989) original observation that people may intend to use a useful system even when their affective response is lukewarm. It also refines it. Ease of use appears to be primarily an affective driver, reducing frustration and building a positive evaluation, whereas usefulness is primarily a cognitive driver, grounded in expected performance gains. For theory, this suggests that attitude is not a uniform channel through which all beliefs pass equally; its mediating role depends on which belief is involved. For practice, it implies that interventions targeting ease of use and those targeting usefulness operate through different mechanisms and should be designed accordingly.

4.3 Comparison with prior studies

The explained variance in intention (59.2%) is comparable to that reported in meta-analyses of TAM in education (Scherer et al., 2019) and higher than typical values for the original TAM, which suggests that the model captures the main drivers of employees' intentions in this setting. The explained variance in attitude (37.8%) is more modest and indicates that other factors, such as institutional support, training, facilitating conditions and social influence, also shape how employees evaluate e-learning (Venkatesh et al., 2003; Abdullah & Ward, 2016). The positive, significant paths from both beliefs to intention match findings from Arab and other developing-country contexts (Tarhini et al., 2014; Salloum et al., 2019), while the dominance of ease of use over usefulness in forming attitude distinguishes the Libyan case from the general pattern. The sample's substantial experience with e-learning is also relevant. Nearly three-quarters of respondents had used e-learning for at least four years. TAM research suggests that ease of use should matter less as experience grows (Venkatesh & Davis, 2000). That ease of use still dominated among experienced users suggests that effort in the Libyan context is not only a learning problem that experience solves, but a continuing feature of working with technology under difficult conditions.

5. Conclusion

This study tested TAM's attitudinal pathway among 365 academic and administrative employees of the University of Tripoli. Perceived usefulness and perceived ease of use both shaped attitude and intention, and attitude partially mediated both relationships. Ease of use was the stronger driver of attitude, attitude was the strongest driver of intention, and the two beliefs reached intention through different routes. Together the variables explained 59.2% of the variance in employees' intention to use e-learning technology.

5.1 Theoretical implications

First, the study provides evidence that attitude should be retained in acceptance models applied to settings where use is encouraged but not yet habitual. Its removal from TAM2 and UTAUT may suit mandatory, mature environments, but in early-stage contexts attitude carries information that beliefs alone do not. Second, the results show that the relative importance of TAM's two beliefs is context-dependent. In a low-infrastructure, post-conflict environment, ease of use outweighed usefulness in forming attitudes, even among experienced users. Acceptance theory should therefore treat the effort costs of the surrounding environment, not only those of the system, as part of what ease of use captures. Third, the mediation analysis distinguishes an affective route, dominated by ease of use and running through attitude, from an instrumental route, dominated by usefulness and running more directly to intention. Recognising these two routes can help future research specify when and why attitude mediates the effects of particular beliefs. Fourth, the study extends TAM research to university employees, including administrative staff, a group rarely studied in e-learning acceptance research, and to Libya, a country largely absent from the empirical literature.

5.2 Practical implications

For university leaders and the Ministry of Higher Education, the results suggest a clear order of priorities. Make systems easy before making them rich. Platform selection and configuration should favour simple navigation, Arabic-language interfaces, low bandwidth demands and offline or mobile options. Adding functions that increase complexity may reduce acceptance. Invest in hands-on training and on-site support. Ease of use is partly a matter of skill. Short, practical workshops for both academic and administrative staff, together with accessible help desks, can lower perceived effort. Build positive attitudes deliberately. Because attitude is the strongest driver of intention, institutions should create positive first-hand experiences: pilot units, peer champions and visible examples of colleagues who use e-learning successfully. Communicate usefulness concretely. Usefulness works largely through a direct, instrumental route. Staff are more likely to form intentions when they see specific evidence that e-learning saves time or reduces workload in their own tasks, rather than general claims about digital transformation. Address the environment, not only the software. Reliable power, connectivity and devices are preconditions for ease of use in the Libyan context. Infrastructure investment is therefore also an investment in acceptance.

5.3 Limitations and future research

The study has limitations that suggest directions for further work. First, the data come from a single public university in Tripoli, selected partly for its relative stability. Employees in other cities, in private institutions or in less stable regions may face different conditions, and multi-institution studies are needed to test the generality of the findings. Second, convenience sampling limits statistical generalisation, even though the sample's composition closely matched the university workforce. Third, the cross-sectional design measures intention at one point in time and cannot establish causal

order or capture change; longitudinal designs could test whether the dominance of ease of use declines as infrastructure improves. Fourth, all variables were measured through self-report in a single survey, which raises the possibility of common method variance (Podsakoff et al., 2003). Future studies should include procedural and statistical remedies and, where possible, objective usage data. Fifth, the model deliberately focused on TAM's core constructs. The 37.8% of variance explained in attitude indicates that other factors, such as facilitating conditions, social influence, institutional support and computer self-efficacy, deserve inclusion (Venkatesh et al., 2003; Compeau & Higgins, 1995). Finally, comparing academic and administrative staff through multi-group analysis, and extending the model to students, would show whether the same routes to acceptance operate for all groups in the university.

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