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Explaining Students' Intention to Use AI-Enhanced E-Learning in Tunisian Higher Education: An Integrative Acceptance Model

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ABSTRACT

Purpose. This study explores what shapes Tunisian university students' intention to use e-learning environments that incorporate artificial intelligence (AI). It brings together selected beliefs from the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT), alongside an exploratory measure of how students perceive AI-related features.

Design/methodology/approach. The analysis draws on 200 complete responses from a cross-sectional online convenience survey, as documented in the available analytical summary. Composite-score diagnostics and multiple regression were used, together with a previously reported bootstrap estimate of an indirect association. The outcome is students' stated intention to use these environments, not observed use.

Findings. Together, the five predictors explain 57.1% of the observed variance in behavioural intention. The strongest unique association is with AI-related acceptability ($\beta = 0.508$), followed by perceived usefulness ($\beta = 0.289$) and social influence ($\beta = 0.184$). Neither perceived ease of use nor facilitating conditions has a statistically significant unique direct association. The reported indirect estimate linking ease of use to intention through AI-related acceptability is positive (0.277; 95% bootstrap CI [0.184, 0.374]), although the full resampling output is unavailable.

Research limitations/implications. The survey relied on a convenience sample, was conducted at one point in time and used a single self-report questionnaire. It therefore cannot support causal claims or population-wide generalisation. Moreover, the AI-related acceptability score combines six different facets, each measured by one item; it should not be treated as a validated multidimensional scale. Privacy concerns were not measured separately, respondents were not asked about one common AI platform, and some diagnostic and mediation details cannot be independently checked.

Practical implications. Universities should make the educational benefits of AI-supported learning visible to students, explain how AI features and data practices work, and provide accessible technical and human support. These suggestions are informed by the wider literature rather than tested intervention effects in this survey.

Originality/value. The findings suggest that students' overall appraisal of AI-enabled features deserves attention alongside established TAM and UTAUT beliefs. By focusing on Tunisian higher education while acknowledging the limits of its exploratory measure, the article offers a basis for more precise measurement and longitudinal investigation.

Keywords- AI-enhanced e-learning; behavioural intention; AI acceptability; technology acceptance; TAM; UTAUT; higher education; Tunisia.

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INTRODUCTION

Digital technologies have become part of everyday university teaching, from learning management systems and virtual classrooms to online assessment and data-informed support. The COVID-19 pandemic accelerated this shift, making online learning essential to educational continuity rather than merely an optional supplement. AI is now changing what these environments can do: conversational assistants, automated feedback, recommendation tools, learning analytics and adaptive activities can support how students organise and pursue their learning. As a result, e-learning increasingly involves more than providing content online; it can also guide, personalise and monitor learning activities (Zawacki-Richter et al., 2019; OECD, 2024; Zheng et al., 2025).

These developments matter in Tunisia, where the higher-education sector serves students across many institutions. Official figures for 2024–2025 list 272,884 students in public institutions and 51,680 in private institutions, or 324,564 students in total. They also identify 207 public and 82 private higher-education institutions (Ministry of Higher Education and Scientific Research, 2026). The size and diversity of this sector underline the need for digital learning that is accessible, credible and sustainable.

The Virtual University of Tunis (UVT) has helped expand this provision through Moodle-based environments, learning resources, pedagogical guidance and technical support. For 2023–2024, the UVT reported 107,967 students and 8,464 teachers registered in its digital environments, together with 59,561 course spaces and 257 e-learning centres in higher-education institutions. Its report also lists 561 open online teaching units and 841 audiovisual resources (Université Virtuelle de Tunis, 2024). The UVT identifies Moodle as its official digital teaching environment and makes it available to teachers and students across Tunisian universities (Université Virtuelle de Tunis, n.d.).

Of course, Moodle is only one part of Tunisia's digital-learning landscape. When face-to-face teaching was suspended, students also communicated and studied through Microsoft Teams, Google Meet and social-media groups, using both synchronous and asynchronous activities (Erragcha et al., 2022). Research with Tunisian university teachers has likewise explored both initial intention and continued use of the UVT Moodle platform. That work highlights a challenge that goes beyond access: whether online learning is accepted and sustained as part of university practice (Sghari & Bouaziz, 2022).

Having a platform available does not, however, mean that students will want to use it. Access to reliable internet, suitable devices, digital skills and support can vary considerably. Students also make judgements about whether a platform helps them learn, whether it is manageable and whether teachers, classmates and institutions encourage its use. The question is therefore not only whether universities provide e-learning infrastructure, but how students experience its value, ease of use and surrounding support.

AI introduces additional considerations into those judgements. Features that recommend resources, generate feedback or identify learning difficulties may be useful, yet they can also depend on personal data and processes that students cannot readily inspect. A student may wonder whether a recommendation is accurate, whether automated outputs are fair or how their information is handled. Earlier research links such concerns about trust, explainability, risk and ethics to people's willingness to rely on intelligent systems (Shin, 2021; Gerlich, 2023; Shahzad et al., 2024). At the same time, trusting one AI feature does not necessarily mean trusting every other feature.

Here, the term AI-enhanced e-learning covers digital learning arrangements that include functions such as automated feedback, conversational assistance, recommendations or content generation. It does not refer to one institutional platform or to an experiment in which everyone used the same AI feature. This inclusive definition allows the study to consider a range of student experiences, but it also makes it harder to link responses to a particular tool, institution or algorithm.

Technology-acceptance theories help organise these questions. TAM emphasises two beliefs: whether a system is useful and whether it is easy to use (Davis, 1989). UTAUT adds the social environment and the resources that make technology use possible, notably social influence and facilitating conditions (Venkatesh

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et al., 2003). Both perspectives are relevant to Tunisian universities, where students' experiences are shaped by teachers' choices, peer practices, institutional expectations and access to support. Rather than claiming to test either theory in full, this article combines selected constructs that address different parts of the acceptance process.

Studies in Tunisia have already examined online-learning experiences, Moodle use and e-learning acceptance. Less is known, however, about how conventional technology beliefs, social and institutional conditions, and students' general evaluations of AI features relate to intention when considered together. There is also a question about the possible indirect link between ease of use and intention: might easier interaction accompany a more favourable view of AI-supported features?

The guiding research question is therefore: Which technological, social, contextual and AI-related evaluations are associated with Tunisian higher-education students' intention to use AI-enhanced e-learning? The claims made here are deliberately limited. Using a convenience sample and a broad AI-acceptability index, the analysis examines reported associations; it does not validate separate trust, ethics, privacy or transparency dimensions, nor can it establish a causal adoption process.

The article first reviews relevant research on e-learning, TAM, UTAUT and AI-related acceptability. It then introduces the proposed model and hypotheses, describes the survey and analyses, and presents the findings. The discussion considers what the associations may mean for research and university practice before addressing the study's limitations and possible directions for further work.

LITERATURE REVIEW

E-Learning Intention and Technology Acceptance Models

Research on students' willingness to adopt e-learning has long drawn on models of information-system acceptance. TAM remains especially influential because it links behavioural intention to perceived usefulness and perceived ease of use (Davis, 1989). Usefulness describes the expected improvement in performance; ease of use refers to how little effort is required to interact with the system.

In a learning environment, usefulness might mean finding resources more easily, working more efficiently, receiving better feedback or improving academic performance. Ease of use is more closely tied to straightforward navigation, clear instructions and manageable technical demands. Both beliefs continue to feature prominently in studies of e-learning and online education (Al-Adwan, 2020; Barz et al., 2024; Naidoo, 2023).

Students are more likely to express an intention to use e-learning when they can see what it contributes to their studies and do not expect a steep learning curve. Yet TAM concentrates mainly on individual perceptions. It says less about the setting in which use takes place, even though universities often introduce, recommend or require particular digital platforms.

For students, decisions about digital learning rarely occur in isolation. Teachers build platforms into coursework, classmates make particular tools familiar, and institutions determine what infrastructure and help are available. An approach that considers both personal beliefs and the surrounding social and organisational context is therefore useful (Venkatesh et al., 2003; Zheng et al., 2025).

The Contribution of UTAUT: Social and Contextual Determinants

UTAUT, developed by Venkatesh et al. (2003) from several earlier acceptance frameworks, identifies performance expectancy, effort expectancy, social influence and facilitating conditions as key determinants of technology acceptance and use. This study retains the TAM terms 'perceived usefulness' and 'perceived ease of use', since the corresponding questions were adapted from Davis (1989). UTAUT informs the addition of social influence and facilitating conditions.

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Social influence describes the sense that people whose opinions matter expect or encourage someone to use a technology. At university, those people may include teachers, classmates and academic staff. When teachers integrate a platform into coursework and peers regularly use it, students may come to see the platform as a normal and legitimate part of studying (Venkatesh et al., 2003; Erragcha et al., 2022).

Facilitating conditions concern whether students believe they have the resources and support needed to use a system. Reliable connectivity, suitable devices, technical assistance and practical know-how can all matter. These conditions may be particularly uneven across learning settings. UTAUT also suggests that their relationship may be closer to actual use than to intention alone (Venkatesh et al., 2003; Venkatesh et al., 2012).

UTAUT broadens the picture beyond TAM, but its original formulation did not specifically address systems that make automated recommendations, draw on extensive personal data or generate responses that users may not understand. Students encountering such functions may also think about trust, explainability, privacy and fairness, concerns that the conventional acceptance beliefs do not directly capture (Shin, 2021; Shahzad et al., 2024).

Artificial Intelligence in E-Learning: A Paradigmatic Transformation

AI is extending e-learning beyond the delivery and management of online materials. Systems can draw on data to recommend activities, adapt resources and offer feedback that responds to individual needs. This makes the learning environment more active in shaping students' interactions, rather than simply serving as a place where materials are stored (Zawacki-Richter et al., 2019; OECD, 2024).

Universities are experimenting with intelligent tutoring, automated marking, conversational assistants, plagiarism detection, recommendation tools, adaptive learning and predictive analytics. Such applications can make support more responsive and help manage large student groups. Their value, however, depends on how carefully they are designed, implemented and governed (Chan & Hu, 2023; Almassaad et al., 2024).

These capabilities also make AI-assisted learning less straightforward to evaluate. Students may receive a recommendation, prediction or assessment without being able to see how it was produced. If explanations are unclear, even an apparently useful system may prompt doubts about its reliability and legitimacy (Shin, 2021).

The possibilities and risks therefore sit side by side. AI can help personalise learning and improve access to support, but biased outputs, poor data protection or unequal access can undermine those benefits. Responsible integration requires attention not only to technical performance but also to fairness, accountability and the place of human judgement (Mittelstadt et al., 2016; Cheng et al., 2022; Al-Zahrani & Alasmari, 2024).

Perceived AI-Related Acceptability as a Sociotechnical Evaluation

In addition to familiar questions of usefulness and usability, AI-supported learning raises questions about whether its features are acceptable to students. In this article, perceived AI-related acceptability means a generally favourable assessment of AI functions used in e-learning. The six available statements touch on trust, understandability, ethical appropriateness, perceived benefits relative to risks, fairness and confidence in using an AI-integrated environment (Gerlich, 2023; Shahzad et al., 2024). These ideas overlap, but they are not the same construct. Accordingly, the combined score is used only as an exploratory index, not as a validated one-factor or higher-order scale.

Trust in an AI system involves believing that it can perform relevant tasks reliably and competently. For a student, this may matter most when feedback, recommendations or predictions influence learning decisions. A tool that works smoothly can still lose students' confidence if its outputs appear inaccurate or unfair (Gefen et al., 2003; Shahzad et al., 2024).

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Understandability concerns whether students can make sense of a system's behaviour, including what information it uses and why it produces a particular output. Clear explanations may help them judge when to trust a recommendation, although making a system easier to understand does not automatically make it trustworthy (Pieters, 2011; Shin, 2021).

Risk is another part of the evaluation. AI-generated errors, biased assessments, privacy breaches or undue reliance on automation may have consequences for feedback and learning opportunities. Students may therefore weigh potential educational benefits against these possible harms (Cheng et al., 2022; Niu & Mvondo, 2024). Ethical appropriateness and fairness concern whether AI is used legitimately and whether it treats students without discrimination. The questionnaire, however, includes only one statement about ethics and one about fairness. Its question about understandability does not directly measure technical explainability or transparency, and a general benefit–risk judgement is not equivalent to a separate risk scale. No dedicated privacy-concern item was collected. The reported index cannot therefore be used to estimate the individual contribution of any of these facets.

Critical Synthesis and Research Positioning

Taken together, the literature suggests that usefulness, ease of use, social influence and facilitating conditions remain relevant to students' intentions to use e-learning. AI adds concerns about trustworthy outputs, understandable operation, risk, fairness and ethical conduct that traditional acceptance variables do not fully describe (Davis, 1989; Venkatesh et al., 2003; Gerlich, 2023).

The present study brings these strands of research together without claiming to replicate TAM or UTAUT in full. Its AI-specific measure is a practical summary of six questions, so the analysis can examine only whether an overall appraisal of AI features is associated with intention. It cannot show that trust, fairness, transparency or ethics has a distinct effect. Nor does the study measure actual use, continued engagement, learning performance or sustainable adoption.

Conceptual Model and Development of Hypotheses

The model combines selected TAM and UTAUT variables with perceived AI-related acceptability. The hypotheses cover associations with intention, the expected link between ease of use and usefulness, and a proposed indirect association involving the AI-related index. The reasoning for each relationship is set out below.

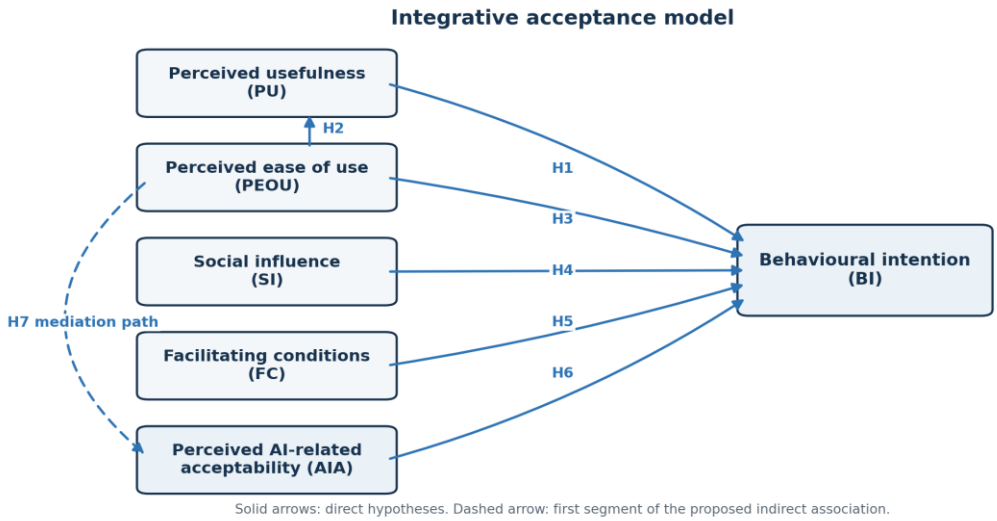


Figure 1. Integrative model of students' intention to use AI-enhanced e-learning.

Figure 1 brings together usefulness, ease of use, social influence, facilitating conditions and the exploratory AI-related acceptability score as proposed correlates of intention. It also includes the ease-of-use/usefulness

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relationship and a possible indirect route through the AI index. These arrows reflect the theoretical questions being tested; with cross-sectional data, they do not establish causal effects.

Theoretical Anchoring and Integrative Logic of the Model

The framework is designed to bring complementary ideas together rather than reproduce an existing theory wholesale. TAM explains how students evaluate a system's usefulness and ease of use (Davis, 1989). UTAUT adds the influence of important others and the conditions that make use possible (Venkatesh et al., 2003). Behavioural intention is the outcome of interest because the survey did not record actual platform use. Three groups of considerations are represented. Usefulness and ease of use describe the system from the student's perspective; social influence and facilitating conditions reflect the surrounding learning context; and AI-related acceptability captures a broader appraisal of intelligent features. Together, they allow the analysis to consider whether intention is associated with expected academic value, manageable interaction, social encouragement, practical support and students' confidence in AI.

Why might the AI-related evaluation matter? Automated recommendations and feedback may offer help while leaving students unsure how the output was generated or whether it is fair. Reliability and understandable operation can therefore become important alongside ease of interaction (Shin, 2021; Shahzad et al., 2024). Because the index combines different facets, however, the available data show only how the overall score relates to intention. They cannot identify a particular ethical concern or reduction in uncertainty as the mechanism.

Perceived Usefulness and Intention

Perceived usefulness refers to students' belief that an AI-enhanced learning environment can improve their studies. Benefits may involve easier access to resources, more flexibility, better organisation, quicker completion of tasks or more helpful feedback. TAM treats usefulness as an important correlate of behavioural intention (Davis, 1989), and evidence from e-learning research continues to support its relevance (Al-Adwan, 2020; Barz et al., 2024; Zheng et al., 2025). Recommendations tailored to a student's needs, automated feedback and learning analytics may make these benefits more visible. Students who expect the environment to help them study are therefore expected to report stronger intention to use it. This leads to H1:

H1: Perceived usefulness is positively associated with intention to use AI-enhanced e-learning.

Perceived ease of use and perceived usefulness

Perceived ease of use describes how manageable students expect the system to be. When navigation is straightforward and interaction demands little effort, students can devote more attention to learning. In TAM, ease of use is expected to relate to usefulness partly because a system that takes less effort to operate can offer greater practical value (Davis, 1989; Venkatesh & Davis, 2000).

An accessible interface may therefore make e-learning feel both less time-consuming and more beneficial. The corresponding hypothesis is:

H2: Perceived ease of use is positively associated with perceived usefulness.

Perceived ease of Use and Intention

Ease of use may also be associated directly with intention. Students who anticipate fewer technical obstacles or less frustration may be more willing to try a platform, particularly when they are unfamiliar with AI-supported features or have limited digital experience (Davis, 1989; Naidoo, 2023).

That association may be weaker once students regard basic usability as something every platform should provide. Nevertheless, the expected direct relationship from TAM is retained for testing:

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H3: Perceived ease of use is positively associated with intention to use AI-enhanced e-learning.

Social Influence and Intention

Social influence captures students' perceptions that teachers, peers and their institution support or expect the use of a platform. Course requirements, classmates' habits and institutional guidance can all shape these perceptions. UTAUT places this normative influence at the centre of technology acceptance, and it is especially relevant when a platform becomes part of assessed or organised university activity (Venkatesh et al., 2003; Erragcha et al., 2022).

When online activities are woven into coursework or group projects, students may see participation as a normal academic expectation. Hence:

H4: Social influence is positively associated with intention to use AI-enhanced e-learning.

Facilitating Conditions and Intention

Facilitating conditions refer to whether students believe they have what they need to use a platform effectively: connectivity, appropriate devices, the necessary knowledge, technical help and guidance from the university. These resources are especially important where access and digital capabilities differ (Venkatesh et al., 2003; Sghari & Bouaziz, 2022). In the original UTAUT, facilitating conditions are more closely linked to actual use than to intention. E-learning research has nonetheless examined their relationship with intention, making it reasonable to test that possibility in this context:

H5: Facilitating conditions are positively associated with intention to use AI-enhanced e-learning.

Perceived AI-Related Acceptability and Intention

Perceived AI-related acceptability concerns how students judge the intelligent features offered within an e-learning environment. It encompasses broad impressions of reliability, understandable operation, ethical appropriateness, fairness and whether expected benefits outweigh possible risks. Unlike behavioural intention, this evaluation concerns the features themselves rather than a student's stated plan to use them.

Students may be more willing to use a platform when they view its AI features as reliable and appropriately governed. Doubts about opaque decisions, privacy or unfair outcomes could point in the opposite direction (Gerlich, 2023; Shahzad et al., 2024). The sixth hypothesis is therefore:

H6: Perceived AI-related acceptability is positively associated with intention to use AI-enhanced e-learning.

Mediating role of Perceived AI-Related Acceptability

Ease of use may be related to intention partly through how students evaluate AI features. A manageable interface can help users feel more in control when they encounter unfamiliar automated functions. In turn, this sense of control may accompany greater confidence in the system's trustworthiness and acceptability (Gefen et al., 2003; Shin, 2021). If students hold a more favourable overall view of those functions, they may also report greater willingness to use the learning environment. This suggests a possible indirect association, rather than only a direct link from convenience to intention:

H7: Perceived AI-related acceptability mediates the association between perceived ease of use and intention to use AI-enhanced e-learning.

Research Contribution and Originality

The main question is whether students' overall assessment of AI-supported features is associated with intention even after familiar technology, social and contextual beliefs are considered. Separating these ideas

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conceptually is useful, although collecting all measures through one questionnaire leaves open the possibility of shared-response effects and overlapping content.

The framework therefore connects familiar acceptance research with questions raised by responsible AI in education. It considers how usefulness and encouragement from others sit alongside students' concerns about reliable outputs, understandable systems, fairness and the balance of benefits and risks.

METHODOLOGY

Research Design

A quantitative, cross-sectional survey was used to examine the relationships among perceived usefulness, perceived ease of use, social influence, facilitating conditions, AI-related acceptability and behavioural intention. The hypotheses draw on prior theory, but all responses were collected at one time point. It is therefore not possible to establish which perception came first, determine the direction of a relationship or exclude other unmeasured explanations.

Data Collection Procedure and Sample Profile

The target population was students enrolled in higher-education institutions in Tunisia. Respondents could have very different levels of experience with e-learning platforms and AI tools. Including students who used these technologies often as well as those who rarely used them was consistent with the study's focus on intention, which can be reported by both current and potential users.

Recruitment took place through a Google Forms questionnaire distributed using convenience sampling over a one-month period. According to the retained summary, 200 respondents provided complete data: 100 were Bachelor/Licence students (50.0%), 65 were Master's students (32.5%) and 35 were doctoral students (17.5%). Women made up 55.5% of the sample, men 40.5%, and 4.0% selected another response or preferred not to disclose gender. Half of the respondents were aged 20–24. These figures describe only the participating students. The archived documentation does not specify the exact recruitment dates, the institutions reached, the number invited or the information needed to calculate a response rate; institutional coverage and participation cannot therefore be independently audited.

Table 1. Sample profile and research context

Variable	Category	Frequency	Percentage
Research context	Tunisia	-	-
Institutional context	Tunisian higher-education institutions	-	-
Data collection period	One month	-	-
Study level	Bachelor/Licence	100	50.0%
	Master	65	32.5%
	Doctorate/Doctorat	35	17.5%
Discipline	Social sciences and humanities	45	22.5%
	Economics and management	47	23.5%

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	Science and technology	46	23.0%
	Health	33	16.5%
	Letters/languages	13	6.5%
	Other	16	8.0%
Age	Under 20	24	12.0%
	20-24	100	50.0%
	25-29	47	23.5%
	30 or older	29	14.5%
Gender	Female	111	55.5%
	Male	81	40.5%
	Prefer not to say	6	3.0%
	Other	2	1.0%
E-learning frequency	Never	16	8.0%
	Rarely	27	13.5%
	Sometimes	47	23.5%
	Often	53	26.5%
	Very often	57	28.5%
AI-tool frequency	Never	23	11.5%
	Rarely	28	14.0%
	Sometimes	43	21.5%
	Often	52	26.0%
	Very often	54	27.0%

Measurement Instrument and Operationalisation

The questionnaire described AI-enhanced e-learning as a digital learning environment, such as Moodle, Google Classroom, Microsoft Teams or Blackboard, that incorporates AI functions directly or indirectly. Examples included conversational assistance, support with writing, automated recommendations, intelligent feedback, automatic correction and generated summaries. The questions thus referred to a general type of learning experience, not a single named platform or an activity completed by every respondent.

This broad framing is important when reading the findings. One student might have pictured a university learning platform, while another might have thought of a general-purpose generative AI assistant used for

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assignments. The questionnaire did not anchor responses to one software version, tool or feature. Differences in reported usefulness, trust or intention might therefore partly reflect differences in the technologies students had in mind, which cannot be separated using the available results.

The usefulness and ease-of-use measures were adapted from TAM, while the social-influence and facilitating-conditions questions drew on UTAUT. Behavioural intention refers to anticipated or preferred future use, rather than recorded activity on a platform. The six AI-related questions address trust, understandability, ethical appropriateness, whether benefits outweigh risks, fairness and confidence. They were combined into an exploratory overall score, without assuming that they form interchangeable reflective indicators or validated subdimensions. Table 2 summarises the available item wording. Before publication, the wording and source adaptation should be checked against the original questionnaire.

Table 2. Constructs and operational items

Construct	Source/adaptation	Operational items
Perceived usefulness (PU)	Davis (1989); TAM	PU1 improves academic performance; PU2 increases learning efficiency; PU3 helps complete academic tasks more quickly; PU4 improves learning quality.
Perceived ease of use (PEOU)	Davis (1989); TAM	PEOU1 learning to use the system is easy; PEOU2 interaction is clear and understandable; PEOU3 becoming competent is easy; PEOU4 the overall system is easy to use.
Social influence (SI)	Venkatesh et al. (2003); UTAUT	SI1 teachers think I should use it; SI2 peers encourage its use; SI3 important people influence my use; SI4 my institution encourages its use.
Facilitating conditions (FC)	Venkatesh et al. (2003); UTAUT	FC1 resources are available; FC2 required knowledge is available; FC3 technical assistance is available; FC4 the platform is compatible with my devices and technical needs.
Perceived AI-related acceptability (AIA)	Gerlich (2023); Shin (2021); Shahzad et al. (2024)	AIA1 trust in AI functions; AIA2 AI functioning is understandable; AIA3 ethical principles are respected; AIA4 benefits outweigh risks; AIA5 AI treats students fairly; AIA6 confidence in using an AI-integrated platform.
Behavioural intention (BI)	TAM/UTAUT behavioural-intention literature	BI1 intention to use regularly; BI2 intention to continue using; BI3 intention to use more in the future; BI4 choice to use AI-enhanced e-learning when possible.

Interpretive scope of the AI-related acceptability index

The items labelled AIA1–AIA6 cover six topics: general trust in AI functions, understandability, adherence to ethical principles, an overall judgement of benefits relative to risks, fairness towards students and confidence in using an AI-integrated learning environment. Each topic is represented by only one item. The combined score may reveal a broad tendency to evaluate AI favourably, but a high reliability coefficient or AVE value cannot replace a properly validated multi-item measure for each distinct dimension.

The questionnaire did not contain separate, fully developed measures of privacy concerns, explainability for a particular algorithm, perceived risk or discriminatory outcomes. It would consequently be misleading to

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report separate effects or reliability estimates for these facets. A future validation study would need several items for each clearly defined construct, expert review of content, appropriate translation and back-translation, and comparisons among plausible reflective, formative or higher-order specifications.

Ethical Safeguards

The form began with information about the study's academic purpose, the voluntary nature of participation and the confidentiality of responses. Students were told that choosing not to participate would carry no penalty, and eligibility and consent questions appeared before the substantive questionnaire. No directly identifying information was required for the analysis described here, and the responses were used for research purposes.

Data Screening and Measurement Diagnostics

The archived analytical summary states that responses were checked for eligibility, consent and missing answers, leaving 200 complete observations. It does not include a case-by-case screening record, timestamps or documentation of duplicate-response checks; these steps cannot be verified from the available material. The summary reports Cronbach's alpha, composite reliability, item loadings, average variance extracted (AVE), Fornell–Larcker comparisons and HTMT ratios. Because the full measurement-estimation procedure is unavailable, these are reported as diagnostic descriptions of the item groups, not as proof that a latent-variable model was validated.

For the established multi-item TAM and UTAUT measures, as well as intention, these statistics provide some information about how consistently students responded. They are less decisive for the AIA index: six questions about different issues do not automatically become a single reflective construct because their internal consistency is high. No confirmatory factor analysis, comparison of alternative factor structures, cross-loading table or group-invariance assessment is available.

All predictors and the outcome were measured in the same self-report questionnaire, raising concerns about shared-method variance, consistent-response patterns and social desirability. The survey reportedly stressed voluntariness, confidentiality and neutral wording. Harman's first unrotated factor explained 31.36% of item variance, but this result does not establish that common-method bias is absent. Likewise, predictor VIF values of 1.141–1.386 indicate relatively limited multicollinearity, not freedom from common-method bias. The retained output includes no marker-variable, independent-source or temporally separated assessment.

Table 3. Measurement-quality indicators

Construct	Loading range	Cronbach's alpha	CR	AVE	VIF
PU	0.782-0.842	0.819	0.880	0.648	1.281
PEOU	0.797-0.827	0.829	0.887	0.662	1.275
SI	0.813-0.845	0.845	0.896	0.683	1.141
FC	0.800-0.831	0.841	0.893	0.677	1.144
AIA	0.791-0.838	0.899	0.923	0.665	1.386
BI	0.787-0.836	0.827	0.886	0.660	-

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Analytical Strategy

As described in the available analytical summary, individual items were combined into scores for the study variables. The main analysis regressed behavioural intention on five predictors entered together: usefulness, ease of use, social influence, facilitating conditions and the AIA index (n = 200). Its standardised coefficients describe associations after accounting for the other predictors in that regression. A separate simple regression examined the link between ease of use and usefulness. The reported PEOU → AIA → BI indirect association was assessed using a non-parametric bootstrap interval, interpreted as excluding zero when both limits had the same sign.

These results come from different analytical specifications and should not be read as though they were generated by one estimated structural-equation model. In particular, the five-predictor regression did not itself estimate every mediation path. The preserved mediation output does not tell us which covariates were included, whether the estimate was standardised, how many bootstrap samples were drawn or which interval method was applied. Only the reported indirect estimate and interval are therefore presented; missing path coefficients are not reconstructed as observed results, and the analysis is not described as causal mediation.

Appendix B provides a limited check of the published figures using the reported sample size and rounded summary statistics. The approximate standard errors in that appendix were calculated from aggregates, not re-estimated from individual responses. They cannot replace the original output or the residual, heteroskedasticity and influential-case checks that would be needed for fuller assessment.

RESULTS

Descriptive statistics

On average, respondents viewed the usefulness of e-learning and their intention to use it favourably. Their assessments of AI-related features were more mixed. These means describe the students who answered the survey; given the broad range of technologies respondents may have considered, they should not be taken as estimates of attitudes across all Tunisian universities.

Table 4. Descriptive statistics of the constructs

Construct	Mean	Standard deviation	Interpretation
Perceived usefulness	3.77	0.97	Highest mean; e-learning is perceived as academically valuable.
Behavioural intention	3.68	1.05	Positive orientation toward continued use.
Perceived ease of use	3.55	1.05	Moderately favorable usability perception.
Perceived AI-related acceptability	3.41	1.11	Moderate and ambivalent acceptance of AI integration.
Social influence	3.27	1.12	Moderate social and institutional influence.
Facilitating conditions	3.34	1.08	Moderate perception of available support and resources.

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Reliability and Measurement Quality

The reported Cronbach's alpha values range from 0.819 to 0.899, composite reliability from 0.880 to 0.923, and AVE from 0.648 to 0.683. In the available tables, the Fornell–Larcker diagonal entries exceed the correlations between constructs, while HTMT values outside the diagonal are below 0.85. Taken together, these results suggest consistent responses and some empirical separation between the reported scores. They do not settle whether the AIA items form a valid reflective dimension or rule out overlap arising from the shared questionnaire.

Hypothesis Testing: Direct Effects

The five-predictor regression explains 57.1% of the variance in behavioural intention ($R^2 = 0.571$; adjusted $R^2 = 0.560$; $F(5, 194) = 51.7$, $p < 0.001$). AIA has the largest standardised coefficient ($\beta = 0.508$), followed by usefulness ($\beta = 0.289$) and social influence ($\beta = 0.184$). The coefficients for ease of use ($\beta = -0.057$, $p = 0.279$) and facilitating conditions ($\beta = 0.079$, $p = 0.117$) are not statistically significant after the other predictors are included. Table 5 presents the retained coefficient summary. Approximate uncertainty intervals derived from rounded figures appear in Appendix B and require confirmation against the original regression output.

Table 5. Results of hypothesis testing: direct effects

Predictor	Standardised beta	p-value	Decision
AIA → BI	0.508	<0.001	Supported
PU → BI	0.289	<0.001	Supported
SI → BI	0.184	<0.001	Supported
PEOU → BI	-0.057	0.279	Not supported
FC → BI	0.079	0.117	Not supported
Model R^2	0.571	<0.001	Adjusted $R^2 = 0.560$; $F(5, 194) = 51.7$

Intermediate relationship between ease of use and usefulness

The separate regression between ease of use and usefulness is positive (standardised $\beta = 0.316$, $R^2 = 0.100$, $p < 0.001$). This is consistent with H2 within the present sample. It does not, however, test mediation through usefulness: the retained indirect-effect analysis did not estimate a PEOU → PU → BI pathway.

Mediating Effect

For the proposed PEOU → AIA → BI route, the archived summary reports an indirect estimate of 0.277 and a 95% bootstrap confidence interval of [0.184, 0.374]. Because zero is outside this interval, the result is consistent with the hypothesised indirect pattern. Interpretation remains limited, however, because the number of resamples, interval procedure, treatment of other predictors, scale of the estimate and individual a, b, c and c′ paths were not retained. The analysis cannot be reproduced independently or treated as causal mediation on the basis of this record. Appendix B separately labels an unadjusted approximation from rounded correlations; it is not the original mediation output.

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Table 6. Mediation effect of perceived AI-related acceptability

Mediation path	Indirect effect	95% confidence interval	Decision
PEOU → AIA → BI	0.277	[0.184; 0.374]	Supported

Summary of hypothesis testing

Table 7. Summary of hypotheses

Hypothesis	Relationship tested	Empirical result	Decision
H1	PU → BI	$\beta = 0.289$; $p < 0.001$	Supported
H2	PEOU → PU	$\beta = 0.316$; $p < 0.001$	Supported
H3	PEOU → BI	$\beta = -0.057$; $p = 0.279$	Not supported
H4	SI → BI	$\beta = 0.184$; $p < 0.001$	Supported
H5	FC → BI	$\beta = 0.079$; $p = 0.117$	Not supported
H6	AIA → BI	$\beta = 0.508$; $p < 0.001$	Supported
H7	PEOU → AIA → BI	Indirect association = 0.277; 95% CI [0.184; 0.374]	Supported

Analytical Synthesis

The pattern is relatively clear within this sample. Students' overall appraisal of AI-supported functions has the strongest association with intention in the simultaneous regression, while usefulness and social influence also matter. Ease of use is associated with usefulness, and the retained indirect-effect estimate is compatible with a link through the AI index. These are relationships among reported perceptions, not evidence that a change in technology or university policy would produce a change in use.

DISCUSSION AND IMPLICATIONS

Interpretation of the Direct Associations

The findings offer partial support for the selected relationships drawn from TAM and UTAUT. Students who expect AI-enhanced e-learning to help them with their studies also tend to report stronger intention to use it, a pattern consistent with earlier acceptance research (Davis, 1989; Al-Adwan, 2020; Zheng et al., 2025). For students, the relevant question may be less whether a platform has advanced functions than whether those functions clearly improve feedback, task completion or learning.

Social influence is also positively associated with intention after the other included predictors are considered. This fits the UTAUT perspective that technology use develops within a social setting (Venkatesh et al., 2003). Teachers decide how a platform enters coursework, classmates make certain practices familiar, and institutions communicate what forms of use are encouraged. The survey captures students' perceptions of these signals; it does not directly measure institutional behaviour.

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Neither perceived ease of use nor facilitating conditions has a statistically significant unique direct coefficient in the main regression. This should not be read as evidence that usability or support is irrelevant. Ease of use still shows a positive association with usefulness, and the available mediation summary reports an indirect association through AIA. Facilitating conditions may relate more closely to actual use, as suggested in the original UTAUT (Venkatesh et al., 2003). Because the survey did not measure actual behaviour, that possibility remains open for future research.

AI-related Acceptability as the Focal Association

A notable result is the size of the AIA coefficient in the simultaneous regression. Respondents who evaluated AI-supported learning features more favourably also tended to express greater intention to use those environments, even when the other reported predictors were included. This is broadly compatible with research highlighting trust and explainability in intelligent systems (Shin, 2021; Gerlich, 2023; Shahzad et al., 2024). Yet the index combines different concerns, and all answers come from one questionnaire, so the association cannot be assigned to a particular aspect of AI acceptability.

The result is best understood as a relationship between a broad exploratory appraisal and intention. It cannot establish that fairness, ethics, risk or transparency independently predicts intention. Privacy was not measured with a dedicated question, and a general statement that AI is understandable does not assess whether a student can explain a specific algorithm. Comparing these concerns would require multi-item measures of each one and a clearly identified AI application.

Indirect Association through AI-Related Acceptability

The reported bootstrap interval is compatible with a possible indirect association from ease of use to intention through the overall AI-related appraisal. One plausible reading is that students who find an environment easier to navigate may also feel more comfortable with its AI features. But other explanations are possible: students with previous AI experience or stronger digital skills might simply respond more positively to both sets of questions. Shared response tendencies could also contribute to the pattern.

The single-wave survey cannot establish that ease of use came before AI-related acceptability or that either preceded intention. Moreover, the component mediation paths and resampling settings are missing from the retained output. The proposed mechanism therefore remains a theoretical interpretation that should be examined using pre-specified longitudinal, repeated-measures or experimental research. It is not evidence that simplifying an interface would itself change students' intentions.

Theoretical Implications

Within the reported sample, the global AIA index contributes a positive coefficient alongside usefulness and social influence in the five-predictor regression. This suggests a reason to study students' evaluations of AI functions in addition to established acceptance beliefs. It does not establish that AIA is a validated multidimensional construct. Nor can the additional variance explained by AIA be quantified without comparing appropriately specified nested models.

The positive association between ease of use and usefulness is consistent with TAM, while the reported indirect estimate raises a separate possibility involving AI-related acceptability. Only the latter was documented as a mediation analysis. Neither finding demonstrates a causal pathway, because the variables were measured at the same point in time.

Practical Implications for Higher Education

For universities, a practical starting point is to show what AI-supported tools can contribute to learning. Students need clear examples of how a feature might improve feedback, help them find resources, organise their work or complete activities more efficiently. These benefits are more persuasive when demonstrated in familiar academic tasks than when presented as abstract claims about innovation.

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Responsible governance is also important, although this survey did not test the effects of particular institutional policies. Universities can explain what AI features do with student data, communicate the limits of automated outputs and offer meaningful routes to human review. Fairness and accessibility should be considered before tools are widely introduced. These recommendations are supported by broader responsible-AI scholarship, not by direct evidence in the present regression that a specific policy would increase adoption.

Students and staff may also need practical support in using AI critically. Training can cover how to check generated information, protect personal data, acknowledge AI-assisted work and recognise the limits of automated recommendations. Technical help remains relevant even though facilitating conditions did not have a significant unique association with intention in this regression. Support should address not only how to operate the tool but also what to do when an output seems inaccurate, biased or difficult to understand.

Finally, students do not all face the same circumstances. Connectivity, access to devices, field of study, digital competence and previous experience with AI may shape what they can gain from these tools. An inclusive approach should therefore provide accessible design, affordable access and workable alternatives for students who cannot or prefer not to use particular AI functions.

LIMITATIONS AND FUTURE RESEARCH

Several limitations are important when interpreting the results. The first is timing: all variables were measured in a cross-sectional observational survey. Even a statistically significant relationship cannot tell us which belief preceded another, eliminate unmeasured explanations or show what would happen after an intervention. Future research could follow students over time, distinguishing initial intention, later use, continued engagement and educational outcomes.

The second limitation concerns the sample. The 200 participants were recruited through convenience sampling and included students from several study levels and disciplines. They cannot be treated as a statistically representative sample of Tunisian higher education. The available records do not provide a sampling frame, recruitment by institution, invitation totals or a response-rate denominator, so coverage and non-response bias cannot be assessed. Future studies could use stratification by region, public or private institution, discipline and study level, while documenting recruitment and participation more fully.

Third, all measures were self-reported in one questionnaire. This leaves room for shared-method variance, self-selection, social desirability and the tendency to answer related questions consistently. Harman's single-factor result is not enough to rule out these concerns, and the regression VIF values address collinearity rather than common-method bias. Where feasible, future studies should measure variables at different times, include suitable methodological controls and compare stated intention with independently recorded platform use or learning analytics gathered with consent.

Fourth, AI-related acceptability was represented by an exploratory score combining six distinct topics, each with a single item. The reliability and AVE statistics do not establish that it is a validated six-dimensional construct, nor do they reveal which topic is most important. Privacy concerns and algorithmic transparency were not measured directly as separate constructs. A stronger instrument would draw on several validated items per concept, including trust, explainability, privacy, risk, fairness and ethics, and would establish content validity and factor structure before testing hypotheses. The choice among correlated, formative and higher-order models would also need a clear theoretical justification.

Fifth, the archived statistical outputs are incomplete. The mediation summary reports an indirect estimate and interval but not the individual paths, associated uncertainty, covariates or bootstrap settings. The main regression summary also lacks original unstandardised coefficients and residual, heteroskedasticity and influential-observation diagnostics. Appendix B contains only approximate calculations from rounded published figures. Access to the original response file, syntax or full software output would be needed to reproduce these analyses, obtain exact intervals, carry out sensitivity checks and determine how the mediation was adjusted.

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Finally, respondents were asked about AI-enhanced e-learning in broad terms rather than one specified platform. Some may have considered Moodle with AI features, while others may have thought of a chatbot or a different learning application. The results cannot be attributed to any one of these technologies. Future work could focus on a defined tool and document students' direct experience with it.

It could also examine moderators such as digital competence, previous AI use, technology anxiety, institutional trust, discipline, gender and access to infrastructure; none was tested in the present study. Interviews, ideally alongside behavioural measures, could help explain how students understand the benefits, risks and fairness of AI-supported learning.

CONCLUSION

This article examined how established technology-acceptance beliefs and an exploratory appraisal of AI features relate to intention to use AI-enhanced e-learning. The analysis draws on a cross-sectional convenience sample of 200 students in Tunisian higher education. Together, the five reported predictors account for 57.1% of the variation in stated intention within this sample.

The strongest association is with the global AI-acceptability score, followed by perceived usefulness and social influence. Ease of use and facilitating conditions do not have significant unique direct coefficients in the main regression. Ease of use is positively related to usefulness, and the saved bootstrap interval is compatible with a possible indirect relationship through the AI index, although the full mediation output is needed for independent verification.

These findings indicate that how students feel about AI-supported functions may deserve a place alongside familiar acceptance beliefs. They do not reveal whether trust, fairness, ethics or risk is individually responsible for the observed relationship, because those facets were not measured with validated separate scales. Suggestions concerning transparency, human oversight and AI literacy should therefore be treated as practical considerations rather than interventions evaluated in this survey.

The evidence concerns self-reported intentions in one non-probability sample. It cannot be generalised statistically to all Tunisian students or taken as proof of actual adoption, better learning or causal effects. Research that follows students over time, measures behaviour, uses a clearly defined AI system and validates distinct AI-related dimensions would provide a firmer basis for understanding their acceptance.

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APPENDIX A. ADDITIONAL MEASUREMENT DIAGNOSTICS

The indicators below come from analytical tables preserved with the manuscript. They were not recalculated from individual questionnaire responses during this revision.

They are included to make the available reporting transparent, but confirmation against the original response file or full archived software output would be needed before treating them as independently verified.

Table A1. Standardised item loadings

Construct	Item	Standardised loading
PU	PU1	0.842
PU	PU2	0.796
PU	PU3	0.799
PU	PU4	0.782
PEOU	PEOU1	0.827
PEOU	PEOU2	0.818
PEOU	PEOU3	0.797
PEOU	PEOU4	0.812
SI	SI1	0.813
SI	SI2	0.845
SI	SI3	0.834
SI	SI4	0.814
FC	FC1	0.831
FC	FC2	0.83
FC	FC3	0.829
FC	FC4	0.8

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AIA	AIA1	0.833
AIA	AIA2	0.815
AIA	AIA3	0.791
AIA	AIA4	0.821
AIA	AIA5	0.838
AIA	AIA6	0.794
BI	BI1	0.787
BI	BI2	0.8
BI	BI3	0.836
BI	BI4	0.826

Fornell-Larcker Criterion

Table A2. Fornell-Larcker criterion

Construct	PU	PEOU	SI	FC	AIA	BI
PU	0.805	0.316	0.260	0.305	0.359	0.525
PEOU	0.316	0.814	0.187	0.181	0.428	0.300
SI	0.260	0.187	0.827	0.199	0.294	0.413
FC	0.305	0.181	0.199	0.823	0.252	0.321
AIA	0.359	0.428	0.294	0.252	0.816	0.661
BI	0.525	0.300	0.413	0.321	0.661	0.812

HTMT ratios

Table A3. HTMT ratios

Construct	PU	PEOU	SI	FC	AIA	BI
PU	—	0.385	0.312	0.367	0.418	0.639
PEOU	0.385	—	0.223	0.217	0.497	0.366
SI	0.312	0.223	—	0.236	0.337	0.498
FC	0.367	0.217	0.236	—	0.293	0.385
AIA	0.418	0.497	0.337	0.293	—	0.767
BI	0.639	0.366	0.498	0.385	0.767	—

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APPENDIX B. RECONSTRUCTED CHECKS FROM PUBLISHED AGGREGATE STATISTICS

The available manuscript contains summary statistics but neither the respondent-level dataset nor the full original model output. The calculations in this appendix check whether selected printed numbers are compatible with one another. They use only the reported sample size of 200, five predictors, $R^2 = 0.571$ and rounded values from the tables. They are not new analyses fitted to the questionnaire responses and should be replaced by exact original results if those records can be recovered.

For a regression with five predictors, the conventional OLS approximation for a standardised coefficient is $SE(\beta j) \approx \text{sqrt}[(1 - R^2) \times VIFj / (n - k - 1)]$. Approximate confidence intervals use $t(0.975, 194) \times SE$. The calculations assume ordinary homoskedastic OLS and depend on rounded inputs. They are not heteroskedasticity-robust intervals, and the residual data needed to test the assumption are unavailable.

Table B1. Approximate OLS coefficient uncertainty reconstructed from rounded published results; confirm against raw software output.

Regressor	**Reported β**	**Approx. SE(β)**	**Approx. 95% CI**
PU	0.289	0.053	[0.184, 0.394]
PEOU	-0.057	0.053	[-0.162, 0.048]
SI	0.184	0.050	[0.085, 0.283]
FC	0.079	0.050	[-0.020, 0.178]
AIA	0.508	0.055	[0.399, 0.617]

Using the correlations for the six variables in Appendix A (Table A2) gives an approximate reconstruction of the main regression: $R^2 \approx 0.571$ and coefficients close to those in Table 5, allowing for rounding. This is a check that the printed aggregates are algebraically compatible. It does not verify the original responses, test the regression assumptions or confirm questionnaire coding.

For an unadjusted standardised mediation estimated only from the printed bivariate correlations, the PEOU–AIA correlation is $r = 0.428$. The partial standardised association between AIA and BI, after adjusting for PEOU, is approximately $(0.661 - 0.300 \times 0.428)/(1 - 0.428^2) \approx 0.652$. Multiplying the two gives approximately 0.279, close to the reported bootstrap indirect estimate of 0.277. This calculation does not recover the original a and b paths or establish whether the archived mediation included other predictors, how the estimate was scaled or which bootstrap method was used.

Before submission, the following records should be checked wherever they are available: original item wording and coding; survey dates and recruitment details; missing-data and duplicate-response screening; software name and version; exact direct-effect coefficients, standard errors and confidence intervals; mediation paths a, b, c and c′, covariates, number of bootstrap samples and interval method; and residual, heteroskedasticity and influential-observation diagnostics. The estimates in this appendix cannot substitute for those records.