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ChatGPT Perceptions Among Undergraduate Students: A Technology Acceptance Model Study at the Higher Education Institutions of Nalut, Libya

Khalid Waregh[a], Jalel Ktari[a], Abdalmonem Tamtam[b,*]

[a] CES Lab, ENIS, National School of Engineers of Sfax (ENIS), University of Sfax, Sfax, Tunisia.
[b] Department of Computer Science, College of Education, Nalut University, Nalut, Libya.

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ABSTRACT

As generative artificial intelligence becomes embedded in higher education worldwide, understanding how students adopt these tools, alongside their moral and ethical concerns, matters more than ever. Grounded in the Technology Acceptance Model (TAM), this study examines the behavioral intentions and perceived ethical risks of 260 Libyan undergraduate students at the University of Nalut and the High Institute of Science and Technology Nalut regarding the use of ChatGPT in their learning. Data were collected through a questionnaire survey and analyzed in the Statistical Package for Social Sciences (SPSS) and by covariance-based structural equation modelling (CB-SEM). The analysis points to three findings. First, students show a "high intention to use, wary attitude" pattern, balancing enthusiasm for the technology against ethical concern. Second, perceived usefulness (PU) is the main driver of adoption, but it also raises concerns about academic integrity, pointing to the dual nature of AI in educational settings. Third, Libyan higher education institutions need clear, ethics-oriented frameworks to support responsible AI use. This study extends the TAM model to the educational context and provides empirical grounding for shaping ethical AI policy at Libyan universities. Because both participating institutions are located in the single region of Nalut, the findings are context-specific and should be read as indicative of that setting rather than as nationally representative of Libya.

تصورات الطلاب الجامعيين تجاه ChatGPT: دراسة لنموذج قبول التكنولوجيا TAM في مؤسسات التعليم العالي في نالوت، ليبيا

خالد ورغ[a]، جلال الكتاري[a]، عبدالمنعم التمتام[b*]

[a] مختبر *CES*، المدرسة الوطنية للمهندسين بصفاقس (*ENIS*)، جامعة صفاقس، صفاقس، تونس
[b] قسم علوم الحاسوب، كلية التربية، جامعة نالوت، نالوت، ليبيا

الكلمات المفتاحية:
ChatGPT
طلاب المرحلة الجامعية
الإدراك الأخلاقي
نموذج قبول التكنولوجيا
التعليم العالي

الملخص

مع تزايد اندماج الذكاء الاصطناعي في التعليم العالي حول العالم، أصبح فهم كيفية تبني الطلاب لهذه الأدوات، إلى جانب مخاوفهم الأخلاقية والمعنوية، أكثر أهمية من أي وقت مضى. استنادًا إلى نموذج قبول التكنولوجيا (TAM)، تبحث هذه الدراسة في النوايا السلوكية والمخاطر الأخلاقية المتصورة لدى 260 طالبًا جامعيًا في جامعة نالوت والمعهد العالي للعلوم والتقنية بنالوت فيما يتعلق باستخدام ChatGPT في دراستهم. تم جمع البيانات من خلال استبيان وتحليلها باستخدام برنامج الحزمة الإحصائية للعلوم الاجتماعية (SPSS) ونمذجة المعادلات البنائية القائمة على التغاير (CB-SEM). تشير النتائج إلى ثلاثة استنتاجات رئيسة: أولاً، يظهر الطلاب نمطًا يجمع بين نية استخدام عالية وموقف حذر، حيث يوازنون بين الحماس تجاه التكنولوجيا والقلق الأخلاقي. ثانيًا، تُعد الفائدة المتصورة (PU) المحرك الرئيسي للتبني، إلا أنها تثير أيضًا مخاوف بشأن النزاهة الأكاديمية. ثالثًا، تحتاج مؤسسات التعليم العالي الليبية إلى برامج عمل واضحة قائمة على الأخلاقيات لدعم الاستخدام المسؤول. توسّع هذه الدراسة نموذج TAM ليشمل السياق التعليمي، وتقدم أساسًا تجريبيًا لصياغة سياسات أخلاقية للذكاء الاصطناعي في الجامعات الليبية. ونظرًا إلى أن المؤسستين المشاركتين تقعان في منطقة نالوت وحدها، فإن النتائج مرتبطة بهذا السياق، وينبغي قراءتها كمؤشر على هذا السياق لا كتمثيل لكامل ليبيا.

*Corresponding author:
E-mail addresses: a.tamtam@nu.edu.ly, (K. Waregh) khalid.waregh@enis.tn, (J. Ktari) jalel.ktari@enis.tn
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1. Introduction

The rapid advancement of large language models (LLMs) has accelerated the spread of generative artificial intelligence (AI) tools and reshaped teaching and learning in higher education worldwide [1] and [2]. Among these tools, ChatGPT has gained global prominence since its release in late 2022 [3] for its ability to synthesize complex information, hold natural language dialogue, and handle problem-solving tasks across domains [4]. Prior work points to its potential for personalized learning and improved academic efficiency [5-8]. Several studies report that ChatGPT-based learning systems raise student engagement, efficiency, and overall academic performance [6-9], and research on medical students has found similar gains in knowledge acquisition and comprehension [10]. Reference [11] identifies four generative AI (GenAI) usage scenarios in higher education based on usage intensity and responsibility (see Fig. 1), ranging from "Transformation," marked by intensive, responsible use, to "Survival," where irresponsible use threatens academic integrity. That study argues educators need to guide use proactively and adapt curricula to capture the pedagogical benefits of AI while limiting the risk to students' critical thinking.

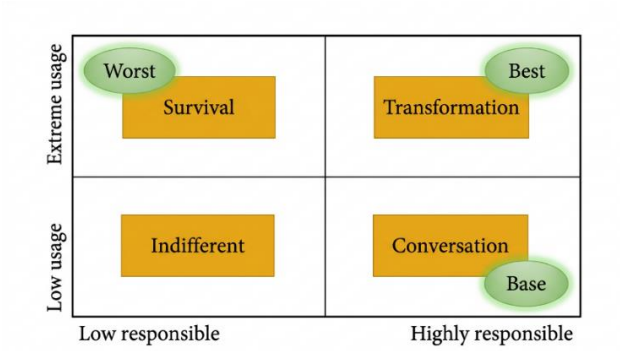


Fig. 1: Overview of possible scenarios based on usage and responsibility.

Issues of algorithmic bias, data privacy, and responsible use remain central to ongoing debates [12-14], and these are especially relevant to students' ethical perceptions of AI. Parallel debates concern academic integrity and the design of assessment [15-17], as well as authorship and accountability in scholarly writing [18]. Existing research has focused mostly on performance and efficiency gains from ChatGPT adoption, with far less attention paid to the ethical tension that comes with its academic use. This creates a paradox: students may strongly accept AI tools for their functional benefits while also seeing them as a threat to academic integrity and independent learning.

The TAM model offers two key factors for analyzing technology adoption: Perceived Usefulness (PU) and Perceived Ease of Use (PEU). Prior studies have applied TAM to AI-related technologies [2] and [4-6], but few have treated ethical perception as a core construct, particularly in developing countries such as Libya. TAM has been validated extensively in technology adoption research, but its application to generative AI in higher education stays conceptually incomplete when it leaves out ethical judgment. This gap is especially clear in developing contexts such as Libya, where institutional AI governance frameworks are still taking shape [19].

This study is limited to the Nalut area. Nalut city lies roughly 260 km southwest of Tripoli on the Nafusah Mountain close to the Tunisian border [20]. ChatGPT adoption among undergraduates at higher education institutions in the Nalut area is increasing, but empirical evidence on their acceptance and ethical perceptions remains limited. These dimensions matter because the high perceived usefulness students report could align with the "Transformation" scenario [11], but only if institutions also reinforce ethical responsibility and avoid the "Survival" trap of compromised integrity. That understanding can help guide responsible AI integration and institutional policy.

This study aims to: (1) examine the behavioral intentions of Libyan undergraduate students toward ChatGPT using an extended TAM framework; (2) investigate the relationship between perceived usefulness and ethical perception; and (3) provide empirical evidence to inform ethical AI policy development at Libyan institutions.

2. Related Works

Research on AI adoption in higher education has expanded rapidly in recent years [21], much of it built on the Technology Acceptance Model (TAM) as a baseline framework. The original model, proposed by [22], defines Perceived Usefulness (PU) and Perceived Ease of Use (PEU) as the main drivers of Behavioral Intention (BI). This simple structure has proven robust across different technologies (see Fig. 2), though it was not designed with complex AI systems in mind.

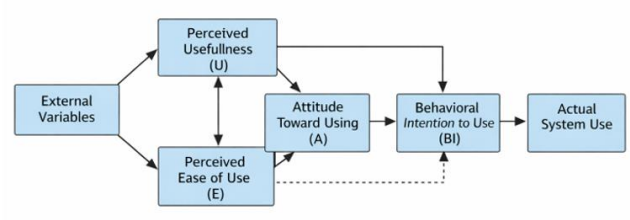


Fig. 2: Original Technology Acceptance Model (TAM) [22]

As a result, many scholars have extended TAM in different directions [5], for example, added trust and perceived risk to the model; their findings suggest user perception is not purely functional and that psychological concerns play a significant role too. The social and ethical variables, which introduced by [23] show that user decisions are shaped by norms and moral considerations, although they do not treat these as core constructs.

Other studies approach the problem from a learning angle. [24] integrated self-regulated learning into TAM, showing how tools like ChatGPT can support cognitive and metacognitive processes and not just usability. This shifts the focus, slightly, from adoption toward learning outcomes, though it still leaves out ethical perception as a central variable.

By contrast [25], do not extend TAM at all. Instead, they offer a broad conceptual discussion of generative AI, examining bias, academic integrity, and governance in some depth. The analysis is insightful but stays theoretical, without being built into an empirical adoption model. A further strand documents student perceptions descriptively [26-27], capturing attitudes and concerns in detail but without embedding them in a formal acceptance model.

Table 1 summarizes how prior studies have extended or approached TAM for AI and ChatGPT.

Table 1: Comparative Analysis of Prior Studies on AI/ChatGPT Adoption

Study	Model Used	Added Variables	Main Contribution	Limitation
Fred D. Davis [22]	TAM	—	Established PU & PEU as key determinants	No ethical dimension
Stylianos Balaskas et al. [5]	TAM Extension	Trust, Risk	Explained psychological drivers of adoption	Ethics not modeled
Mustofa et al. [23]	Extended TAM	Social, Ethical factors	Highlighted moral/social influence	Ethics is not a central construct
Dahri et al. [24]	TAM Extension	Self-regulated learning	Linked AI to learning behavior	Ignores ethical perception
Yogesh K. Dwivedi et al. [25]	Conceptual	AI Ethics	Emphasized ethical risks	No empirical TAM model

A closer look at Table 1 shows a somewhat fragmented picture. Many studies extend TAM, but each tends to emphasize one dimension: sometimes psychological, sometimes social, sometimes cognitive. This variety is useful, but it also leaves the field short on coherence. The models don't fully align, and their explanatory scope stays limited. Ethical concerns illustrate the problem clearly: in some

studies they appear only as secondary variables, in others they're discussed in isolation without being formally built into the adoption framework. Either way, their influence isn't captured consistently, which leaves our understanding of how students actually engage with AI tools incomplete.

This gap is more pronounced in developing contexts, where institutional policies are still evolving and students tend to rely more on personal judgment when using tools such as ChatGPT. Under these conditions, ethical perception is likely to play a more direct role in shaping behavior.

For this reason, the present study takes a different approach: it extends the TAM framework by placing Ethical Perception (EP) alongside User Experience (UE) as a central construct. The goal is to explain adoption patterns and, more importantly, to capture the tension between perceived usefulness and ethical concern in academic settings.

3. Research Design and Methodology

3.1 Context and Participants

This study used a cross-sectional survey design [28] to evaluate the attitudes and ethical perceptions of 260 undergraduate students from two public institutions in the Nalut area of western Libya [29-31]. Data collection ran for one semester, from mid-February 2026 to the end of May 2026. The research instrument was adapted from the validated modified-TAM scale [32]. The PU, PEU and BI items were taken from that instrument, whose own wording derives from [22] and [33], and were reworded for ChatGPT; the UE and EP items were written for this study to capture ethical variables, perceived efficacy, and institutional challenges.

To check content validity, the questionnaire was reviewed by two experts, a professor and an associate professor with extensive experience in educational technology, for conceptual clarity, precision of wording, and the comprehensiveness of the ethical perception subscale. Refinements were made in response to their feedback. The survey was distributed through student networks on WhatsApp and Facebook, yielding 260 valid responses (190 female, 70 male). SPSS-based reliability analysis showed acceptable internal consistency for the twenty items (Cronbach's $\alpha = 0.733$), while sampling adequacy was confirmed by the Kaiser–Meyer–Olkin measure (KMO = 0.711) and the exploratory factor solution reported in Section 3.3 accounted for 68.37% of the variance. All procedures followed ethical protocols including anonymization, informed consent, and data encryption [34].

3.2 Instrumentation and Validation

The questionnaire used a 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). It measured five core constructs across twenty items: Perceived Usefulness (PU, 3 items), Perceived Ease of Use (PEU, 3 items), User Experience (UE, 3 items), Behavioral Intention (BI, 4 items, BI1–BI4), and Ethical Perception (EP, 7 items, EP1–EP7). Each construct was operationalized through multiple items adapted from validated TAM-based instruments [22] and [32-33] and adjusted for ChatGPT use in higher education.

3.3 Data Processing and Factor Analysis

Only Likert-scale items were kept for analysis; selective and open-ended questions were excluded. The analysis focused on students' perceptions of ChatGPT's usefulness and ease of use, their behavioral intention to adopt it in learning, concerns about academic integrity and data privacy, responsible use, and overall user experience.

As shown in Fig. 3 and grounded in the extended Technology Acceptance Model developed by [22], an exploratory factor analysis (EFA) was conducted to examine the underlying structure of the twenty questionnaire items.

The results identified seven primary factors accounting for 68.37% of total variance. These seven empirical factors map onto the five theorized constructs as follows: PU, PEU, UE and BI each emerged as a single factor, while EP resolved into three correlated sub-dimensions, giving four plus three, that is seven, extracted factors in total. The five-construct specification was therefore retained for the confirmatory stage and for the structural model. Factor loadings ranged from 0.61 to 0.89, and communalities (h^2) fell within acceptable thresholds (0.42-0.79), confirming the adequacy of the factor structure.

The first factor (Perceived Usefulness) had the strongest explanatory power (eigenvalue = 6.42), with three PU items loading above 0.85. This shows Libyan students strongly associate ChatGPT with better academic efficiency, improved understanding of complex material, and time savings in research and studying.

The second factor (Behavioral Intention) showed high internal consistency, with loadings from 0.82 to 0.88 across its four items (BI1–BI4), reflecting students' willingness to invest time in learning to use ChatGPT effectively (BI1), to adopt it regularly (BI2), to recommend it to peers (BI3), and their expectations regarding its long-term academic impact (BI4).

The third factor (User Experience) had moderate to high loadings (0.74-0.81), capturing students' overall satisfaction, the perceived credibility of the information ChatGPT provides, and its contribution to learning quality.

The fourth factor (Perceived Ease of Use) loaded cleanly (0.77-0.84), covering items on ease and clarity of use, accurate direction from ChatGPT, and skillful use without technical assistance.

The remaining three factors aligned with Ethical Perception (EP), splitting into distinct sub-dimensions: academic integrity concerns (EP1-EP2, loadings 0.73-0.79); data privacy and over-reliance fears (EP3-EP4, loadings 0.68-0.75); and critical thinking impact combined with regulatory expectations (EP5-EP7, loadings 0.61-0.70). This split shows that ethical concerns among Libyan students aren't monolithic, but span plagiarism, skill erosion, data privacy, and the perceived need for institutional governance.

Overall, PU showed the strongest explanatory power with the largest number of high-loading items, while the remaining factors showed moderate to high loadings, together supporting a stable factorial structure and the validity of the extended TAM framework in the Libyan higher education context.

A confirmatory factor analysis (CFA) was then performed to validate the main TAM-derived constructs, including PU, PEU, BI, EP, and UE. Factor loadings ranged from 0.72 to 0.96, supporting construct validity.

The measurement model showed acceptable fit ($\chi^2 = 261.350$, df = 94, $p < 0.001$; Comparative Fit Index, CFI = 0.956; Tucker–Lewis Index, TLI = 0.944; Root Mean Square Error of Approximation, RMSEA = 0.067; Standardized Root Mean Square Residual, SRMR = 0.038).

3.4 Data Analysis and Hypotheses

The analytical workflow had two parts. First, EFA and CFA established the measurement foundation. Second, seven directional hypotheses were tested using covariance-based structural equation modelling (CB-SEM) with maximum-likelihood estimation, rather than the partial least squares variant (PLS-SEM), because the objective was to test a hypothesized model against global fit criteria rather than to maximize predictive variance; this choice follows the selection guidelines [35]. Descriptive statistics, the reliability analysis and the EFA were computed in SPSS, and the CFA and structural model were estimated in [INSERT CB-SEM PACKAGE AND VERSION]. Based on these hypotheses, the proposed conceptual framework for this study is shown in Fig. 3. This extended model builds Ethical Perception (EP) and User Experience (UE) into the original TAM structure to examine what specifically drives ChatGPT adoption among students at the University of Nalut and the High Institute of Science and Technology.

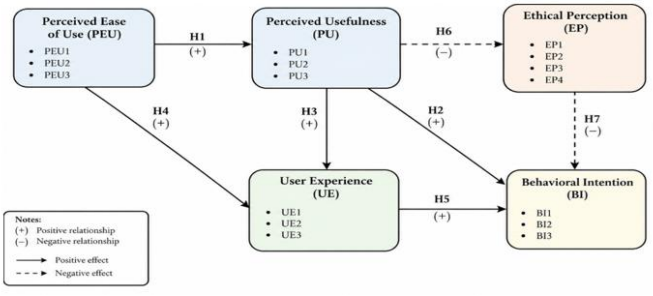


Fig. 3: Extended TAM for ChatGPT: hypotheses

Descriptive statistics address Research Question 1, while path analysis addresses the determinants behind Research Question 2. The complete sequence of design, instrumentation, validation, estimation and interpretation steps is set out in Fig. 4.

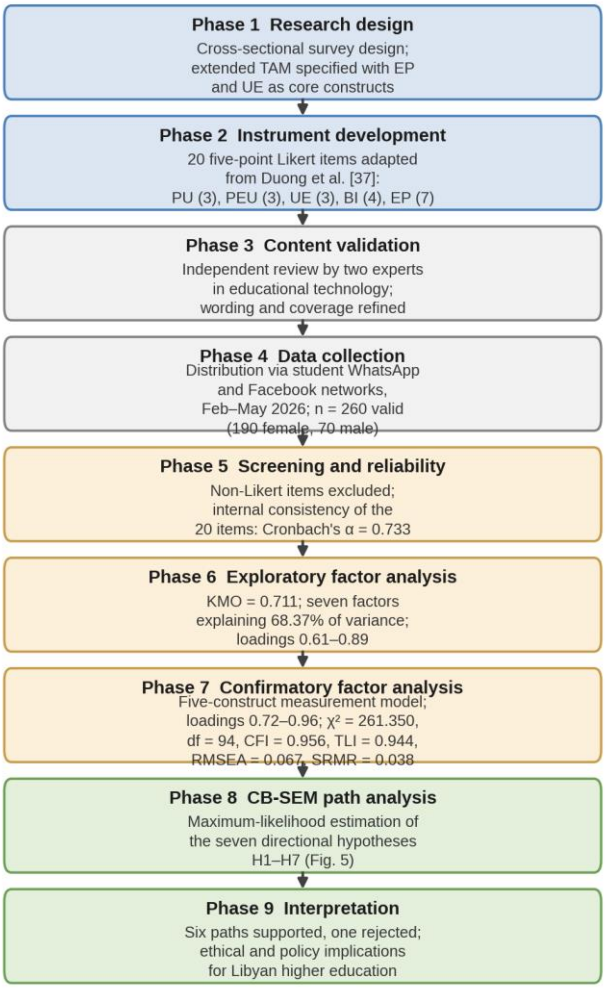


Fig. 4: Research workflow, from design through to interpretation.

4. Results

The table below presents the distribution of demographic information, including gender, field of study, and ChatGPT experience.

Table 2: Frequencies of Demographic Information

Demographic factor	Category	Frequency	Percent
Gender	Male	70	26.9%
	Female	190	73.1%
Field of Study	Engineering	30	11.5%
	Sciences	39	15.0%
	Humanities	15	5.8%
	Other Specialty	176	67.7%
ChatGPT Experience	Less than 3 months	17	6.5%
	3 to 6 months	54	20.8%
	More than 6 months	189	72.7%

4.1 Acceptance Intentions and Ethical Perceptions

Descriptive analysis showed high concentration and consistency in participant responses. The strongest consensus appeared in BI1 (willingness to invest time exploring AI), with a high median (~4) and a narrow interquartile range (IQR). BI2 and BI3 also had high medians, but variability increased around the practical integration of ChatGPT into coursework. BI4 showed the most divergence: opinions on long-term academic impact were polarized. On the ethical constructs, participants expressed moderate-to-high apprehension about academic integrity and cognitive over-reliance on AI. This suggests high usage intention is tempered by a distinct ethical caution.

4.2 Path Analysis Results

As shown in Table 3, six of the seven hypothesized paths reached statistical significance. PEU had a significant positive effect on PU ($\beta = 0.412$, $p < 0.001$), supporting H1. PU was the most dominant determinant, positively influencing UE ($\beta = 0.587$, $p < 0.001$, H2) and BI ($\beta = 0.562$, $p < 0.001$, H3). PU also had a significant negative correlation with EP ($\beta = -0.348$, $p < 0.001$, H4), confirming that as perceived utility increases, ethical anxiety intensifies. PEU had a positive impact on UE ($\beta = 0.236$, $p < 0.01$), supporting H5, but showed no significant direct effect on BI ($\beta = 0.048$, $p > 0.05$), so H6 was not supported. This suggests ease of use alone does not drive adoption intentions among Libyan students; usefulness and user experience are the primary motivational pathways instead.

User Experience (UE) significantly predicted BI ($\beta = 0.384$, $p < 0.001$), supporting H7. Students who report positive, satisfying, and trustworthy interactions with ChatGPT are more likely to continue using it and to recommend it to peers.

Overall model fit indices confirmed the structural model's robustness: $\chi^2 = 261.35$, df = 94, $p < 0.001$; CFI = 0.956; TLI = 0.944; RMSEA = 0.067; SRMR = 0.038. The estimated research mechanism, showing every path with its standardized coefficient and significance level, is given in Fig. 5.

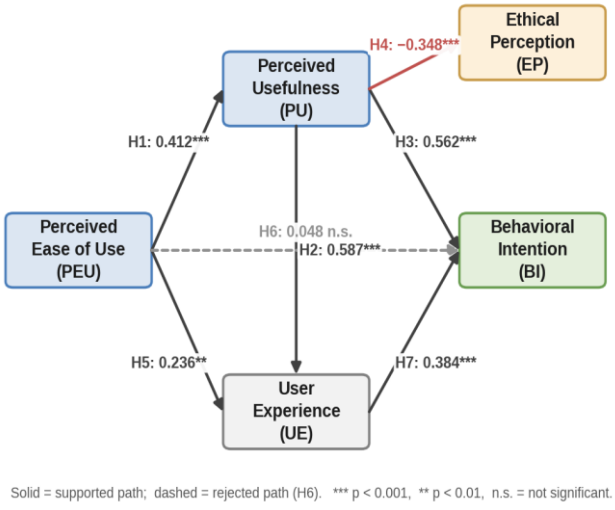


Fig. 5: Estimated research mechanism with standardized path coefficients**.**

Table 3: Path Analysis Results

Hypothesis	Path	Direction	Expected Sign	Result	β
H1	PEU → PU	Direct	Positive (+)	Supported	0.412
H2	PU → UE	Direct	Positive (+)	Supported	0.587
H3	PU → BI	Direct	Positive (+)	Supported	0.562
H4	PU → EP	Inverse	Negative (−)	Supported	-0.348

Hypothesis	Path	Direction	Expected Sign	Result	β
H5	PEU → UE	Direct	Positive (+)	Supported	0.236
H6	PEU → BI	Direct	Positive (+)	Not Supported	0.048
H7	UE → BI	Direct	Positive (+)	Supported	0.384

5. Discussion

5.1 Complex Attitudes and Ethical Perceptions

Undergraduate students in the Nalut area show a high intention to adopt ChatGPT, yet they maintain a notable level of caution about its long-term ethical implications [36]. This finding reflects the socio-technical complexity of AI adoption, beyond what prior work on digital educational environments [24] and [29-30] captures when it focuses on pure practicality. Our results suggest PU functions as the primary determinant of adoption, but it is closely tied to ethical cognition rather than acting as an isolated predictor. This challenges the "trust-centric" view in [5-8]: in academic settings, functional utility may outweigh trust, provided ethical awareness acts as a regulating factor. The inverse PU-EP relationship suggests that recognizing AI's power triggers counterintuitive concerns about plagiarism, pointing to the need for stronger institutional governance, as [13-14] argue.

5.2 Contextual and Ethical Considerations

Two notable points emerged. First, unlike findings from Vietnam [32], PEU had no significant effect on adoption intention in our sample. This may be due to the demographic profile: 26.5% of respondents were engineering and science students with high technological self-efficacy [34]. For these students, ease of use is a baseline expectation rather than a driver of intent [37]. Second, the PU-EP tension reveals a "rational duality" [38]: students use ChatGPT for efficiency while fearing its impact on independent thinking. This suggests ethical perception is not a peripheral factor but an integrated part of the acceptance process itself.

5.3 Limitations and Future Directions

Two main limitations stand out. First, the TAM framework may be missing local variables, such as digital literacy, ethical awareness, and cultural attitudes, needed for a more context-sensitive "Extended TAM" model. Second, the single region focus (both institutions are in the Nalut area) limits generalizability to Libya as a whole. Future research should build variables like digital literacy and cultural attitudes into an "Extended TAM" and run comparative studies across major Libyan universities, such as Tripoli, Benghazi, and Sebha.

6. Conclusion

This study examined the relationship between technology acceptance and ethical perception around ChatGPT among Libyan undergraduates. The findings characterize students as having a high intention to use ChatGPT alongside an ethically cautious attitude, balancing real technological value against systemic ethical risks. Perceived usefulness drives adoption, but it also triggers ethical friction: utility and responsibility turn out to be closely linked rather than separate concerns. Libyan higher education institutions should move from passive observation to active governance by establishing AI-ethics guidelines. Future research should expand to national samples and longitudinal designs to track how these perceptions change as AI becomes a permanent part of academic life, so its educational value can be maximized without compromising academic integrity.

7. Acknowledgements

Any use of AI tools was limited to aiding translation and prose. All models and research presented in this work are original. The data presented in this research is available under request.

8. Abbreviations and Acronyms

TAM – Technology Acceptance Model
PU – Perceived Usefulness
PEU – Perceived Ease of Use
UE – User Experience
BI – Behavioral Intention
EP – Ethical Perception
SPSS – Statistical Package for Social Sciences
SEM – Structural Equation Modelling
CB-SEM – Covariance-Based Structural Equation Modelling
EFA – Exploratory Factor Analysis
CFA – Confirmatory Factor Analysis
KMO – Kaiser-Meyer-Olkin (measure of sampling adequacy)
CFI – Comparative Fit Index
TLI – Tucker-Lewis Index
RMSEA – Root Mean Square Error of Approximation
SRMR – Standardized Root Mean Square Residual
LLM – Large Language Model
AI – Artificial Intelligence

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