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Who Benefits More from E-Learning? A Gender-Based SEM-PLS Analysis of Adoption, Outcomes, and Future Optimization Paths in Digital Education

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Abstract

The current research analyzes how essential variables influence E-Learning Benefits (ELB) through gender-based perspectives for students enrolled at the university level. A research analysis using SEM and MGA examines the impact of MOT, DR, and PEU and PU on ELE and ELB across genders from students at the University. The results stemmed from 330 participants (174 females and 156 males) who completed structured surveys. Data shows that females show a stronger relationship between motivational factors leading to educational benefits compared to males, as evidenced by a 0.023 significance value. The variable DR demonstrates a positive relationship with ELB outcomes in both male (β = 0.521) and female students (β = 0.298). The results indicate that females experience greater ELE impacts from PEU (p = 0.037) than males experience greater ELE impacts from PU (p = 0.007). The research did not show any significant indirect effects between variables in either study group. The study suggests that institutions should work on motivating female students through specific strategies and utilize tools with clear benefits for male students, as they enhance digital readiness for all students.

Keywords: *E-Learning Acceptance, Gender Differences, Digital Education Outcomes, Female Empowerment, Technology Adoption Models.*

Introduction

Gender differences increase barriers to educational access for women because of their social responsibilities and workplace discrimination, coupled with restricted tech access and traditional gender norms (Retno Wulandari & Ahmad, 2025; Stattkus et al., 2025), (Mohsan Iqbal et al., 2025). E-learning provides versatile access while enabling women to study education in their selected timeframe and locations(Berezhna et al., 2025) (B. Shannaq, 2025) (B. Shannaq et al., 2025). Current research needs to analyze how women use e-learning because it will guide the creation of digital education strategies to eliminate gender differences and boost educational opportunities for women.

Lossless learning through digital platforms has become a fundamental educational instrument

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alongside career advancement during our digital transformation period (Boltsi et al., 2024) (Alazzawi et al., 2025) (B. Shannaq, 2024c). The learning advantages of digital environments for male and female learners require more investigation. This research examines gender discrepancies in how online learning platforms are received and used by students through the evaluation of women's e-learning experiences versus men's experiences(Dai et al., 2022) (.Boumedyen Shannaq, 2024). This particular research initiative holds great importance because it promotes women's flexible learning opportunities through self-directed models, which advance their academic potential and career growth across cultures where conventional learning faces specific barriers (Peterson & Cox, 2025) (B. Shannaq, 2024a) (B. Shannaq, 2024b).

This research uses Structural Equation Modeling (SEM) as its quantitative approach to analyze e-learning acceptance factors and the associated benefits between male and female participants (Abu-Taieh et al., 2022). The research framework combines the Technology Acceptance Model (TAM) with performance results and personal characteristics like motivation and digital understanding (B. Shannaq, 2024d) (Shakir et al., 2024). The research seeks to establish through empirical data how gender impacts digital learning success along with guidelines for institutions to create equal digital learning opportunities (Barikzai et al., 2025) (Alshamsi et al., 2024) (Rashid Al-Shamsi & Shannaq, 2024) (B. Shannaq et al., 2024).

This research will produce outcomes that help shape educational policy, advance institutional e-learning system design, and produce strategies for digital learning that consider gender differences. The investigation seeks to strengthen women through barrier analysis and valuation of e-learning participation factors, which leads to knowledge economy inclusion methods.

Research Problem

Research into the impact of gender on user perception of e-learning utility and ease of use, together with platform achievement, remains insufficient despite increasing e-learning system adoption rates. E-learning system developers commonly create their solutions with generic approaches since they do not examine how males and females interact with these platforms differently and derive advantages. Unintentional exclusion or underperformance among one group, particularly women, becomes more likely due to their unique learning needs and potential barriers.

Research Gap

Research on e-learning mainly investigates technology specifications, user satisfaction rates, and system effectiveness, but offers limited analysis of gender-based factors. Most research examining user gender differences fails to establish comprehensive measures for specific program advantages and long-term evaluation methods [10].

Research Questions

The field requires research that should focus on the following three areas:

- Research analyzes educational achievements instead of only evaluating user access for both female and male students.

- The study investigates what affects acceptance rates through psychological foundations and socio-cultural influences.

- A gender-conscious methodology should be incorporated to evaluate e-learning effectiveness.

Research Objectives

1. The study evaluates how male and female students accept e-learning platforms through assessment.

2. The research determines how participants from both genders benefit from e-learning and their learned outcomes.

3. The research identifies motivational and personal factors that differently affect e-learning engagement between male and female students.

4. The authors aim to develop strategies that enhance gender-sensitive e-learning models.

Hypotheses:

The proposed hypotheses are presented in Table 1

Table. Hypothesis

Hypothesis	Description	Mapped Link
H1	Gender significantly affects acceptance of e-learning	Gender → PU, PEU
H2	Female learners perceive higher usefulness	GEN → PU
H3	Gender moderates PEU → ELE	GEN moderates PEU → ELE
H4	Motivation & Digital Literacy influences ELB differently by gender	(MOT + DR) → ELB (moderated by GEN)
H5	Women benefit more from e-learning in constrained contexts	GEN → ELB

The proposed conceptual framework is presented in Figure 1

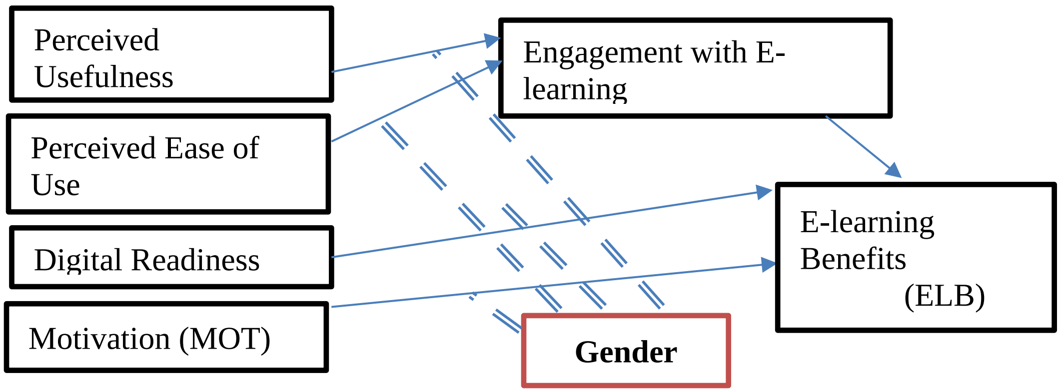

Figure 1. Conceptual Framework

Literature Review

The acceptance of e-learning platforms is an important, multifarious issue, making it a subject of several factors, including gender. While there are studies showing gender as critical to e-learning acceptance and usage, other studies show that gender differences are small or nonexistent.

Gender and Technology Acceptance

The TAM model is helpful for several studies that establish gender differences in adopting e-learning. Research conducted in Chile and Spain found that statistically, there were no significant gender differences in accepting an e-learning platform; these findings can be inferred from the way both genders behave in adopting technology (P. Ramírez-Correa et al., 2010) (P. E. Ramírez-Correa et al., 2015) .

On the other hand, a slight gender divide was reported in South Africa, where women tend to accept e-learning systems more than men. Thus, it can be said that gender shapes their perceptions towards e-learning, though subtly (Shanmugam & Marsh, 2016).

Perceived Ease of Use and Usefulness

The perception of ease of use and usefulness is critical in accepting e-learning platforms. For example, a study in Taiwan showed that men were more confident in using technology and reported higher levels of system interactivity and usefulness than women. However, these factors did not lead to significant differences in usage intention in his e-learning systems among respondents (Chen & Tsai, 2007) (Ong & Lai, 2006).

Another study implied perceptions of enjoyment and results demonstrability for managing the relationship between the effect of ease of use and usefulness, with little differences of gender intervening in these relations (P. E. Ramírez-Correa et al., 2015).

Moderating Effects of Gender

Among other things, gender is a moderating factor in the relationship between several predictors and intention to use e-learning systems. In Iraq, gender slightly moderated the relationship between e-learning self-efficacy and acceptance of a Learning Management System (LMS) in beneficiary students, wherein self-efficacy strongly influenced a male individual's intention to use LMS (Al-Azawei, 2019) (B. Shannaq & Al Shamsi, 2024) (Al-Shamsi et al., 2024) .

After that, the research was conducted in Pakistan during the COVID-19 pandemic. The study found that the gender differentials modestly restrained the acceptance of the Aaghi LMS Portal, revealing that gender affects how e-learning platforms operate efficiently in various contexts (Shah et al., 2022) (Shamsi & Shannaq, 2023) .

Gender Based Outcomes in Digital Learning Environments

Gender outcomes in digital learning environments are quite complex, as they cut across numerous other influencing factors that may determine how each gender experiences or benefits from digital education (Yang & Zhu, 2025; Yu, 2021). The transition to digital learning, spurred by COVID-19, has created opportunities and challenges in achieving gender equity in these educational areas (Tella, 2025). This literature review merges various studies into a cohesive discussion to fully understand gender differences in digital learning environments regarding performance, engagement, empowerment, local and global demands (.Boumedyen Shannaq & Alabri, 2025).

Methodology

This research utilizes Structural Equation Modeling (SEM) to perform statistical analysis on the differences between genders in e-learning platform acceptance and educational results. SEM provides researchers with a mechanism to investigate intricate patterns between measured and hidden constructs in the proposed conceptual model(Khattak et al., 2024).

Step 1

Develop Conceptual Models

The research begins with designating Step 1 to Develop Conceptual Models and Formulate Hypotheses.

The first research step required creating a conceptual design alongside hypothesis development to investigate relationships at direct and indirect levels and moderation effects. The primary constructs identified are presented in Figure 1.

Step 2

Data Collection & Sampling

A structured questionnaire was distributed through Google Forms as part of the study method. The authors obtained validation from academic experts before distributing the survey. The research included students from various academic backgrounds and gender groups to conduct a comprehensive analysis. Digital active learners across higher education institutions formed the subject of responses through a convenience sampling strategy. The study sample consisted of two gender-based groups. The female group included 174 participants, while the male group comprised 156. This distribution allowed for a comparative analysis of e-learning acceptance and outcomes across genders.

Step 3

Measurement Model Validation

Confirmatory Factor Analysis (CFA) executed in SmartPLS evaluated construct reliability and validity(Hair et al., 2020). It was crucial for the reliability benchmarks to achieve the following standards:

- Cronbach's Alpha > 0.7
- Composite Reliability (CR) > 0.7
- Average Variance Extracted (AVE) > 0.5

Quality indicators that featured loadings under 0.7 were eliminated to improve model reliability.

Step 4

Structural Model Evaluation

The analysis with SmartPLS provided evaluations of path coefficients (β), T-statistics, and P-values to validate hypotheses. The model fit indicators and 5,000 sample bootstrapping procedures evaluated the structural paths to check their stability and robustness.

Step 5

Interpretation & Policy Recommendations

This research evaluated results versus existing findings to showcase variations between male and female acceptance of e-learning methods. The research findings suggest gender-responsive digital education system design standards for educational institutions.

Data Analysis and Results

Measurement Model

Figure 2 presents the factor loading of the proposed model, Table 2: Construct Reliability and Validity. Tables 2 and 2 analyze the measurement model's internal consistency, convergent validity, and reliability. The measurement model achieves robust internal consistency because all constructs demonstrate Cronbach's Alpha (CA) and Composite Reliability (rho_c) values above 0.7, which extend from 0.911 to 0.957.

The measurement model demonstrates convergent validity because every construct explains a minimum variance of 0.739 to 0.817 from its indicators, which exceeds the standard 0.5 threshold.

The reliability and confidence levels of Digital Readiness (DR), Motivation (MOT), Perceived Ease of Use (PEU), Perceived Usefulness (PU), E-learning Engagement (ELE), and E-learning Benefits (ELB) enable their use in the structural model. The measurement model exhibits both reliability and validity at a high level, which enables vigorous testing of structural models. Table 3: Discriminant Validity – Fornell-Larcker Criterion

Table 3 confirms that all constructs maintain their uniqueness relative to other constructs included in the analysis. Discriminant validity becomes possible when the square root of AVE is greater than the intercorrelations found in the same row and column elements. All constructs meet this requirement. The 0.881 diagonal figure for DR demonstrates a higher value than the 0.916 PEU and 0.882 PU interrelations. The discriminant validity passes acceptance standards because the square root of AVE values listed along the diagonal remain higher than corresponding cross-column values. The relationships between constructs (DR↔PU and PEU↔PU) show high closeness so researchers should further examine their impact on multicollinearity. Table 4: Variance Inflation Factor (VIF)VIF measures multicollinearity among indicators: The VIF values ranging from 2.27 to 4.94 are lower than 5; hence, no substantial multicollinearity exists.

The predictive variables PU and ELB demonstrate VIF scores of about 4.9, indicating an

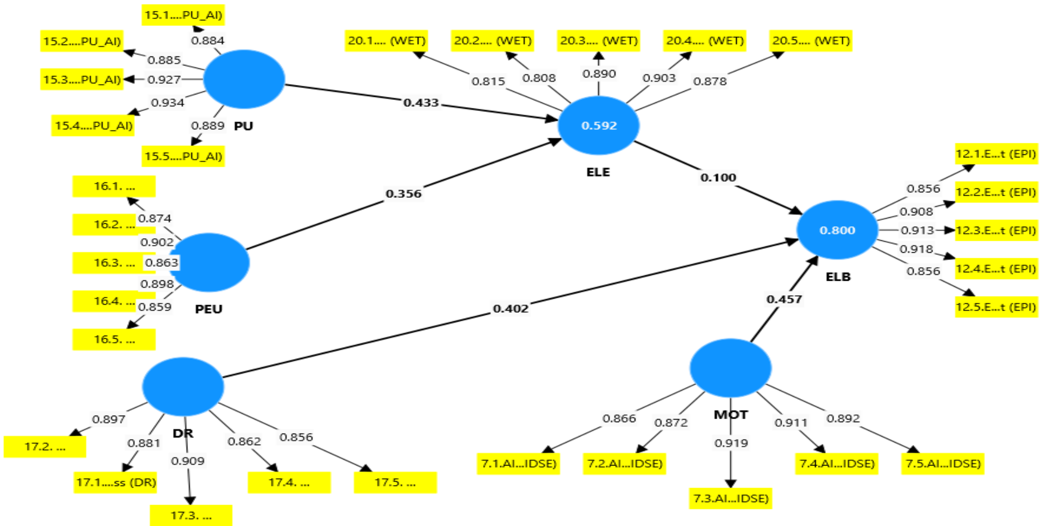

Figure 2. Factor Loading

intermediate yet accepted level of relationship between predictors. The model shows no multicollinearity, yet some predictive variables, particularly between PU and ELB, display overlapping explanation capabilities.

	Cronbach's alpha	**Composite reliability (rho_a)**	**Composite reliability (rho_c)**	**Average variance extracted (AVE)**
DR	0.928	0.929	0.945	0.776
ELB	0.934	0.936	0.95	0.793
ELE	0.911	0.917	0.934	0.739
MOT	0.936	0.939	0.951	0.796
PEU	0.927	0.929	0.945	0.774
PU	0.944	0.946	0.957	0.817

Table 2. Construct Reliability and Validity

Table 3 presents the Discriminant Validity using Fornell-Lacker Criterion

	DR	**ELB**	**ELE**	**MOT**	**PEU**	**PU**
DR	0.881					
ELB	0.841	0.890				
ELE	0.788	0.754	0.860			
MOT	0.788	0.847	0.738	0.892		
PEU	0.916	0.892	0.747	0.816	0.880	
PU	0.882	0.873	0.755	0.835	0.905	0.904

Table 3. Fornell-Lacker

Average for all items representing the construct	VIF
ELB	2.61
PU	3.142
PEU	2.921
DR	2.791
DR	2.58
MOT	2.273
ELB	2.755

Table 4. VIF

Structural Model Assessment

Figure 3 presents the bootstrapping MGA for the female Group, and Figure 4 presents the bootstrapping MGA for the Male group

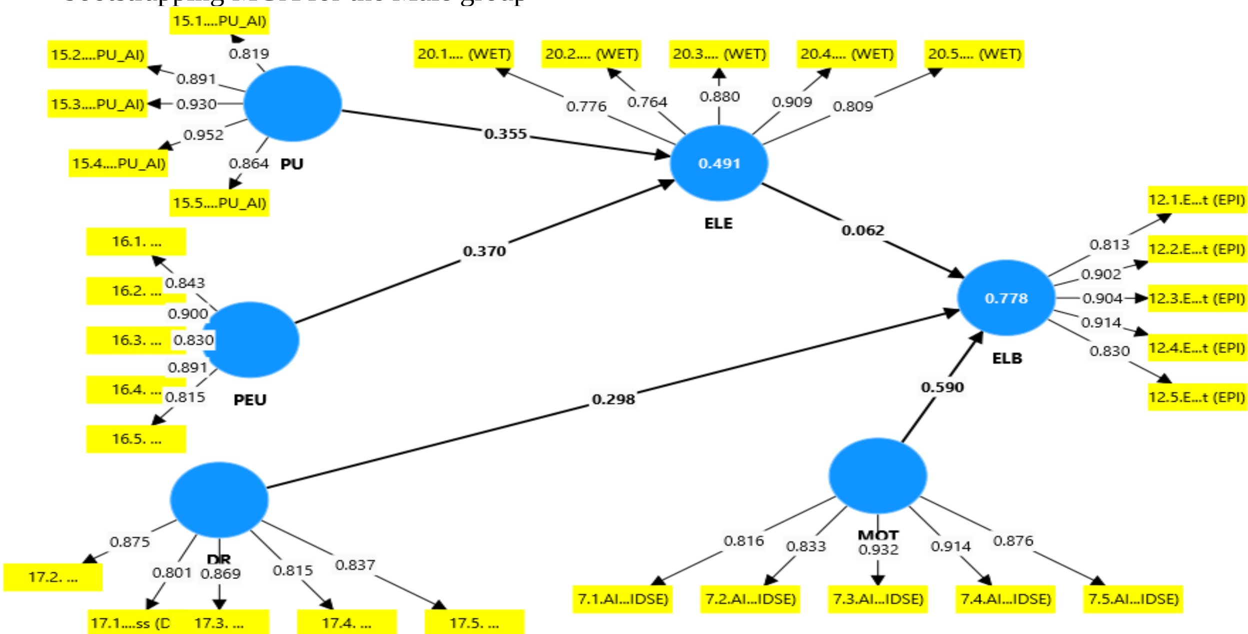

Figure 3. Group Female

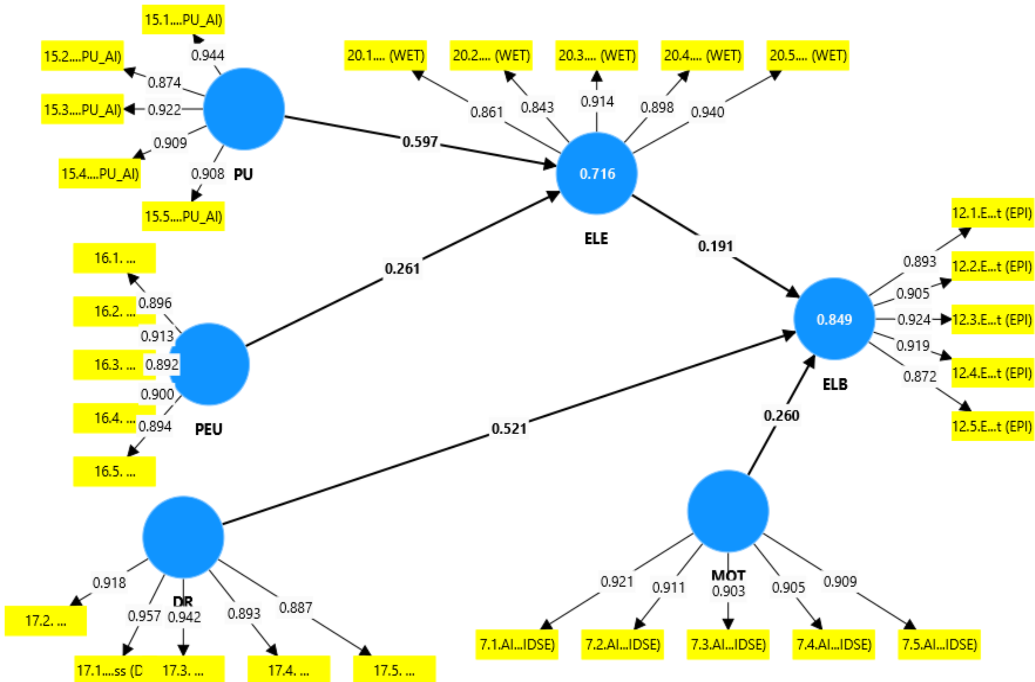

Figure 4. Group Male

Table 5: Path Coefficients (MGA)

The path MOT → ELB produces statistically important gender differences, demonstrating better outcomes for female employees (p = 0.023).

The variables show no meaningful differences between male and female participants, thus indicating their relationships remain equivalent across genders.

	Difference (Group_Femal - Group_Male)	**1-tailed (Group_Femal vs Group_Male) p value**	**2-tailed (Group_Femal vs Group_Male) p value**
DR -> ELB	-0.223	0.898	0.203
ELE -> ELB	-0.129	0.747	0.507
MOT -> ELB	0.330	0.023	0.046
PEU -> ELE	0.109	0.375	0.750
PU -> ELE	-0.242	0.789	0.422

Table 5. Path coefficient: Bootstrap MGA

Based on statistical analysis, the research demonstrates that motivation has a more substantial impact on ELB for female subjects than for males (β = 0.590, p = 0.000).

The negative relationship between Perceived Usefulness → ELE exists exclusively for male participants based on their statistical significance at p = 0.007.

	Original (Group_Femal)	Original (Group_Male)	Mean (Group_Femal)	Mean (Group_Male)	STDEV (Group_Femal)	STDEV (Group_Male)	t value (Group_Femal)	t value (Group_Male)	p value (Group_Femal)	p value (Group_Male)
DR -> ELB	0.298	0.521	0.299	0.505	0.102	0.146	2.935	3.574	0.003	0.000
ELE -> ELB	0.062	0.191	0.063	0.195	0.093	0.163	0.667	1.170	0.505	0.242
MOT -> ELB	0.590	0.260	0.590	0.271	0.097	0.118	6.057	2.214	0.000	0.027
PEU -> ELE	0.370	0.261	0.383	0.245	0.178	0.238	2.082	1.093	0.037	0.274
PU ->	0.355	0.597	0.347	0.615	0.199	0.220	1.780	2.712	0.075	0.007

E L E										

Table 6. Bootstrap Results

No significant gender moderation via indirect paths (PEU/PU → ELE → ELB); p-values > 0.3.

The mediation results between male and female groups appear identical as far as measured variables are concerned.

	Difference (Group_Femal - Group_Male)	**1-tailed (Group_Femal vs Group_Male) p value**	**2-tailed (Group_Femal vs Group_Male) p value**
PEU -> ELE -> ELB	-0.027	0.561	0.879
PU -> ELE -> ELB	-0.092	0.808	0.385

Table 7. Specific Indirect Effect

Table 8: Accepted Hypotheses

The results indicate that motivational strategies should receive specialized attention for both genders, given the stronger relationship of motivation toward errorless learning behaviors among females.

Digital readiness as a predictor of electronic learning behavior (ELB) is established for male and female students.

Hypothesis	**Path**	**Significance**	**Interpretation**	**Recommendation**
H4	**MOT -> ELB**	Significant Difference between Females and Males (**p = 0.023**)	Motivation has a **stronger positive effect** on E-Learning Benefits for **females** (β = 0.590) compared to males (β = 0.260).	**Support and enhance motivational strategies** targeted at female learners. Personalized feedback, goal setting, and mentoring programs may amplify this effect. For males, use gamification or competitive elements to boost motivation.
H1 (Partially Supported)	**DR -> ELB**	Not significant difference (**p = 0.898**), but both groups show a **significant**	Digital Readiness positively impacts E-Learning Benefits for both males (**β = 0.521**)	Since the relationship is significant in both groups, to boost readiness, focus on improving infrastructure, access, and device training

Hypothesis	Path	Significance	Interpretation	Recommendation
		direct effect.	and females (**β = 0.298**)	equally for both genders.
H4 (Partial)	**PEU -> ELE** (only significant for females)	No significant difference (p = 0.375), but **significant only for females** (p = 0.037)	Perceived Ease of Use influences E-Learning Engagement **significantly among females** but not males.	Consider simplifying digital interfaces, offering onboarding tutorials, and providing user support targeted especially at female learners.

Table 8. Accepted Hypotheses (Significant Differences Between Groups or Significant Paths)

Table 9: Rejected Hypotheses

No significant gender moderation for PU → ELE or indirect paths via ELE.

The relationship between engagement (ELE → ELB) does not achieve statistical significance for the female group, indicating that better interactive learning resources must be developed.

Hypothesis	Path	Significance	Interpretation	Recommendation
H2	**PU -> ELE**	No significant difference (**p = 0.789**), but **only significant for males** (p = 0.007)	Perceived Usefulness impacts males more than females	This indicates **males may require clear value propositions** to engage. For improvement, show the practical or job-related advantages of digital tools during instruction.
H3	**Gender moderates PEU -> ELB via ELE**	Indirect effect is **non-significant** (p = 0.879)	No evidence that **gender moderates** the relationship from ease of use to learning benefits through engagement	No specific action needed; this is **normal**. Continuing general usability improvements for all users.
H5	**ELE -> ELB**	No significant difference (**p = 0.747**) and not significant path for females (**p = 0.505**)	Engagement does not show a strong impact on benefits, especially among females	Consider enhancing **interactive features** (discussions, real-time feedback) to increase the impact of engagement. Investigate if students are passively participating.
H3 (continued)	**PU -> ELE -> ELB**	Indirect effect is **non-significant** (p = 0.385)	No gender-based difference in usefulness influencing benefits	This suggests the **mechanism is the same across genders**; improvements can be

Hypothesis	Path	Significance	Interpretation	Recommendation
			through engagement	applied **universally**, not separately.

Table 9. Rejected Hypotheses (No Significant Differences or Non-Significant Paths)

Summary of Results:

- **Motivation (MOT)** plays a **key role** in e-learning success for **females**, making **H4 accepted** in part.
- **Digital Readiness (DR)** significantly improves learning outcomes for both genders — an essential shared factor.
- **Perceived Ease of Use (PEU)** is more relevant for females.
- **Perceived Usefulness (PU)** is more relevant for males.
- **E-Learning Engagement (ELE)** does **not** significantly impact benefits directly for females, but it needs further exploration.

Area	Suggestion
Female Learners	Focus on motivational techniques, interface ease, and self-paced learning models.
Male Learners	Highlight the usefulness and career alignment of e-learning tools.
For Both Genders	Improve digital readiness and build intuitive, engaging platforms.
Engagement Factor	Revising content to be more interactive and relevant — passive usage may reduce effectiveness.

Recommendations Overview:

General Recommendation: Limitations and Future Work

- The statistical indicators demonstrate that the measurement model functions well. Research should investigate combining these overlapping dimensions into a higher-order construct named "Technology Orientation" because of their high intercorrelations, particularly between PU, PEU, and DR.
- Research should improve measure quality or remove conceptual overlap between items that approach VIF violation thresholds.
- The high level of reliability and validity strengthens the trustworthiness of your gender-based structural analysis, enabling accurate interpretation of group difference measurements.

Discussions

This investigation addresses the essential query “Who Cares More about E-Learning?” through research on female and male acceptance and academic results from digital learning systems. Past research about e-learning mainly focused on technical aspects. However, existing evidence reveals how psychological factors and cultural surroundings modify the differences related to gender experiences in online learning programs.

Motivation is a decisive factor that enhances e-learning advantages through the lens of female students more than the male population. Interior motivation makes female students more active in their e-learning adoption, generating superior academic achievements and behavioral returns. Research results show that female students see better outcomes when they enter e-learning initiatives with psychological readiness accompanied by emotional investment, suggesting that e-learning platforms require motivational design elements, including recognition platforms, support groups, and mentorship programs.

A stronger relationship exists between male students' perceived usefulness of e-learning systems because they tend to use digital resources when they directly contribute to their academic achievements and skill progression. Implementing realistic, practical projects combined with experiential learning and performance-focused results is the best approach to engaging male students in education.

The influence of Digital Readiness (DR) on both genders proves positive, but male students display stronger statistical relationships. Research supports universal backing for digital skills and access because they serve as essential e-learning success factors that require infrastructure development, technical support, and digital literacy education.

The research study addresses an important scholarly gap by investigating how gender shapes e-learning acceptance patterns and learning results. A gender-conscious educational approach should provide personalized learning platforms because of their importance. Institutions should study cultural standards combined with emotional profiles to improve digital learning performance, specifically for regions where gender roles strongly impact the education process. Leveraging these findings in e-learning policies will enhance educational inclusivity, student success, and retention rates.

Conclusion

The research strengthens gender difference studies within digital learning environments through SEM and MGA analysis to understand motivational and technological factors influencing student success. Female students obtain better E-Learning Benefits when their motivation level increases, since gender-specific learning strategies help improve their academic interaction. Public perception of technology usefulness substantially impacts male students who require intervention strategies to deliver learning value. This investigation illustrates Digital Readiness's crucial function for every learner since equipment, skills development, and digital platform capability should remain essential for all students.

The plan should focus on motivational programs such as mentorship, goal-oriented strategies for female students, and relevant real-world learning opportunities to engage male students. As a key institutional initiative, the administration must make digital infrastructure and training for the learning system usability equal for everyone. These findings help inform inclusive e-learning designs and strategic interventions to optimize student success in diverse academic settings.

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