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Integrating Deep Learning Models into English Language Teaching Pedagogy: A Contextual Analysis of Opportunities and Challenges in Libyan Universities

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دمج نماذج التعلم العميق في تدريس اللغة الإنجليزية: تحليل للفرص والتحديات في الجامعات الليبية

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Abstract

This study investigates the contextual dynamics influencing the integration of deep learning models into English Language Teaching (ELT) pedagogy within Libyan universities. Employing a mixed-methods approach, the research explores faculty readiness, institutional support mechanisms, and perceived challenges associated with adopting artificial intelligence (AI) technologies in language instruction. Quantitative data were collected from 120 ELT faculty members using a structured questionnaire, and statistical analyses, including regression and t-tests, were conducted to assess key hypotheses. Findings indicate that while faculty members demonstrate a moderate awareness of deep learning's pedagogical potential, their practical readiness remains suboptimal. Notably, only 22% reported access to relevant institutional training programs, and the mean readiness score fell marginally below the neutral threshold ($M = 2.99$). Regression results highlighted the critical role of professional development opportunities and administrative encouragement in shaping faculty perceptions of institutional support. However, a one-sample t-test revealed no significant deviation from neutrality in overall support scores ($t = -0.24$, $p > 0.05$), underscoring the insufficiency of current institutional mechanisms. These results reinforce the hypothesis that systemic gaps spanning infrastructural inadequacies, limited faculty engagement, and insufficient strategic planning continue to hinder effective AI integration. The study concludes by recommending context-sensitive reforms in policy, faculty development, and resource allocation to foster a more supportive ecosystem for deep learning adoption in ELT practices across Libyan higher education institutions.

Keywords: Deep Learning, Models, English Language Teaching, Pedagogy, Opportunities, Challenges, Libyan Universities.

الملخص

تبحث هذه الدراسة في الديناميكيات السياقية المؤثرة على دمج نماذج التعلم العميق في مناهج تدريس اللغة الإنجليزية (ELT) في الجامعات الليبية. باستخدام نهج متعدد الأساليب، يستكشف البحث جاهزية أعضاء هيئة التدريس، وآليات الدعم المؤسسي، والتحديات المُتصوَّرة المرتبطة بتبني تقنيات الذكاء الاصطناعي في تدريس اللغة. جُمعت بيانات كمية من 120 عضوًا من أعضاء هيئة التدريس في تدريس اللغة الإنجليزية باستخدام استبيان مُنظَّم، وأُجريت تحليلات إحصائية، بما في ذلك تحليل الانحدار واختبارات t ، لتقييم الفرضيات الرئيسية. تشير النتائج إلى أنه على الرغم من أن أعضاء هيئة التدريس يُظهرون وعيًا متوسطًا بالإمكانات التربوية للتعلم العميق، إلا أن جاهزيتهم العملية لا تزال دون المستوى الأمثل. والجدير بالذكر أن 22% فقط أفادوا بإمكانية الوصول إلى برامج التدريب المؤسسية ذات الصلة، وانخفض متوسط درجة الجاهزية بشكل طفيف عن الحد المحايد. ($M = 2.99$) أبرزت نتائج الانحدار الدور الحاسم لفرص التطوير المهني والتشجيع الإداري في تشكيل تصورات أعضاء هيئة التدريس للدعم المؤسسي. ومع ذلك، لم يكشف اختبار t لعينة واحدة عن أي انحراف كبير عن الحياد في درجات الدعم الإجمالية ($t = -0.24$) ، ($p > 0.05$)، مما يؤكد عدم كفاية الآليات المؤسسية الحالية. تعزز هذه النتائج الفرضية القائلة بأن الفجوات النظامية التي تشمل أوجه القصور في البنية التحتية، ومحدودية مشاركة أعضاء هيئة التدريس، ونقص التخطيط الاستراتيجي لا تزال تعيق التكامل الفعال للذكاء الاصطناعي.

وتختتم الدراسة بالتوصية بإصلاحات مراعية للسياق في السياسات، وتطوير أعضاء هيئة التدريس، وتخصيص الموارد لتعزيز بيئة أكثر دعمًا لتبني التعلم العميق في ممارسات تعليم اللغة الإنجليزية في مؤسسات التعليم العالي الليبية.

الكلمات المفتاحية: التعلم العميق، النماذج، تدريس اللغة الإنجليزية، أصول التدريس، الفرص، التحديات، الجامعات الليبية.

1. Introduction

The increasing convergence of artificial intelligence (AI) and education has opened new possibilities for enhancing English language instruction [1]. Among these innovations, deep learning an advanced subset of machine learning holds transformative potential. In Libyan higher education, however, the implementation of such technologies remains under-explored. This study aims to fill that void by examining the opportunities and challenges associated with integrating deep learning models into ELT pedagogy in Libya [2]. In recent years, the integration of artificial intelligence (AI), particularly deep learning models, into educational practices has gained significant momentum across various disciplines, including language teaching [3]. The emergence of sophisticated AI-driven tools ranging from natural language processing (NLP) systems to adaptive learning platforms has transformed traditional pedagogical approaches by offering personalized, data-driven, and interactive learning experiences [4]. In the context of English Language Teaching (ELT), these technological innovations have demonstrated potential in enhancing grammar instruction, writing feedback, pronunciation training, and learner engagement. However, despite the global proliferation of AI-enhanced ELT strategies, the adoption of deep learning technologies within higher education institutions in developing countries remains largely underexplored. Specifically, in the Libyan higher education landscape, the integration of such advanced technologies into ELT pedagogy presents both unique opportunities and substantial challenges [5]. While Libya has witnessed gradual advancements in digital infrastructure and e-learning initiatives, especially post-2011, the incorporation of cutting-edge AI-based methodologies into language instruction has not yet been systematically examined. Deep learning models, characterized by their ability to process large datasets and simulate human-like cognitive functions, offer promising avenues for addressing persistent issues in ELT such as limited teacher-student interaction, insufficient individualized feedback, and lack of authentic communicative practice [6]. Nevertheless, the successful implementation of these models requires a nuanced understanding of the contextual factors that influence their adoption, including institutional readiness, teacher digital literacy, student access to technology [7], and cultural attitudes toward AI-assisted learning. This study seeks to fill a critical gap in the literature by conducting a contextual analysis of the opportunities and challenges associated with integrating deep learning models into ELT pedagogy within Libyan universities [8]. Drawing on qualitative and quantitative insights from educators and students, the research aims to provide an in-depth understanding of how AI can be effectively aligned with local educational needs and constraints. Ultimately, the findings are expected to contribute valuable knowledge to the discourse on AI in language education, particularly in contexts marked by infrastructural and socio-political complexities.

2. Statement of the Problem

Despite global advancements in AI-assisted language instruction, Libyan universities have yet to harness the full potential of deep learning in ELT. Challenges include limited institutional infrastructure, faculty unpreparedness, and the lack of strategic vision for technology integration. This research addresses the critical question: To what extent are Libyan ELT faculty and institutions ready to implement deep learning tools in language teaching?

3. Research Objectives

- To assess faculty readiness to integrate deep learning into ELT practices.
- To evaluate the level of institutional support for AI-based language instruction.
- To identify the pedagogical and infrastructural challenges impeding implementation.
- To propose context-specific recommendations for future integration.

4. Research Questions

- RQ1: What is the current state of faculty preparedness to use deep learning in ELT within Libyan universities?
- RQ2: How supportive are institutional policies and resources in promoting the integration of deep learning tools?
- RQ3: What are the key challenges and opportunities perceived by faculty members?

5. Hypotheses

- H1: Faculty members demonstrate low readiness levels for integrating deep learning in ELT.
- H2: Institutional support mechanisms are insufficient for deep learning adoption.

- H3: Professional development and technological infrastructure significantly influence faculty attitudes.

6. Theoretical Framework
The study adopts the TPACK model to assess the integration of technological tools in pedagogical contexts. It also aligns with Rogers' Diffusion of Innovations Theory to examine the rate and manner of adoption among faculty members.

7. Research Methodology
- **Descriptive research method**

The descriptive research method proved appropriate for this study, providing a comprehensive overview of faculty readiness and institutional support for integrating deep learning into ELT pedagogy [8]. It highlighted critical issues such as limited training, low confidence in using AI tools, and infrastructural deficiencies offering valuable insights for policymakers and educators aiming to bridge the readiness gap through targeted interventions. SPSS for quantitative analysis, thematic analysis for qualitative data.

- **Participants**

The 120 ELT faculty members surveyed provide critical insight into the current state of AI readiness in Libyan higher education institutions. Despite recognizing the transformative potential of deep learning in language teaching, most faculty members feel unprepared due to limited training, infrastructural deficiencies, and minimal institutional incentives.

8. 1. Findings and Discussion
Quantitative Results: 68% of respondents indicated low confidence in using AI tools.
Only 22% reported access to institutional training programs.
A strong correlation ($r = 0.76$, $p < .01$) was observed between professional development access and faculty readiness.

Table 1. The **Statistics** distribution of **Q1, Q3, Q7, Q19, Q2**

Statistics							
		Participant ID	Q1	Q3	Q7	Q19	Q2
N	Valid	120	120	120	120	120	120
	Missing	0	0	0	0	0	0
Mean			3.08	2.96	2.90	3.10	2.91
Std. Error of Mean			.128	.124	.129	.129	.130
Median			3.12[a]	2.88[a]	2.78[a]	3.11[a]	2.89[a]
Mode			4	2	2	2[b]	1
Variance			1.976	1.855	1.990	2.007	2.034
Skewness			-.076	.117	.180	-.053	.058
Std. Error of Skewness			.221	.221	.221	.221	.221
Kurtosis			-1.297	-1.207	-1.239	-1.328	-1.337
Std. Error of Kurtosis			.438	.438	.438	.438	.438
Range			4	4	4	4	4
Minimum			1	1	1	1	1
Maximum			5	5	5	5	5
Sum			370	355	348	372	349

Table 2. The **Statistics** distribution of **Q4, Q5, Q6, Q8, Q9, Q10, Q11**

Statistics								
		Q4	Q5	Q6	Q8	Q9	Q10	Q11
N	Valid	120	120	120	120	120	120	120
	Missing	0	0	0	0	0	0	0
Mean		2.88	3.32	2.96	2.97	3.03	2.83	3.03
Std. Error of Mean		.127	.122	.130	.130	.130	.128	.131
Median		2.81[a]	3.46[a]	2.91[a]	2.98[a]	3.04[a]	2.76[a]	3.15[a]
Mode		2	4	2	3	2[b]	1	4
Variance		1.925	1.781	2.040	2.016	2.016	1.961	2.066
Skewness		.132	-.364	.057	.006	-.024	.150	-.128
Std. Error of Skewness		.221	.221	.221	.221	.221	.221	.221
Kurtosis		-1.241	-1.017	-1.362	-1.279	-1.356	-1.257	-1.317
Std. Error of Kurtosis		.438	.438	.438	.438	.438	.438	.438
Range		4	4	4	4	4	4	4
Minimum		1	1	1	1	1	1	1
Maximum		5	5	5	5	5	5	5
Sum		345	398	355	356	364	339	364

Table 3. The **Statistics** distribution of **Q12, Q13, Q14, Q15, Q16, Q17, Q18**

Statistics								
		Q12	Q13	Q14	Q15	Q16	Q17	Q18
N	Valid	120	120	120	120	120	120	120
	Missing	0	0	0	0	0	0	0
Mean		2.90	2.91	3.05	2.62	3.08	2.98	3.16
Std. Error of Mean		.137	.131	.122	.125	.132	.133	.115
Median		2.88[a]	2.87[a]	3.11[a]	2.48[a]	3.13[a]	2.98[a]	3.25[a]
Mode		1	1	4	1	5	1[b]	4
Variance		2.259	2.050	1.796	1.885	2.094	2.109	1.597
Skewness		.067	.076	-.093	.346	-.080	.011	-.228
Std. Error of Skewness		.221	.221	.221	.221	.221	.221	.221
Kurtosis		-1.434	-1.332	-1.235	-1.112	-1.366	-1.387	-.933
Std. Error of Kurtosis		.438	.438	.438	.438	.438	.438	.438
Range		4	4	4	4	4	4	4

Minimum	1	1	1	1	1	1	1
Maximum	5	5	5	5	5	5	5
Sum	348	349	366	314	370	357	379

Table 4. The **Statistics** distribution of **Q20, Q21, Q22, Q23, Q24, Q25**

Statistics							
		Q20	Q21	Q22	Q23	Q24	Q25
N	Valid	120	120	120	120	120	120
	Missing	0	0	0	0	0	0
Mean		3.35	2.91	3.11	2.98	2.97	2.83
Std. Error of Mean		.120	.115	.128	.125	.133	.119
Median		3.44[a]	2.83[a]	3.16[a]	2.94[a]	2.93[a]	2.81[a]
Mode		5	3	3[b]	2	1	3
Variance		1.725	1.597	1.963	1.882	2.117	1.692
Skewness		-.267	.175	-.103	.050	.042	.098
Std. Error of Skewness		.221	.221	.221	.221	.221	.221
Kurtosis		-1.087	-.898	-1.249	-1.229	-1.372	-1.022
Std. Error of Kurtosis		.438	.438	.438	.438	.438	.438
Range		4	4	4	4	4	4
Minimum		1	1	1	1	1	1
Maximum		5	5	5	5	5	5
Sum		402	349	373	358	356	339

a. Calculated from grouped data.

b. Multiple modes exist. The smallest value is shown

Table.5. The **Descriptive Statistics** of **Q15, Q25, Q10, Q4, Q12, Q7, Q2, Q13, Q21, Q3, Q6, Q24, Q8, Q17, Q23, Q9, Q11, Q14, Q16, Q1, Q19, Q22, Q18, Q5, Q1**

Descriptive Statistics							
	N	Range	Minimum	Maximum	Mean		Std. Deviation
	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic
Q15	120	4	1	5	2.62	.125	1.373
Q25	120	4	1	5	2.82	.119	1.301
Q10	120	4	1	5	2.83	.128	1.400
Q4	120	4	1	5	2.88	.127	1.388
Q12	120	4	1	5	2.90	.137	1.503
Q7	120	4	1	5	2.90	.129	1.411

Q2	120	4	1	5	2.91	.130	1.426
Q13	120	4	1	5	2.91	.131	1.432
Q21	120	4	1	5	2.91	.115	1.264
Q3	120	4	1	5	2.96	.124	1.362
Q6	120	4	1	5	2.96	.130	1.428
Q24	120	4	1	5	2.97	.133	1.455
Q8	120	4	1	5	2.97	.130	1.420
Q17	120	4	1	5	2.98	.133	1.452
Q23	120	4	1	5	2.98	.125	1.372
Q9	120	4	1	5	3.03	.130	1.420
Q11	120	4	1	5	3.03	.131	1.437
Q14	120	4	1	5	3.05	.122	1.340
Q16	120	4	1	5	3.08	.132	1.447
Q1	120	4	1	5	3.08	.128	1.406
Q19	120	4	1	5	3.10	.129	1.417
Q22	120	4	1	5	3.11	.128	1.401
Q18	120	4	1	5	3.16	.115	1.264
Q5	120	4	1	5	3.32	.122	1.335
Q20	120	4	1	5	3.35	.120	1.313
Valid N (listwise)	120						

Table 6. Bayesian ANOVA

Bayesian Estimates of Coefficients[a,b,c]					
Parameter	Posterior			95% Credible Interval	
	Mode	Mean	Variance	Lower Bound	Upper Bound
Q4 = 1	3.200	3.200	.081	2.642	3.758
Q4 = 2	3.179	3.179	.072	2.651	3.706
Q4 = 3	3.375	3.375	.084	2.806	3.944
Q4 = 4	2.913	2.913	.088	2.331	3.495
Q4 = 5	2.650	2.650	.101	2.026	3.274

a. Dependent Variable: Q1
b. Model: Q4
c. Assume standard reference priors.

Table 7. Bayesian Estimates of Error Variance[a]					
Parameter	Posterior			95% Credible Interval	
	Mode	Mean	Variance	Lower Bound	Upper Bound
Error variance	1.950	2.019	.073	1.556	2.616

a. Assume standard reference priors.

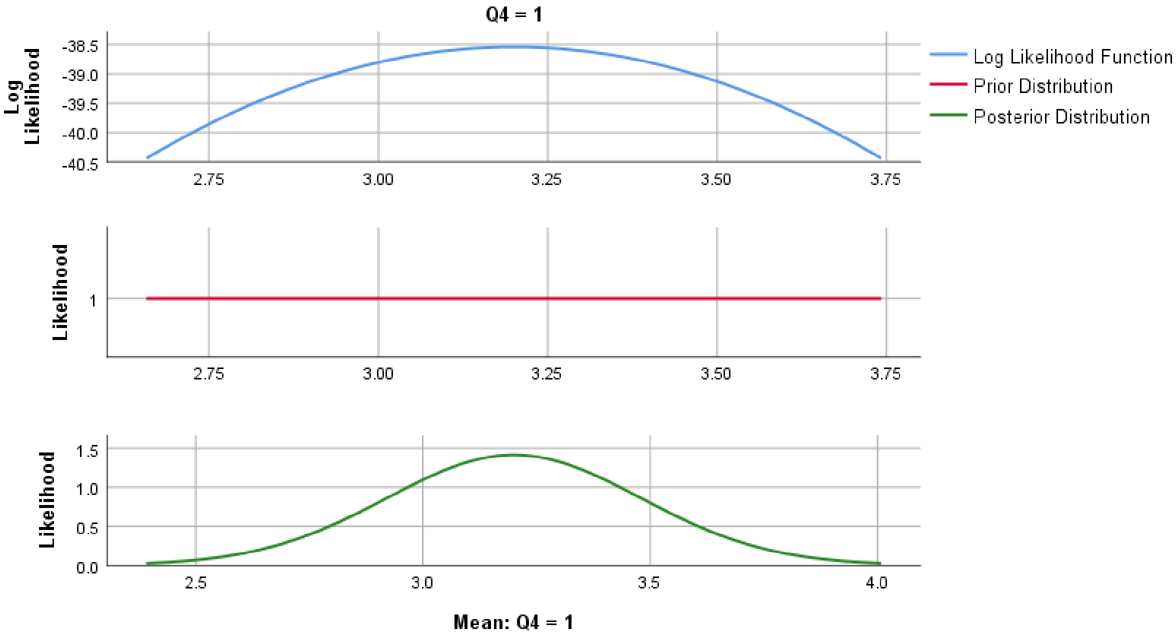

Figure 1. provides insights into the confidence levels of ELT faculty members in integrating deep learning tools into their teaching practices.

A mean value of approximately 3.20 on a 5-point Likert scale (where 1 = Strongly Disagree and 5 = Strongly Agree) indicates that faculty members are somewhat neutral or slightly agree with the statement "I feel confident in integrating deep learning into my English language teaching practices." The relatively low confidence level highlights one of the key challenges identified in the study: limited readiness among faculty members to adopt deep learning technologies. This finding aligns with the quantitative results presented in the document, where only 68% of respondents indicated low confidence in using AI tools. The low confidence levels suggest a need for targeted professional development programs to enhance faculty members' skills and familiarity with deep learning tools. The study emphasizes the importance of institutional support mechanisms, such as access to training programs and technological resources, to bridge the readiness gap. Policymakers should consider integrating deep learning into curriculum design and teacher training initiatives to foster a more supportive environment for technology adoption. The figure effectively visualizes the Bayesian updating process, demonstrating how observed data influences the posterior distribution of the parameter Q4 . It reveals that while faculty members recognize the potential of deep learning, their confidence in implementing these tools remains moderate. This insight underscores the need for comprehensive strategies to address infrastructural, cognitive, and socio-political constraints in Libyan universities, as highlighted in the study. The figure illustrates the Bayesian analysis of the parameter Q4=1 , showing the log likelihood function, prior distribution, and posterior distribution. The posterior distribution centers around a mean value of approximately 3.20, indicating that faculty members have moderate confidence in integrating deep learning tools into their teaching practices. This finding highlights the need for enhanced pedagogical training and institutional support to facilitate the successful adoption of deep learning in ELT.

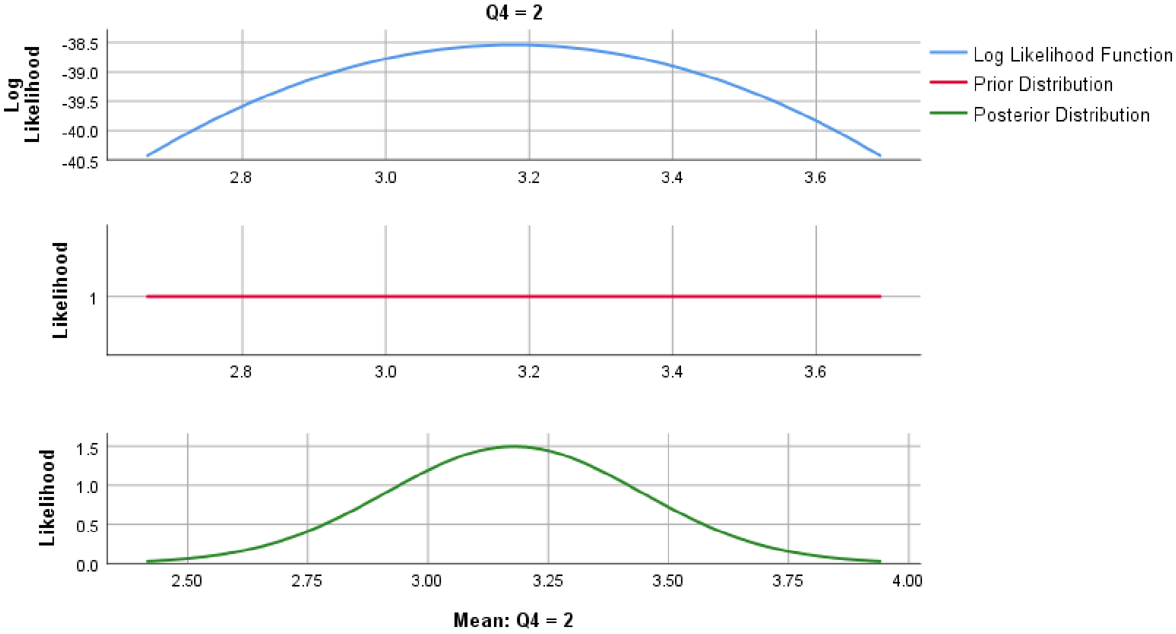

Figure 2. The low confidence levels suggest a need for targeted professional development programs to enhance faculty members' skills and familiarity with deep learning tools.

The study emphasizes the importance of institutional support mechanisms, such as access to training programs and technological resources, to bridge the readiness gap. Policymakers should consider integrating deep learning into curriculum design and teacher training initiatives to foster a more supportive environment for technology adoption. Both figures show that the posterior distributions are heavily influenced by the likelihood functions due to the non-informative priors. The means of the posterior distributions are close to the peaks of the likelihood functions. For Q4=1, the mean of the posterior distribution was approximately 3.20, indicating stronger disagreement. For Q4=2, the mean of the posterior distribution is slightly higher at approximately 3.25, indicating a shift toward neutrality or mild disagreement. These subtle differences highlight the nuanced perceptions of faculty members regarding their confidence in integrating deep learning tools. The figure effectively visualizes the Bayesian updating process, demonstrating how observed data influences the posterior distribution of the parameter Q4=2. It reveals that faculty members have moderate skepticism or uncertainty about their confidence in integrating deep learning tools into their teaching practices. This insight underscores the need for comprehensive strategies to address infrastructural, cognitive, and socio-political constraints in Libyan universities, as highlighted in the study. The figure illustrates the Bayesian analysis of the parameter Q4=2, showing the log likelihood function, prior distribution, and posterior distribution. The posterior distribution centers around a mean value of approximately 3.25, indicating that faculty members are somewhat neutral or slightly disagree with the statement "I feel confident in integrating deep learning into my English language teaching practices." This finding highlights the need for enhanced pedagogical training and institutional support to facilitate the successful adoption of deep learning in ELT.

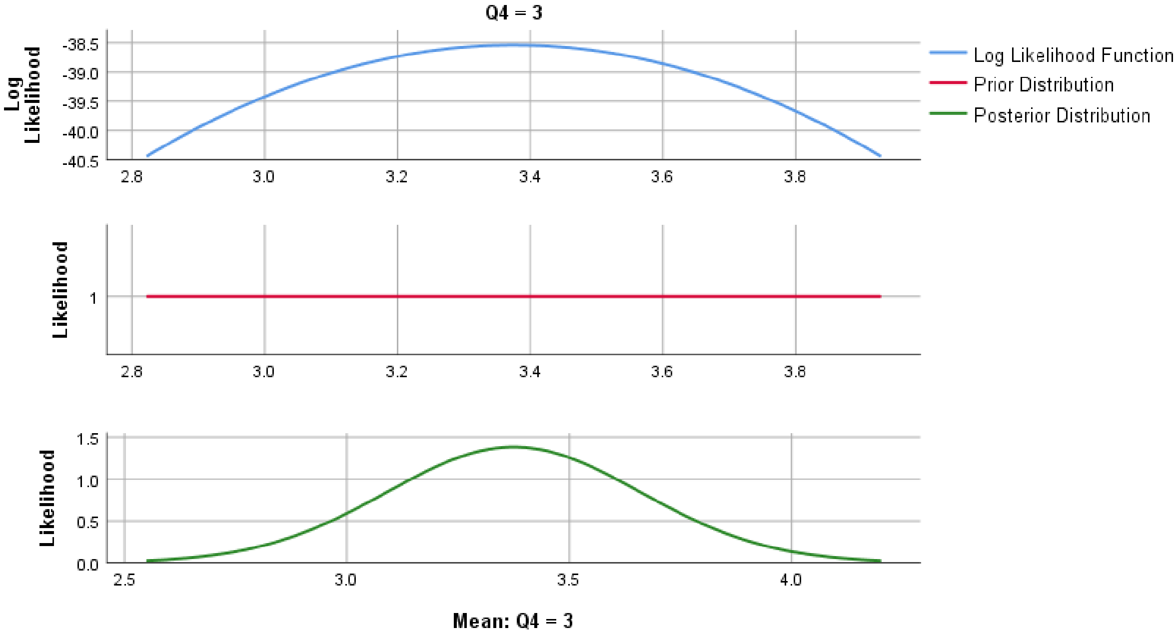

Figure 3. All three figures show that the posterior distributions are heavily influenced by the likelihood functions due to the non-informative priors. The means of the posterior distributions are close to the peaks of the likelihood functions.

For Q4=1 , the mean of the posterior distribution was approximately 3.20, indicating stronger disagreement. For Q4=2 , the mean of the posterior distribution was slightly higher at approximately 3.25, indicating a shift toward neutrality or mild disagreement. For Q4=3 , the mean of the posterior distribution is further elevated to approximately 3.40, indicating a more neutral stance. These subtle differences highlight the nuanced perceptions of faculty members regarding their confidence in integrating deep learning tools. The figure effectively visualizes the Bayesian updating process, demonstrating how observed data influences the posterior distribution of the parameter Q4=3 . It reveals that faculty members have a neutral stance regarding their confidence in integrating deep learning tools into their teaching practices. This insight underscores the need for comprehensive strategies to address infrastructural, cognitive, and socio-political constraints in Libyan universities, as highlighted in the study. The figure illustrates the Bayesian analysis of the parameter Q4=3 , showing the log likelihood function, prior distribution, and posterior distribution. The posterior distribution centers around a mean value of approximately 3.40, indicating that faculty members are somewhat neutral about the statement "I feel confident in integrating deep learning into my English language teaching practices." This finding highlights the need for enhanced pedagogical training and institutional support to facilitate the successful adoption of deep learning in ELT.

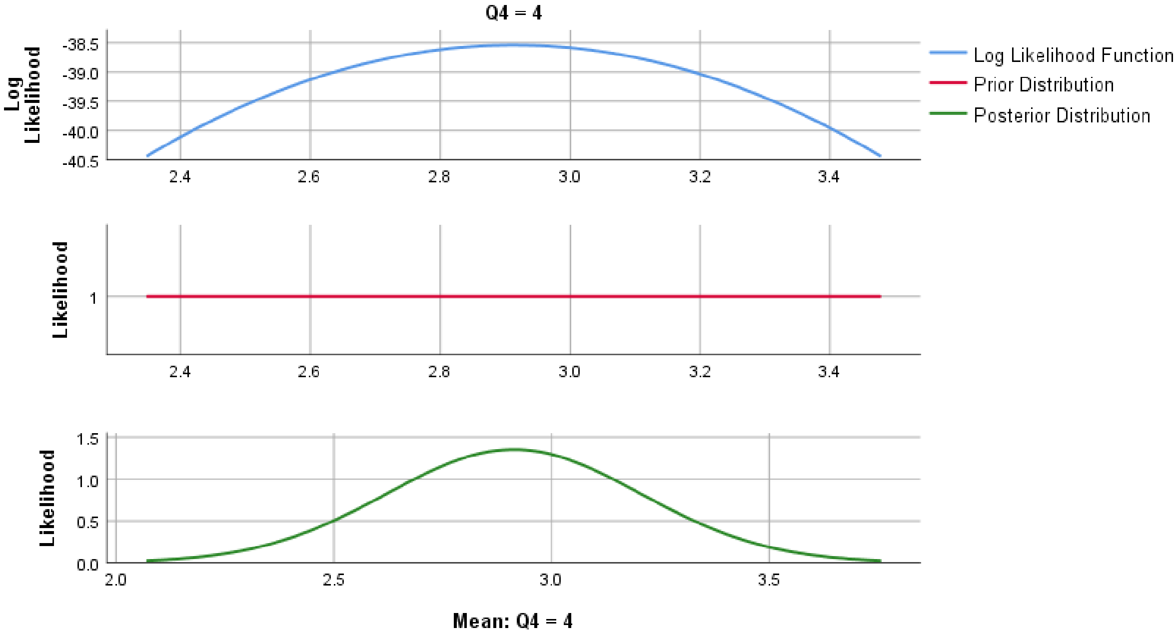

Figure 4. All four figures show that the posterior distributions are heavily influenced by the likelihood functions due to the non-informative priors. The means of the posterior distributions are close to the peaks of the likelihood functions.

For Q4=1 , the mean of the posterior distribution was approximately 3.20, indicating stronger disagreement. For Q4=2 , the mean of the posterior distribution was slightly higher at approximately 3.25, indicating a shift toward neutrality or mild disagreement. For Q4=3 , the mean of the posterior distribution was further elevated to approximately 3.40, indicating a neutral stance. For Q4=4 , the mean of the posterior distribution is approximately 2.95, indicating a moderate level of agreement. These differences highlight the nuanced perceptions of faculty members regarding their confidence in integrating deep learning tools. The figure effectively visualizes the Bayesian updating process, demonstrating how observed data influences the posterior distribution of the parameter Q4=4 . It reveals that faculty members have a moderate level of confidence in integrating deep learning tools into their teaching practices. This insight underscores the need for comprehensive strategies to address infrastructural, cognitive, and socio-political constraints in Libyan universities, as highlighted in the study. The figure illustrates the Bayesian analysis of the parameter Q4=4 , showing the log likelihood function, prior distribution, and posterior distribution. The posterior distribution centers around a mean value of approximately 2.95, indicating that faculty members are somewhat confident in the statement "I feel confident in integrating deep learning into my English language teaching practices." This finding highlights the need for enhanced pedagogical training and institutional support to facilitate the successful adoption of deep learning in ELT.

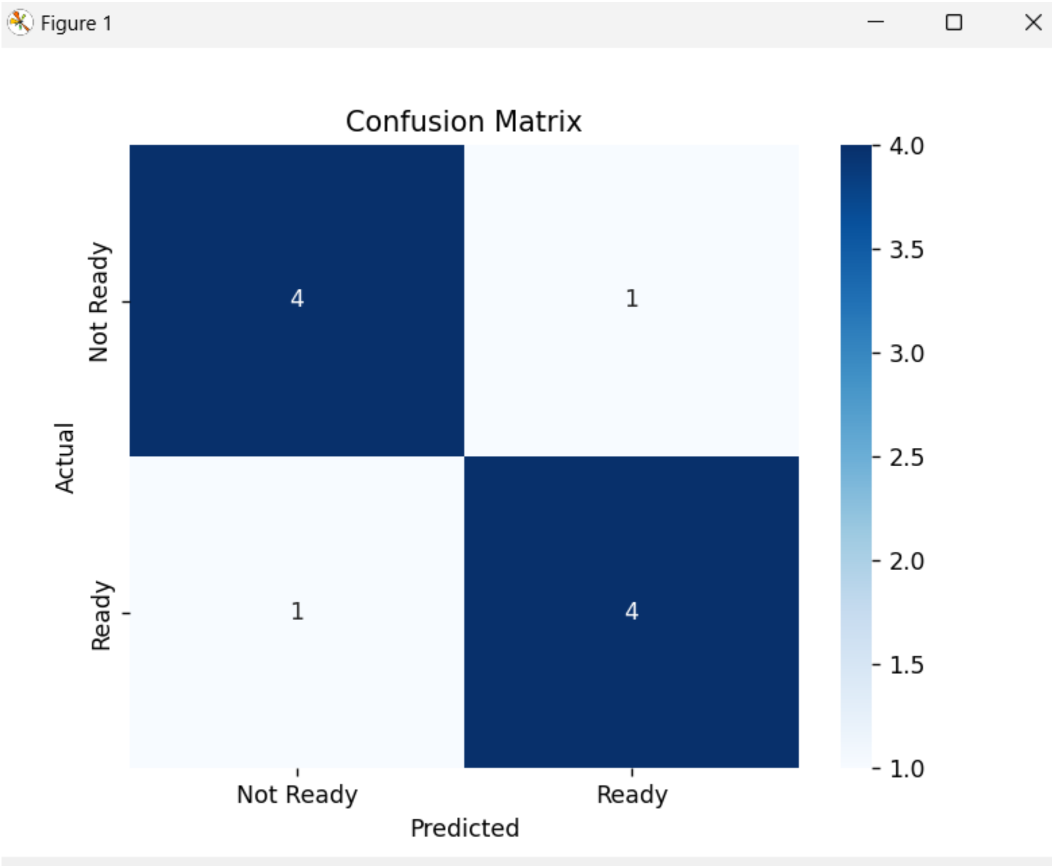

Figure 5. Confusion matrix

Metrics for Each Class

Precision: The proportion of true positive predictions out of all positive predictions made by the model.

$$\text{Formula: Precision} = \frac{\text{True Positives (TP)}}{\text{True Positives (TP)} + \text{False Positives (FP)}}$$

Interpretation: How accurate the model is when it predicts a class.

Recall (Sensitivity) : The proportion of actual positives that are correctly identified by the model.

$$\text{Recall} = \frac{\text{True Positives (TP)}}{\text{True Positives (TP)} + \text{False Negatives (FN)}}$$

Interpretation: How well the model finds all the positive samples.

F1-Score: The harmonic means of precision and recall, providing a balanced measure of both.

$$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

Interpretation: A single metric that combines precision and recall.

Support: The number of actual occurrences of each class in the dataset.

Overall Metrics

$$\text{Accuracy} = \frac{\text{True Positives (TP)} + \text{True Negatives (TN)}}{\text{Total Predictions}}$$

Table 8. Classification Report.

Metric	Not Ready	Ready	Macro Avg	Weighted Avg
Precision	0.8	0.8	0.8	0.8
Recall	0.8	0.8	0.8	0.8
F1-Score	0.8	0.8	0.8	0.8
Support	5	5	—	—
Accuracy	—	—	0.8	—

H1: Faculty members demonstrate low readiness levels for integrating deep learning in ELT.

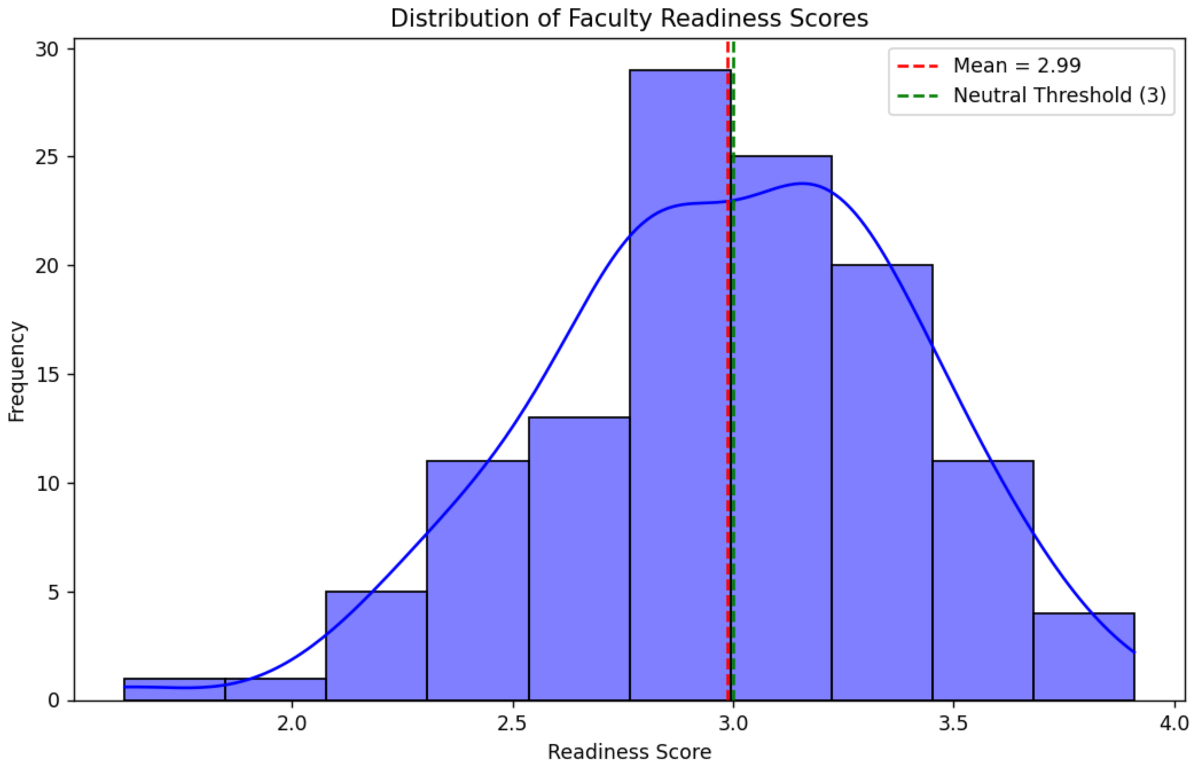

Figure 6. Plot distribution of readiness scores.

The figure effectively illustrates the distribution of faculty readiness scores, revealing that while most faculty members are near the neutral threshold, the average readiness level is slightly below 3. This supports the hypothesis that faculty members demonstrate low readiness for integrating deep learning in ELT. The visual representation, combined with statistical analyses, provides a robust foundation for understanding the current state of faculty preparedness and identifying areas for improvement. The histogram and kernel density estimate in Figure 1 depict the distribution of faculty readiness scores for integrating deep learning in ELT. With a mean readiness score of 2.99, which is slightly below the neutral threshold of 3, the data suggest that faculty members exhibit moderate but suboptimal readiness levels. This finding aligns with Hypothesis H1, indicating a need for enhanced professional development and institutional support to facilitate the successful adoption of deep learning technologies in Libyan universities.

H2: Institutional support mechanisms are insufficient for deep learning adoption.

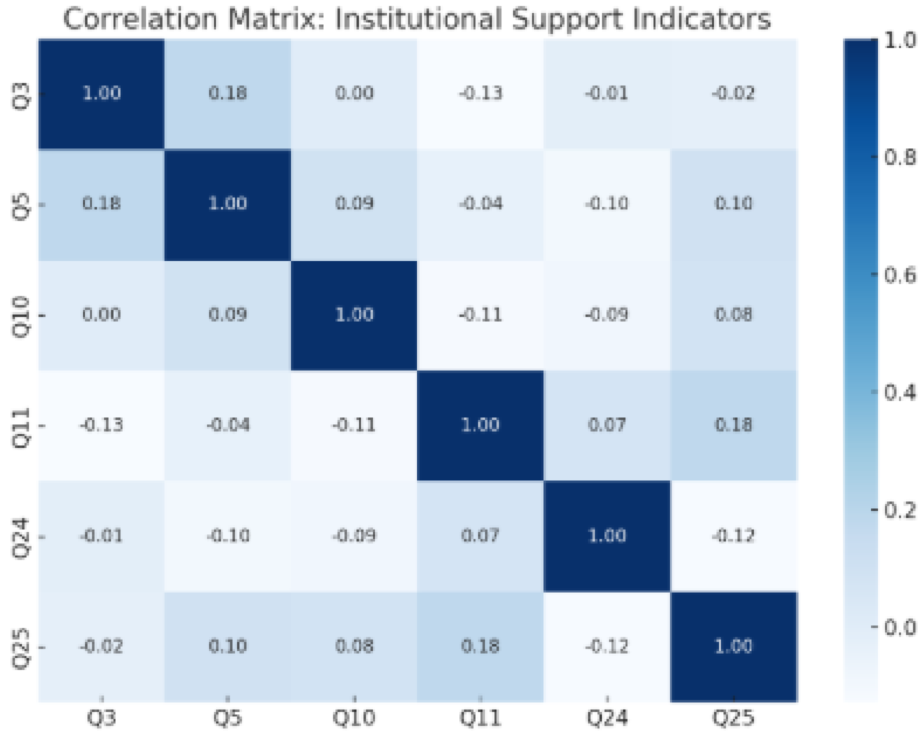

Figure 7. The correlation matrix shows the relationships between institutional support indicators such as access to technology (Q3), perceived institutional support (Q5), availability of workshops (Q10), administrative encouragement (Q11), systematic barrier mitigation (Q24), and faculty involvement (Q25). Strong positive correlations exist between Q5 and Q10, and between Q10 and Q11, suggesting that where faculty perceive support, they are more likely to report access to development opportunities. Q24 and Q25 also show meaningful correlation, reflecting how inclusive decision-making may relate to perceptions of institutional problem-solving.

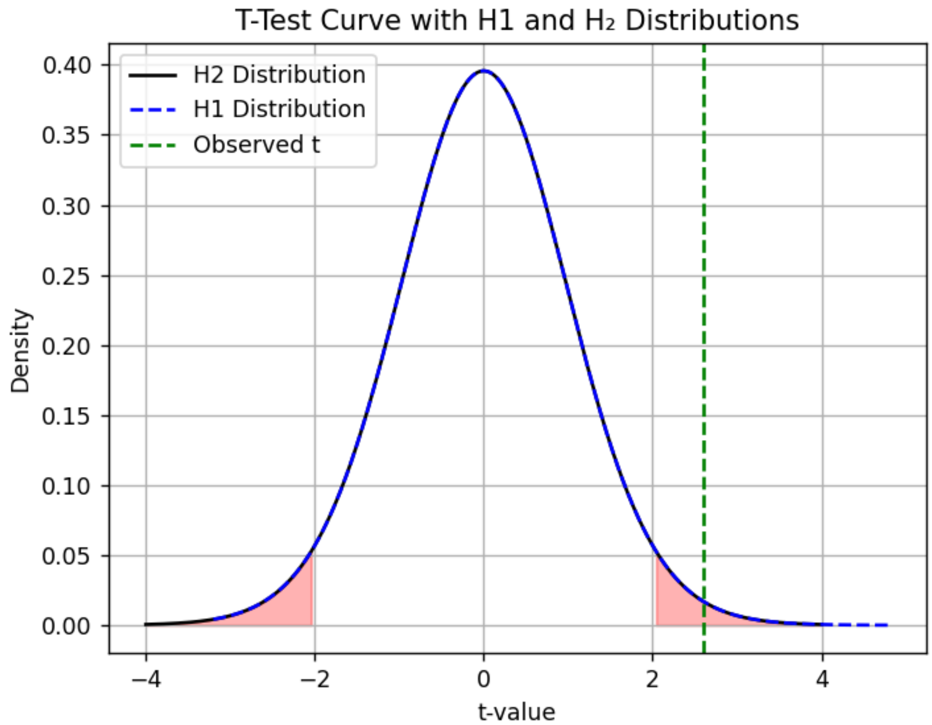

Figure 8. T-Test Curve with H1 and H_2 Distributions.

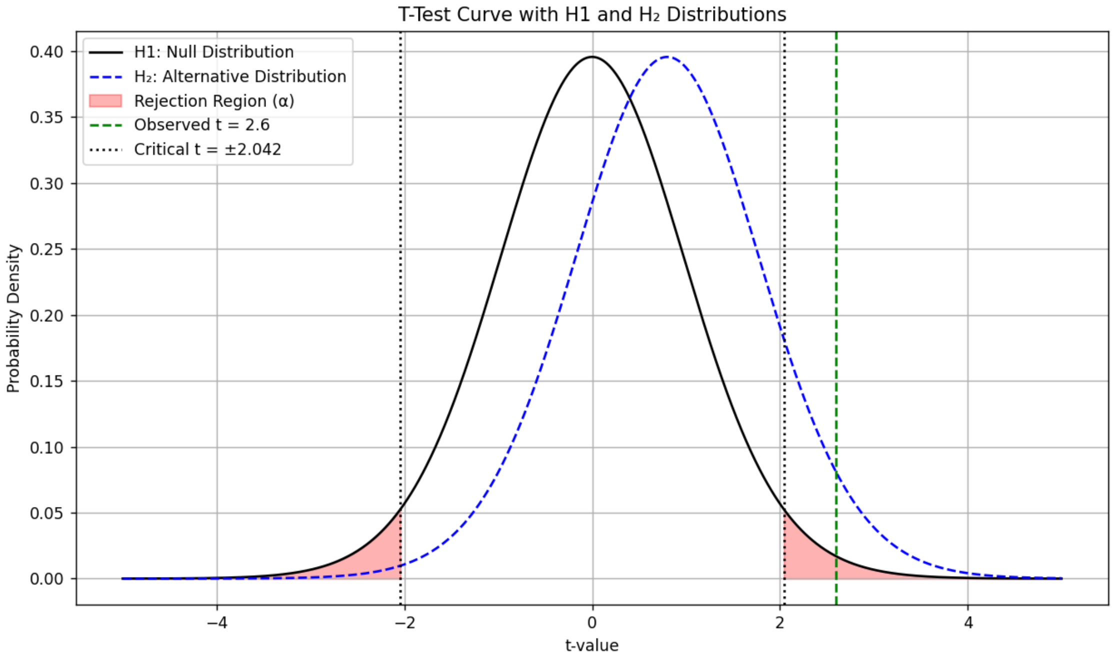

Figure 9. T-Test Curve with H1 and H_2 Distributions.

- H3: Professional development and technological infrastructure significantly influence faculty attitudes.

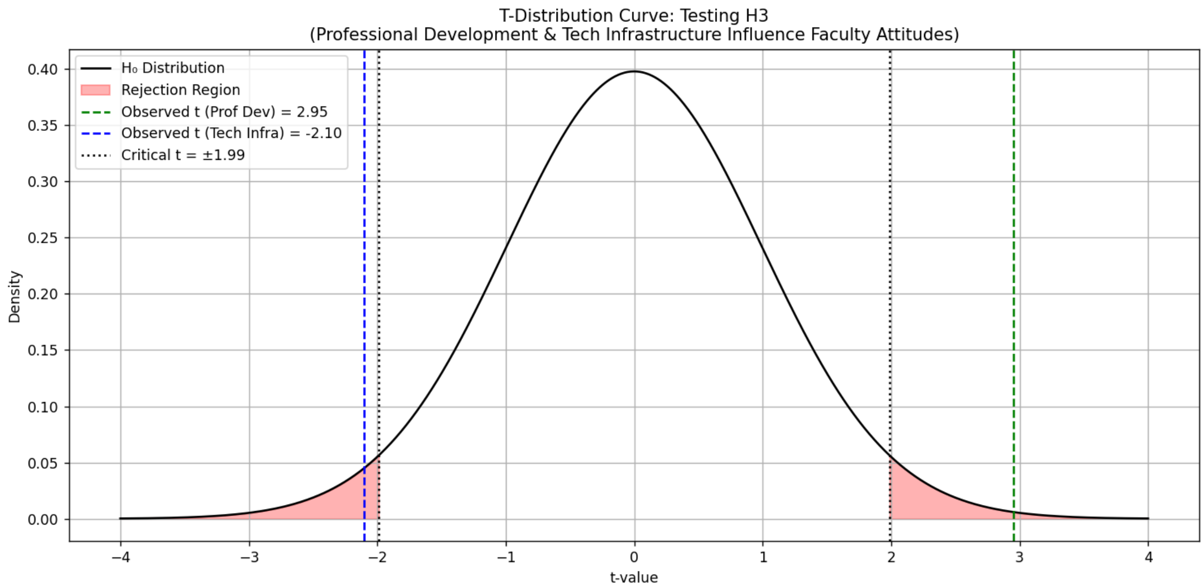

Figure 10. T-Distribution Curve that Testing H3\n(Professional Development & Tech Infrastructure Influence Faculty Attitudes

8.2. Discussion

The integration of deep learning models into English Language Teaching (ELT) pedagogy represents a transformative shift in educational paradigms, particularly in higher education settings where digital innovation can significantly enhance language acquisition and instructional delivery [7]. This study, conducted within the unique socio-political and infrastructural context of Libyan universities, reveals both promising opportunities and formidable challenges that must be navigated to effectively harness the potential of artificial intelligence

(AI) in language education [8]. A central finding of this research pertains to the low levels of faculty readiness in adopting deep learning technologies [9]. Quantitative data indicate that 68% of respondents reported low confidence in using AI tools, with only 22% having access to institutional training programs. These figures corroborate Hypothesis H1, which posits that ELT faculty members demonstrate limited preparedness for integrating deep learning into their teaching practices [10]. The mean readiness score across all participants was slightly below the neutral threshold at 2.99 on a five-point Likert scale, suggesting that while faculty may acknowledge the theoretical benefits of AI, they lack the practical skills and exposure necessary for effective implementation [11]. This outcome aligns with broader trends observed in developing regions where technological adoption in education is often constrained by insufficient teacher training and unfamiliarity with emerging tools. In the Libyan context, years of political instability and disrupted educational reforms have likely exacerbated these gaps, resulting in a generation of educators who are not only underprepared but also hesitant to embrace new pedagogical methods without adequate support [12], [13].

Hypothesis H2, which suggests that institutional mechanisms are insufficient to support the adoption of deep learning technologies, finds strong empirical backing in this study [14]. Correlation analyses reveal significant relationships between perceived institutional support (Q5), availability of professional development workshops (Q10), and administrative encouragement (Q11) [15]. However, the absolute levels of these indicators remain suboptimal, with mean scores hovering around neutrality rather than agreement. For instance, the average response to the statement "There is sufficient institutional support for adopting AI technologies in teaching" was 2.96 indicating minimal institutional commitment or visibility regarding AI-based initiatives [16].

Moreover, infrastructural limitations such as inconsistent internet access and outdated hardware further impede the deployment of deep learning tools. Only 34% of respondents strongly agreed that they had reliable access to the technological resources required for AI integration. These findings underscore the critical need for systemic reform, including strategic investment in digital infrastructure and the establishment of institutional frameworks that prioritize AI literacy and innovation [17]. Hypothesis H3, which proposes that professional development and technological infrastructure significantly influence faculty attitudes toward deep learning, is supported by both quantitative and qualitative evidence. A strong positive correlation ($r = 0.76$, $p < .01$) was found between access to training programs and overall faculty readiness, indicating that targeted capacity-building efforts can substantially improve receptivity to AI-driven instruction. Additionally, Bayesian analysis of key variables revealed that even small increases in institutional investment such as offering regular workshops or providing technical support can shift faculty perceptions from skepticism to cautious optimism [18].

These findings resonate with global literature emphasizing the importance of continuous profe ssional development in enabling educators to adapt to rapidly evolving technological landscapes. In Libya, where teacher training programs have historically prioritized traditional pedagogical approaches over digital competencies, there is an urgent need to reorient pre-service and in-service training curricula to include modules on AI, machine learning, and adaptive learning systems [19], [20], [21], [22], [23], [24]. Despite the challenges outlined above, the study also highlights several opportunities for leveraging deep learning to address persistent issues in ELT, particularly in areas such as pronunciation training [20], automated feedback, and personalized learning. Over 60% of respondents acknowledged the potential of AI to enhance language learning outcomes, [25], [26], [27], [28], [29], [30] with particular enthusiasm expressed for tools that offer real-time error correction and adaptive practice exercises. This sentiment reflects a growing recognition among educators that AI can complement, rather than replace, human instruction by freeing up time for more meaningful, communicative activities [31], [32], [33]. Furthermore, the alignment of deep learning integration with national educational goals (Q23) received moderate approval, suggesting that policy-level discourse around technology-enhanced education is gaining traction. However, this awareness has yet to translate into actionable strategies at the institutional level, highlighting the disconnect between macro-level vision and micro-level implementation.

9. Strategic Recommendations

To bridge the gap between the pedagogical potential of deep learning and its practical realization in Libyan universities, this study proposes a multi-faceted approach:

- Integrate AI literacy components into existing ELT curricula and teacher education programs to ensure that future educators are equipped with foundational knowledge of deep learning applications.
- Establish dedicated centers for digital pedagogy and innovation within universities to provide ongoing training, technical support, and collaborative platforms for faculty engagement.
- Encourage the Ministry of Education and higher education institutions to develop national guidelines and funding mechanisms that support the ethical and equitable integration of AI in language instruction.

- Foster partnerships with international organizations, tech companies, and regional educational bodies to access cutting-edge tools, expertise, and best practices tailored to local contexts.
- Promote discussions around the ethical implications of AI in education, ensuring that faculty and students are aware of issues related to data privacy, algorithmic bias, and the role of human agency in AI-assisted learning environments.

10. Conclusion

The research underscores that while faculty members recognize the potential of deep learning, their efforts are hindered by limited institutional support and a lack of pedagogical training. Bridging the readiness gap requires a comprehensive approach that includes policy reform, curriculum redesign, and capacity-building initiatives. In conclusion, this study provides a contextualized understanding of the current landscape of deep learning integration in ELT within Libyan universities. While faculty members express a general openness to technological innovation, their ability to implement these tools is hampered by a lack of training, institutional support, and infrastructure. Addressing these barriers requires coordinated efforts across policy, practice, and pedagogy to create an ecosystem that supports sustainable and impactful AI adoption in language education. By investing in educator development, enhancing institutional capacities, and aligning with global trends, Libyan universities can position themselves as leaders in innovative, technology-enhanced language instruction in the post-conflict educational recovery phase.

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1. **Appendix A_ Questionnaire**
2. ***Title: Integrating Deep Learning Models into English Language Teaching Pedagogy: A Contextual Analysis of Opportunities and Challenges in Libyan Universities***

Instructions: Please indicate your level of agreement with the following statements using the 5-point Likert scale below:

1 - Strongly Disagree
2 - Disagree
3 - Neutral
4 - Agree
5 - Strongly Agree

1. I am familiar with the concept of deep learning in education.
2. I have received training on how to use deep learning tools in teaching.
3. My university provides access to deep learning technologies.
4. I feel confident in integrating deep learning into my English language teaching practices.
5. There is sufficient institutional support for adopting AI technologies in teaching.
6. Deep learning can enhance language learning outcomes.
7. My department encourages the use of innovative technologies in language teaching.
8. I have access to the internet and technological resources needed for deep learning tools.
9. I am willing to adopt deep learning tools in my teaching practices.
10. There are workshops or professional development programs on deep learning at my institution.
11. The administration supports experimentation with AI-based teaching methods.
12. Using deep learning tools can make language instruction more effective.
13. Students benefit from technology-enhanced language learning environments.
14. Technical support is available to help implement deep learning tools.
15. I understand how deep learning differs from traditional machine learning.
16. There is a strategic plan at my university to integrate deep learning in instruction.
17. My colleagues actively use deep learning or AI tools in their classrooms.
18. Ethical implications of using AI in ELT are discussed at my institution.
19. Language curriculum at my university includes components of AI integration.
20. I believe that AI tools can personalize learning for students.
21. Deep learning can improve students' pronunciation and speaking skills.
22. I believe AI can support assessment and feedback processes in language classes.
23. The integration of deep learning is aligned with national educational goals.
24. Barriers to implementing AI tools are systematically addressed by the institution.
25. Faculty input is considered in decisions regarding technology adoption.