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A Sustainable E-Learning Ecosystem: Linking Readiness, Teaching Efficiency, Culture, and Employability

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Abstract

This paper hypothesizes and justifies a Sustainable E-Learning Ecosystem Framework that incorporates the readiness, teaching efficiency, and cultural enablers to improve the reputation of the institution, as well as graduate competency and employability. The model that was built based on the data collected by higher education institutions, and which was run on the Partial Least Squares Structural Equation Modeling (PLS-SEM), displayed a high explanatory power with high path coefficients. The direct effects were strong: readiness had a positive impact on the teaching efficiency (b = 0.131, t = 3.649, p < 0.001), teaching efficiency had a significant impact on the e-learning adoption (b = 0.522, t = 13.729, p < 0.001), and the e-learning adoption had the impact on the student performance (b = 0.512, t = 13.734, p < 0.001). The highest influence on sustainability indicators had student performance and competence; competence was a strong predictor of the university's reputation (b = 0.581, t = 16.134, p < 0.001), and reputation led to job employment (b = 0.814, t = 46.630, p < 0.001). Other critical effects were also present, like TE - AeL - SP - SC - UR - JE (b = 0.100, t = 6.548, p < 0.001), which proved the cascading impact of drivers of operation on long-term outcomes. There were mixed outcomes in terms of cultural factors: the mediating effect of information culture on competence and reputation (b = 0.289, t = 7.556, p < 0.001) was significant, and organizational and national cultural moderation was not significant. Policy support and training were both found to have a good direct influence on teaching efficiency (Ps b = 0.380, t = 7.914; TP b = 0.387, t = 8.869; p < 0.001) but did not act as moderators. According to these results, readiness and teaching efficiency are identified as key drivers, and competence and reputation are key to sustainable education outcomes and employability.

Keywords:

Sustainable E-Learning;
Teaching Efficiency;
Readiness; Cultural Enablers;
Institutional Reputation;
Employability; Policy Support;
Higher Education;
Structural Equation Modeling;
Training Programs.

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1- Introduction

Nevertheless, even with the increased pace of digitalization, especially in the developing world, there are still several institutions that are facing the challenge of maintaining e-learning programs beyond the implementation cycles [1]. Issues surrounding institutional preparedness, instructional performance, cultural fit, and policy have been a reason to question the future educational image and workability of digital learning systems. Sustainability, as opposed to adaptation, has therefore become one of the major issues in the modern-day research on e-learning.

With the extensive adoption of e-learning in institutions of higher learning, numerous institutions in developing countries continue to struggle with the issue of the sustainability of e-learning programs [2, 3]. Such obstacles are associated with ineffective teaching processes, inadequate student and technological preparation, and ineffective institutional policies or cultural orientation [4]. As a result, the short-term effect of digital adoption on students in terms of competence, performance, employability, and university reputation has been understudied [5-7]. Therefore, the long-term effects have not been examined. There is a critical shortage of the environmental view of the problem, whereby readiness, teaching efficiency, cultural enablers, and policy support relate to the sustainability outcomes [8, 9].

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E-learning has shifted its position to be a support instruction method to a core element of higher education globally, with the provision of better access [10], flexibility, and learning outcomes. In spite of these advantages, the numerous institutions, especially those in the developing world, find it difficult to maintain e-learning programs because of institutional preparedness, pedagogical capacity, acceptance by the cultures, and policy congruency. The majority of the available research is based on the adoption or short-term effects, with minimal regard to the sustainability of e-learning as an ecosystem [10]. Readiness, efficiency of teaching, culture, and policy support are the main factors that are usually studied separately [11], which means that the long-term correlations between the adoption of e-learning, student competence, reputation of an institution, and graduate employability have not been properly depicted, particularly in the developing higher education settings. As a way of seeking to fill these gaps, the current research suggests and empirically analyzes a Sustainable E-Learning Ecosystem Framework that entails the integration of operational drivers, cultural and policy enablers, with long-term sustainability outcomes. Based on the data of institutions of higher learning in Oman and the application of PLS-SEM, the study provides a comprehensive explanation of how e-learning initiatives can be transformed into sustainable educational and employability results.

Figure 1 shows that the use of e-learning is increasing at a rapid pace in the developing regions, but it is also not clear whether it will be sustainable. Issues like variable teaching effectiveness, student and technological literacy make success in the long-term difficult. Lack of a cohesive ecosystem viewpoint of linking readiness, teaching efficacy, cultural facilitators, and policy underlying also undermines the principles of sustainable digital learning.

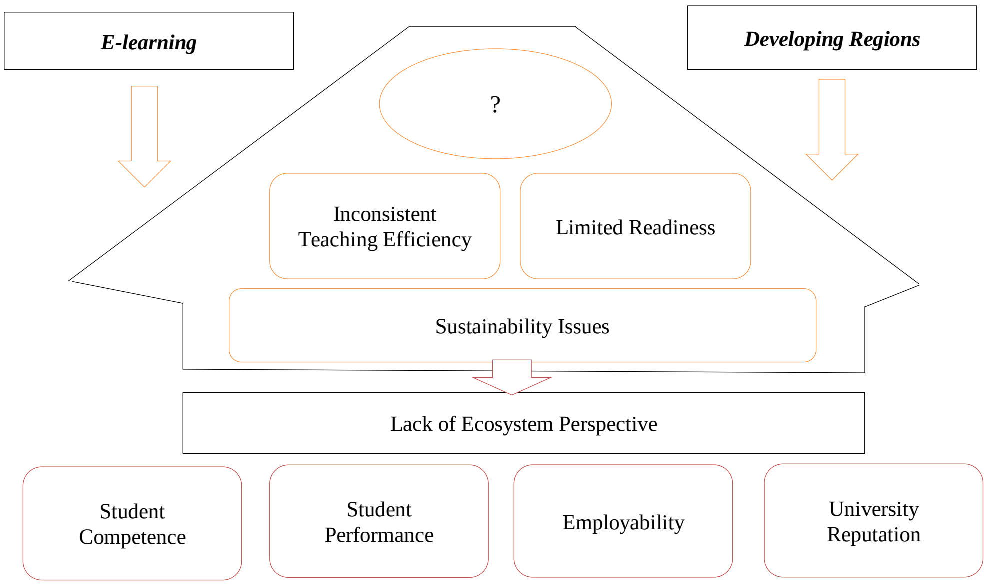


Figure 1. Problem description

Consequently, there is inadequate exploration of the long-term effects on competence in students, academic performance, employability, and university reputation. To fill these gaps, a holistic strategy will be necessary to integrate policies of the institutions, cultural forces, and technological preparedness to facilitate the creation of a sustainable e-learning environment that can deliver sustainable educational influence.

Figure 2 demonstrates the proposed solution for achieving a sustainable e-learning ecosystem framework. The proposed conceptualization of sustainability presented in Figure 2 represents the aggregate results of three key dimensions, namely educational effectiveness, institutional reputation, and graduate employability. The framework is essentially a combination of technology and human factors to achieve success in the long term.

Operational drivers of the ecosystem are Readiness (RS), Teaching Efficiency (TE), and Adoption of E-Learning (AeL). These factors are combined to establish a solid base of e-learning implementation. Since these drivers are operative, they cause intermediate results like Students Performance (SP) and Students Competence (SC), which measure the immediate education gains of the system.

Based on such intermediate results, the framework focuses on long-term sustainability indicators: University Reputation (UR) and Job Employment (JE). These results show the extended consequences of e-learning on the institutional reputation and success of graduates in the employment sector.

Also, the framework involves Cultural factors (NC, OC, IC) and Policy factors (PS, TP) as enabling and moderating factors. These factors affect the effectiveness of the ecosystem operation by determining the alignment of institutions, governance, and the acceptability of digital learning activities. Combining the above components is a holistic model that focuses on the short and long-term sustainability objectives along with the short-term educational objectives.

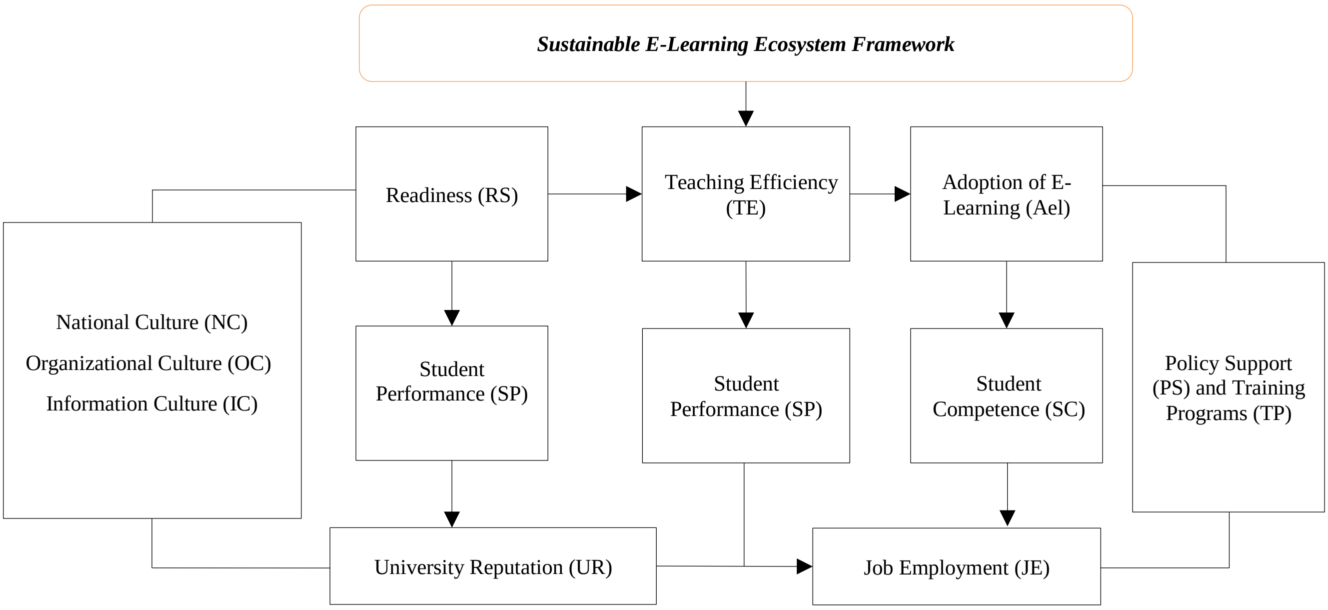


Figure 2. The proposed sustainable e-learning ecosystem framework Solution

1-1- Research Questions

- What is the relationship between teaching efficiency, adoption of e-learning, and preparedness in the context of sustainable educational outcomes in teaching and learning in higher education?
- How does the student performance and competence mediate the relationship between e-learning adoption and university reputation and employability?
- What effect do organizational culture, national culture, and information culture have on e-learning ecosystems' sustainability?
- How effective are policy support and training programs in teaching efficiency and e-learning adoption?
- What is the way the combination of these factors can facilitate a sustainable e-learning ecosystem that meets the institutional and societal aspirations?

1-2- Research Objectives

- To investigate the effects of readiness and teaching efficiency regarding the use of e-learning systems.
- To determine the impact of adopting e-learning on the performance and competence of the students.
- To assess the extent to which better competence and performance are important in enhancing reputation and graduate employability in a university.
- To investigate the moderating/mediating influence of organizational, national, and information culture, policy, and training backup to maintain the effects of e-learning.
- To create and test a Sustainable E-Learning Ecosystem Framework towards sustainable education in the long run.

1-3- Research Hypotheses

1-3-1- Direct Relationships

H1: Readiness (RS) has a positive effect on Teaching Efficiency (TE).

H2: Teaching Efficiency (TE) has a positive effect on the Adoption of E-learning (AeL).

H3: E-learning (AeL) has a positive effect on Students' Performance (SP).

H4: The Performance (SP) of students positively affects the Competence (SC) of students.

H5: Competence (SC) among students has a positive effect on the University Reputation (UR).

H6: University Reputation (UR) has a positive impact on Job Employment (JE).

1-3-2- Moderating/Mediating Roles

H7: Teaching Efficiency and E-learning Adoption are linked by the moderation of the Organizational Culture (OC).

H8: There is a Moderating role of National Culture (NC) between E-learning Adoption and Student Performance.

H9: Information Culture (IC) is the mediating variable in the correlation between Student Competence and University Reputation.

H10: Policy Support (PS) and Training Programs (TP) have a combined positive effect on the relationship between the Readiness and Teaching Efficiency.

Figure 3 represents the framework, which represents an unbroken cycle in which an institutional Readiness (RS) improves Teaching Efficiency (TE). This, in its turn, promotes the increased number of people to E-Learning (AeL), which in its turn results in improved student performance (SP) and student competence (SC). Consequently, the process increases University Reputation (UR) and leads to Job Employment (JE) as a sustainability outcome. The links between the RS and TE, as well as between the TE and AeL, and between AeL and SP, are reinforced by Policy Support (PS) and Training Programs (TP) and moderated by Organizational Culture (OC) and National Culture (NC). Additionally, the SC and UR relationships are facilitated through Information Culture (IC) to ensure the information-driven institutional reputation and sustainable employability.

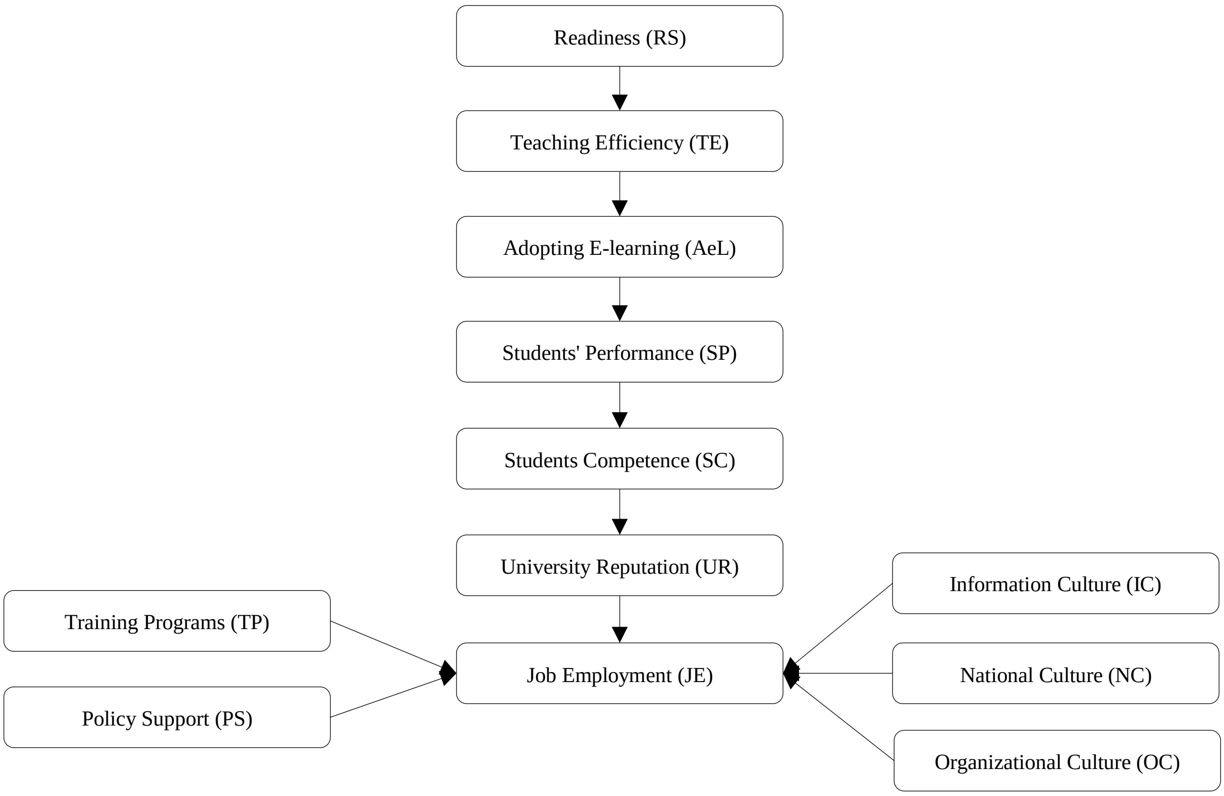


Figure 3. Conceptual Framework for a Sustainable E-Learning Ecosystem

2- Literature Review

E-learning in higher learning came as a reaction to the conventional distance learning models. Since then, it has grown to holistic technology-enhanced learning (TEL) paradigms, which integrate information and communication technologies (ICT), open educational resources (OER), and collaborative online degree programs in numerous settings [12, 13]. This change demonstrates the transition to an ecosystem-based thinking instead of focusing on technology-related thinking, as the interaction of pedagogical, technological, organizational, and cultural variables influences the course of education [14]. The COVID-19 pandemic boosted the use of digital technologies and emphasized four primary dimensions of influence: techno-economic, personal/psychological, teaching/assessment, and social influences [7, 15]. Other work observed a recent increase in attention to online delivery and request the alignment of e-learning strategy with institutional to improve Knowledge Retention [16]. This alignment is fundamental in the development of sustainable e-learning settings that have the ability to endure any disruption to the setting and still offer quality education to the students.

2-1- Concept of Sustainable E-Learning Ecosystems

The sustainable e-learning ecosystem includes a number of interconnected elements: technological systems, pedagogy, institutional regulations, teacher knowledge and skills, student preparedness, and cultural practices [13, 17, 18]. The pilot programs reveal that the development of faculty capacity and the development of partnership programs can establish the online degree pathways that can be sustained and meet SDG 4 in the developing communities [13]. Sustainability is also known to include the environmental, economic, pedagogical, social justice, and institutional aspects [19, 20]. A successful ecosystem is one that achieves balance between innovation and stability so that projects can rise without taking excessive resources and faculty becoming exhausted [21].

E-learning rests on the integration of knowledge as one of its prerequisites. IS-TAM models show that the quality of content, instructor effectiveness, as well as the system quality, have a combined effect on the perceived usefulness and use of the platform by students [22], which has a subsequent effect on academic performance [23]. This viewpoint stresses the fact that the profits of one field (technology) should be followed by the enhancement of pedagogy, support service, and organizational culture [24]. The knowledge-management theories emphasize the value of sharing, shared repositories, and intelligent learning design in reinforcing the value of the digital platform [25]. The latest concept in the e-learning ecosystem is the smart learning environment, facilitating the creation, transfer, and application of knowledge [26].

The transition to emergency distance learning revealed major vulnerabilities in the overall institutional preparedness, faculty preparedness, and technological infrastructure, particularly in new contexts [27, 28]. The systematic reviews reveal that there is a rapid digital adaptation in COVID-19, but also emphasize persistent issues with assessment integrity, student wellbeing, digital equity, and quality of infrastructure that have to be mitigated with a view to continuing e-learning projects [15, 28].

The world is shifting its resources towards learning management systems (LMS), video-conferencing software, and learning analytics systems [29-31]. However, technology itself is not a guarantee of enhanced learning; the redesign of pedagogies, the development of the faculty, and the service provided to students are also important [32, 33]. The post-pandemic period also gives a chance to get rid of emergency solutions and concentrate on the planned, sustainable e-learning systems [34]. Relationship between Pedagogical, Technological, and Organizational Factors. Empirical research indicates that it is important to align organizational policies, technical support, and pedagogical design to convert e-learning investments into actual learning benefits [23, 35]. To ensure successful coordination, one has to pay attention to: readiness factors such as faculty digital skills, institutional infrastructure, student access to technology, and organizational change readiness [36-38]; teaching efficiency, such as quality of instructional design, faculty workload, pedagogical innovation, and assessment effectiveness [39, 40]; cultural enablers such as an innovation-friendly culture, national attitudes toward online learning, and a culture of sharing knowledge [41]; and outcome linkages such as the links between e-learning quality, student performance, skill development, institutional reputation, and graduate employability. The existing studies have been a response to the desire to have an integrated model to capture these intricate relationships as a sustainable e-learning ecosystem framework [42].

3- Research Methods

The research design of this study was a quantitative survey-based design that empirically tested the hypothesized relationship between readiness, teaching efficiency, e-learning adoption, student performance, competence, university reputation, and job employment. Also assist in the mediation of policy support, training programs, organizational culture, information culture, and national culture. The choice of the quantitative approach was due to the fact that it is possible to measure constructs with validated indicators and statistically test the relationships between variables [43, 44]. The analysis was conducted with the Partial Least Squares Structural Equation Modeling (PLS-SEM) of Smart PLS 4, which is specifically designed to work with complex models involving mediating and moderating variables and is not limited by data normality [45].

The quantitative survey design permits the standardized data to be collected from a large sample, permitting statistical generalization of the results. The measures of the constructs were taken with the help of the established scales with references to the earlier literature to provide the content validity and reliability. The research design is in line with the aim and scope of the research, which is to establish the causality between variables like Readiness, Teaching Efficiency, E-learning Adoption, Student Performance, Competence, University Reputation, and Job Employment in the context of higher education institutions.

3-1- Research Design

In this section, the general research design is outlined, including the fact that this is a cross-sectional (data obtained at a given point in time) explanatory research design that seeks to establish hypothesized causal relationships between constructs. The PLS-SEM was taken because it has a predictive nature and would be applicable to exploratory models where moderating and mediating effects are used.

3-2- Population and Sampling

The population for this survey consisted of students from higher education institutions in Oman. Convenience sampling was used in this study because it is practical and efficient in terms of collecting data on a limited population that is readily available and accessible, such as university students and faculty members [46]. The approach suits well in educational and behavioural studies where participants share similar characteristics within an institution or a culture pertinent to the research aims [47].

Convenience sampling is one technique among non-probability methods that most researchers employ to collect high data volumes within resource and time limitations, which is why it has become very popular in the social sciences and e-learning research. Etikan et al. [48] argue that convenience sampling works well in situations where the researcher wants to get an indication of the participants who are readily available and ready to take part in the research. Equally, Bornstein et al. [49] stated that convenience samples are capable of delivering useful and representative results in cases of higher education, where the population is relatively homogeneous, like students pursuing relevant academic programs.

This was not a statistical generalization but instead research that aimed at determining some relationships and patterns among constructs (e.g., readiness, teaching efficiency, and e-learning adoption) in a context specific to a particular university. Therefore, convenience sampling offered an effective and contextually applicable methodology of generating valid and meaningful findings in line with the objectives of the study.

Justification of sample size, potentially ruled out with Hair et al. [45] rule of thumb (10 times the largest number of inner or outer model paths). The same rule is frequently used to verify the adequacy of the sample. This rule says: "The minimum sample size must be at least 10x the maximum number of structural paths possible to direct towards any latent construct (inner model) or the maximum number of indicators measuring any construct (outer model)". Note that PLS bootstrapping and reliability analysis were used to verify the adequacy of the data.

Step-by-step Calculation ([45]- 10-Times Rule):

For the most outer indicators (measurement model), the calculation will be:

The number of items (questions) used in each construct is 5, so the result will be $10 \times 5 = 50$. Optimal inner model path count (structural model), the calculation will be:

The construct that contains the highest number of predictors has six incoming paths, $6 \times 10 = 60$. The bigger is 60, which is the minimum recommended sample size. So, based on the collected data, the Actual sample size was $n = 775$ after data cleaning. Thus, our sample size of 60 and above is far higher than what is required to present a study that is considered reliable based on PLS-SEM estimation; therefore, we can confirm that our study has achieved and slightly exceeded the recommended sample size when it comes to a robust PLS-SEM estimation.

The suitability of the sample size was checked according to the rule of thumb suggested by Hair et al. [45]. To use in PLS-SEM, which suggests at least a sample size that is ten times larger than the most significant number of structural paths leading to a specific construct or the largest number of indicators of a construct. In this re-search, the construct that had the most incoming paths was six, and the constructs had five indicators. As such, the minimal sample size was 60 (10×6). The real dataset on which the analysis was performed comprised 775 valid responses, which is much above this value, and it has a high statistical power and a stable model estimation. Thus, the sample size can be regarded as quite sufficient for the PLS-SEM analysis.

3-3- Data Collection Procedure

This section describes the method of collecting data by a structured questionnaire that was sent electronically. The ethical aspects include confidentiality and voluntary participation. The questionnaire contained Likert-scale items (e.g., 1-5) based on validated literature.

The measurement scales in this study were based on the previously validated scales to guarantee the content validity and comparability with previous studies. The instruments of every construct were chosen according to their established reliability and usefulness in the research on E-learning adoption and performance in the situations of higher education [45].

To determine the clarity, reliability, and suitability of the questionnaire items, 270 respondents who reflected the target population were used as a pilot test. After the feedback, slight changes to the words were implemented to enhance the level of understanding of the items, and the reliability coefficients (Cronbach's Alpha above 0.70) assured the internal consistency of the scales prior to the primary collection of data.

3-4- Data Analysis Technique

Both the measurement model (validity and reliability tests) and the structural model (hypothesis testing) have been evaluated using Smart PLS 4.0.

Key steps include:

Evaluating indicator reliability, composite reliability, and average variance extracted (AVE). Testing the discriminant validity based on Fornell-Larcker and HTMT.

Collinearity test based on VIF:

Evaluation of path coefficients, t-values, and p-values through bootstrapping 10000 subsamples. Comparing the R2, f2, and Q2 to model fit and predictive relevance.

3-5- Ethical Considerations

All ethical guidelines that were accepted by the University of Buraimi Research Committee were followed in this research. Ethical permission was received before the data collection process, and the objective and outcomes of the research were communicated to participants. The questionnaire was administered via Google Forms, and all directions were clearly written, with instructions written in both English and Arabic to give a complete understanding to all the respondents.

The surveys were carried out on a voluntary basis, and informed consent was taken before each participant started the survey. There were no personal identifiers (e.g., names or email addresses) obtained, so anonymity and confidentiality were guaranteed. Data obtained was strictly used for academic and research purposes, not at all, and no third party was disclosed with the information that was obtained.

3-6- Summary

Sum it up by stating that the methodology adopted guarantees reliability, validity, and strength of findings, which offers a strong empirical basis to the discussion and implications.

4- Data Analysis and Results

A non-probability convenience sampling method was used to collect the survey data, as it was chosen because of the convenience of those whom the research aimed to investigate. The method is quite appropriate when the entire population is hard to access or when the research is exploratory in character [48-50]. Convenience sampling enables the researcher to collect data easily by collecting data that is easily accessible, e.g., students and faculty members in an e-learning setting.

On 17 October 2025, a total of 937 responses were obtained, of which 61.7% female responses and 38.3% were male responses, as illustrated in Figure 4. First, the survey tool lacked the variable of Adaptive E-Learning (AEL). This variable was included in the questionnaire after the first 19 responses. This resulted in the first 19 entries having missing values of AEL and were not included in the analysis, so that the data completeness and consistency of the data were achieved. This cut down the dataset to 917 valid responses, omitting the first entry of only variable labels.

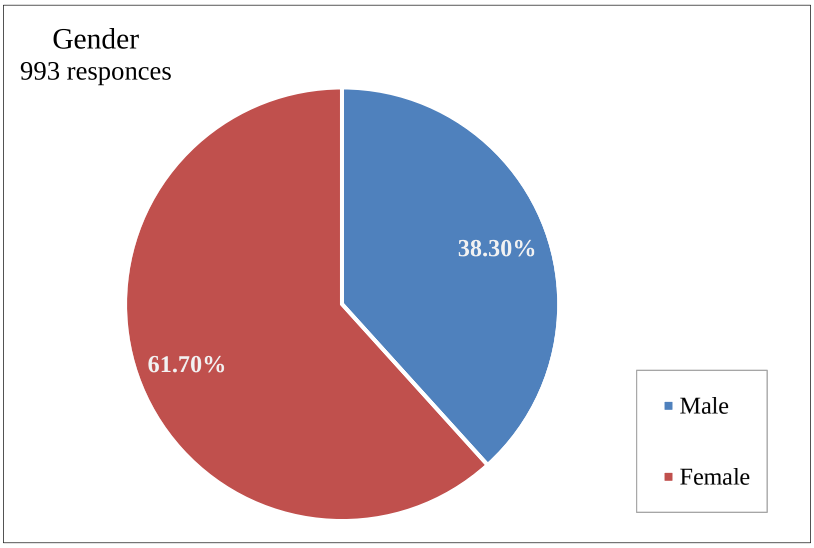


Figure 4. Gender Distribution

4-1- Data Cleaning and Screening

Standard deviation (SD) analysis was used to filter the data set against anomalies and non-responsive trends. An SD of zero or above abnormality will indicate that there is no variability in the responses and thus all the respondents gave the same answer to all the items, thus decreasing the reliability of the data. Specifically:

They were found to have 109 responses and an SD of 0.

The number of responses was 32 with an SD of 0.124.

Under statistical convention, data points that have such a high degree of low variability may be treated as outliers or invalid [45]. Thus, cases that had an SD below 1.645 were eliminated. The critical z-value of 0.05 level of significance (a = 0.05) of a one-tailed test is identified, and the threshold of 1.645 is the minimum acceptable variation in standardized data distributions as stated in Table 1.

Table 1. Standard deviation (SD)

Significance Level (α)	Critical z-value	Meaning	Tailed Test
0.05 (5%)	1.645	95% confidence (one-sided)	One-Tailed Test
0.05 (5%)	±1.96	95% confidence interval	Two-Tailed Test

The minimum SD that was achieved was 0.174 after cleaning, and the maximum SD was 1.563, which is within the acceptable limits when using the one-tailed test. After this process, the ultimate dataset consisted of 775 valid responses that were further subjected to a later analysis by way of statistical and structural equation modelling.

Table 2 illustrates internal consistency reliability and convergent validity evaluation of each construct based on Cronbach's Alpha, Composite Reliability, and extracted Average Variance (AVE). The Alpha of the Cronbach coefficients range between 0.724 and 0.849, which is higher than the suggested value of 0.70, and the coefficient values are good. The value of Composite Reliability (0.827-0.893) ranges between 0.827 and 0.893, which proves high construct reliability. As well, the values of AVE lie between 0.545 and 0.630 and exceed the minimum standard of 0.50, which indicates sufficient convergent validity. In general, these findings reaffirm that the measurement model is valid and can be further analysed in terms of structure.

Table 2. Reliability and Convergent Validity criteria

Metric	Acceptable Threshold	References	Result Summary
Cronbach's Alpha (α)	> 0.70	Hair et al. [45]	All constructs range from 0.724 to 0.849, indicating high internal consistency.
Composite Reliability (ρa, ρc)	> 0.70	Fornell & Larcker [51]	All constructs between 0.827 and 0.893, confirming construct reliability.
Average Variance Extracted (AVE)	> 0.50	Fornell & Larcker [51]	All constructs between 0.545 and 0.630, indicating adequate convergent validity.

Figure 5 shows that the majority of indicators load above 0.70, which rationalizes good indicator reliability. Articles NC(1) and OC(4), which were slightly lower than 0.70, were kept as overall reliability and theoretical relevance are good.

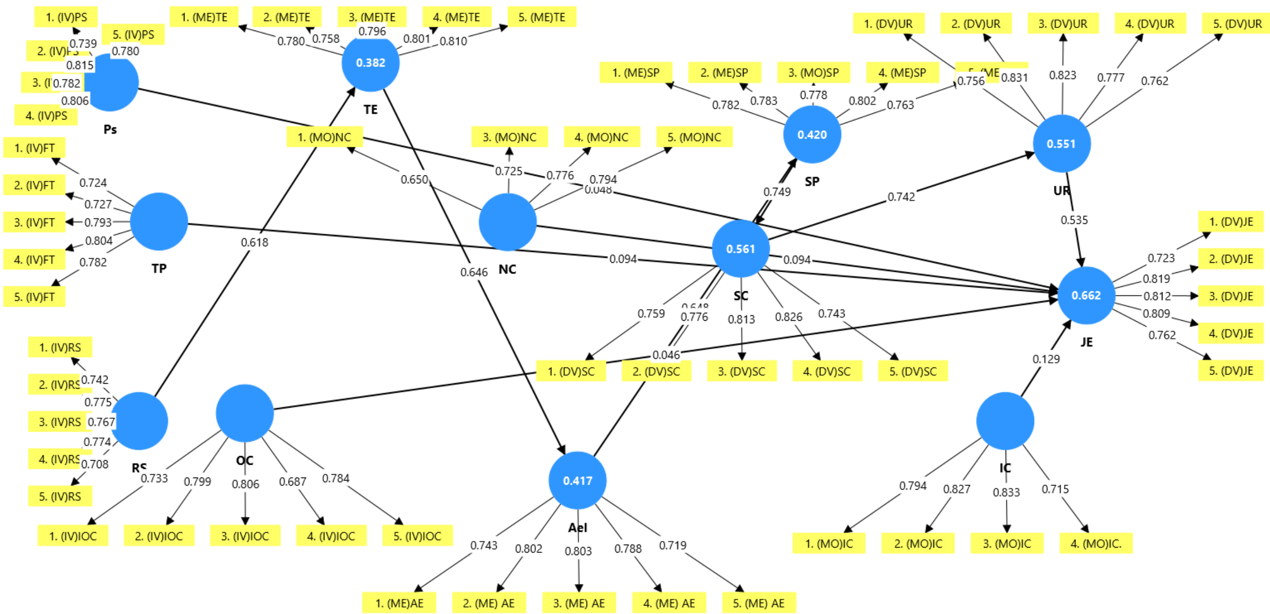


Figure 5. Conceptual Model

After the process of cleaning the measurement model, Table 3 shows the updated outer loading of all indicators. The findings reveal that most of the indicators have been loaded above the recommended level of 0.70, which is a very high indicator reliability. There are a few items (e.g., NC and OC indicators) with a little less loading, but were not dropped because of theoretical relevance, and overall construct reliability and convergent validity are in the acceptable range. On the whole, the findings prove that the refined measurement model implies sufficient indicator reliability and can be the next step in structural model analysis.

Table 3. Cleaning Outer Loadings for all variables

	Outer loadings		Outer loadings
1. (DV)JE ← JE	0.723	3. (IV)RS ←RS	0.767
1. (DV)SC ←SC	0.759	3. (ME) AE ←Ael	0.803
1. (DV)UR ←UR	0.756	3. (ME)TE ←TE	0.796
1. (IV)FT ←TP	0.724	3. (MO)IC ←IC	0.833
1. (IV)IOC ←OC	0.733	3. (MO)NC ←NC	0.725
1. (IV)PS ←Ps	0.739	3. (MO)SP ←SP	0.778
1. (IV)RS ←RS	0.742	4. (DV)JE ←JE	0.809
1. (ME)AE ←Ael	0.743	4. (DV)SC ←SC	0.826
1. (ME)SP ←SP	0.782	4. (DV)UR ←UR	0.777
1. (ME)TE ←TE	0.780	4. (IV)FT ←TP	0.804
1. (MO)IC ←IC	0.794	4. (IV)IOC ←OC	0.687
1. (MO)NC ←NC	0.650	4. (IV)PS ←Ps	0.806
2. (DV)JE ←JE	0.819	4. (IV)RS ←RS	0.774
2. (DV)SC ←SC	0.776	4. (ME) AE ←Ael	0.788
2. (DV)UR ←UR	0.831	4. (ME)SP ←SP	0.802
2. (IV)FT ←TP	0.727	4. (ME)TE ←TE	0.801
2. (IV)IOC ←OC	0.799	4. (MO)IC. ←IC	0.715
2. (IV)PS ←Ps	0.815	4. (MO)NC ←NC	0.776
2. (IV)RS ←RS	0.775	5. (DV)JE ←JE	0.762
2. (ME) AE ←Ael	0.802	5. (DV)SC ←SC	0.743
2. (ME)SP ←SP	0.783	5. (DV)UR ←UR	0.762
2. (ME)TE ←TE	0.758	5. (IV)FT ←TP	0.782
2. (MO)IC ←IC	0.827	5. (IV)IOC ←OC	0.784
3. (DV)JE ←JE	0.812	5. (IV)PS ←Ps	0.780
3. (DV)SC ←SC	0.813	5. (IV)RS ←RS	0.708
3. (DV)UR ←UR	0.823	5. (ME) AE ←Ael	0.719
3. (IV)FT ←TP	0.793	5. (ME)SP ←SP	0.763
3. (IV)IOC ←OC	0.806	5. (ME)TE ←TE	0.810
3. (IV)PS ←Ps	0.782	5. (MO)NC ←NC	0.794

The internal consistency is high according to all constructs, with the Cronbach's Alpha and Composite Reliability being over 0.70. The AVE of more than 0.50 indicates that there is at least satisfactory convergent validity because each construct describes enough variance in its indicators as presented in Table 4.

Table 5 presents the Heterotrait-Monotrait (HTMT) ratios to measure the discriminant validity. All the values of HTMT are less than the recommended value of 0.90, which implies sufficient levels of discriminant validity among the constructs. Though a slightly high value can be perceived between University Reputation and Job Employment (UR–JE), theoretically, it is not too high because they are closely conceptualized. In general, the findings verify that the constructs are empirically differentiated and appropriate to analyze them in a structural model.

Table 4. Reliability and Convergent Validity

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average Variance Extracted (AVE)
Ael	0.830	0.831	0.880	0.596
IC	0.804	0.814	0.871	0.630
JE	0.845	0.847	0.890	0.618
NC	0.724	0.743	0.827	0.545
OC	0.819	0.821	0.874	0.582
Ps	0.844	0.846	0.889	0.616
RS	0.809	0.811	0.868	0.568
SC	0.843	0.844	0.889	0.615
SP	0.841	0.842	0.887	0.611
TE	0.848	0.849	0.892	0.623
TP	0.824	0.827	0.877	0.588
UR	0.849	0.850	0.893	0.625

Table 5. HTMT Table

	Ael	IC	JE	NC	OC	Ps	RS	SC	SP	TE	TP	UR
Ael												
IC	0.897											
JE	0.757	0.784										
NC	0.769	0.812	0.664									
OC	0.665	0.656	0.677	0.522								
Ps	0.764	0.770	0.734	0.611	0.827							
RS	0.668	0.621	0.588	0.521	0.802	0.809						
SC	0.788	0.825	0.878	0.681	0.747	0.811	0.713					
SP	0.773	0.767	0.806	0.698	0.799	0.870	0.741	0.889				
TE	0.768	0.780	0.722	0.663	0.782	0.883	0.744	0.806	0.902			
TP	0.719	0.744	0.716	0.597	0.869	0.926	0.795	0.811	0.820	0.890		
UR	0.780	0.790	0.918	0.620	0.694	0.748	0.614	0.876	0.853	0.769	0.694	

Table 6 shows the Fornell-Larcker criterion of measuring discriminant validity. The square roots of the Average Variance Extracted (AVE) indicated on the diagonal are larger than the inter-constructs correlations in the row and the column. This confirms that every construct has a larger amount of variance with its indicators as compared to other constructs, which proves that the amount of discriminant validity is adequate and that the constructs represent different ideas in the model.

Table 6. Fornell-Larcker Criterion

	Ael	IC	JE	NC	OC	Ps	RS	SC	SP	TE	TP	UR
Ael	0.772											
IC	0.735	0.794										
JE	0.636	0.652	0.786									
NC	0.610	0.636	0.532	0.738								
OC	0.550	0.535	0.563	0.413	0.763							
Ps	0.640	0.639	0.621	0.496	0.688	0.785						
RS	0.547	0.508	0.486	0.408	0.653	0.667	0.754					
SC	0.660	0.685	0.742	0.547	0.621	0.684	0.588	0.784				
SP	0.648	0.634	0.680	0.557	0.665	0.734	0.612	0.749	0.782			
TE	0.646	0.648	0.612	0.537	0.655	0.746	0.618	0.682	0.762	0.789		
TP	0.597	0.612	0.601	0.476	0.719	0.773	0.650	0.679	0.686	0.747	0.767	
UR	0.656	0.655	0.778	0.502	0.578	0.635	0.507	0.742	0.722	0.655	0.586	0.790

The Variance Inflation Factor (VIF) values, which were used to measure the multicollinearity between the constructs, are reported in Table 7. All the VIFs are less than the conservative value of 3.0, which implies that there is no issue of multicollinearity. This proves that all the constructs are independent contributors to the model, and the estimated path coefficients are not distorted due to collinearity effects.

Table 7. VIF value

	VIF		VIF
1. (DV)JE	1.572	3. (IV)RS	1.602
1. (DV)SC	1.660	3. (ME) AE	1.857
1. (DV)UR	1.680	3. (ME)TE	1.867
1. (IV)FT	1.426	3. (MO)IC	1.794
1. (IV)IOC	1.542	3. (MO)NC	1.321
1. (IV)PS	1.621	3. (MO)SP	1.722
1. (IV)RS	1.608	4. (DV)JE	2.003
1. (ME)AE	1.536	4. (DV)SC	2.087
1. (ME)SP	1.685	4. (DV)UR	1.747
1. (ME)TE	1.690	4. (IV)FT	1.943
1. (MO)IC	1.586	4. (IV)IOC	1.432
1. (MO)NC	1.323	4. (IV)PS	1.911
2. (DV)JE	1.968	4. (IV)RS	1.641
2. (DV)SC	1.750	4. (ME) AE	1.799
2. (DV)UR	2.206	4. (ME)SP	1.898
2. (IV)FT	1.570	4. (ME)TE	1.900
2. (IV)IOC	1.811	4. (MO)IC.	1.439
2. (IV)PS	1.918	4. (MO)NC	1.532
2. (IV)RS	1.701	5. (DV)JE	1.774
2. (ME) AE	1.878	5. (DV)SC	1.650
2. (ME)SP	1.746	5. (DV)UR	1.625
2. (ME)TE	1.608	5. (IV)FT	1.732
2. (MO)IC	1.817	5. (IV)IOC	1.778
3. (DV)JE	1.946	5. (IV)PS	1.737
3. (DV)SC	1.960	5. (IV)RS	1.420
3. (DV)UR	2.117	5. (ME) AE	1.514
3. (IV)FT	1.762	5. (ME)SP	1.687
3. (IV)IOC	1.860	5. (ME)TE	1.886
3. (IV)PS	1.752	5. (MO)NC	1.380

4-2- Interpretation

All the indicators are within the suggested cut-offs, indicating that our latent variables are reliable and internally consistent. The value of AVE is greater than 0.50, which proves that, on average, each construct predicts over 50 percent of the variance of its indicators - a very effective measure of convergent validity [45].

4-2-1- Discriminant Validity (Fornell-Larcker and HTMT)

Fornell-Larcker Criterion:

The square roots of the AVE (diagonal values) in our Fornell-Larcker table have higher values than all inter-construct correlations, indicating the presence of discriminant validity [51, 52].

Example:

E-learning AVE (Ael) = 0.772 is greater than the correlations it has with other constructs (0.735, 0.636, etc.). The same can be said of all constructs.

Conclusion: The constructs are distinct as each has more variance with its indicators as compared to other constructs.

4-2-2- HTMT Values

As it was demonstrated above, the majority of HTMT ratios are lower than 0.90 [53], which proves the validity of discrimination. Theoretically, slightly high correlations (e.g., UR-JE = 0.918) are justified by the fact that they both are the results of employability [54-56].

4-2-3- Multicollinearity (VIF)

VIFs across all the constructs are between 1.3 and 2.2, which is way less than the 3.3 cutoff value as prescribed by Diamantopoulos & Siguaw [57] and Hair et al. [45].

Interpretation:

There are no issues regarding multicollinearity, and the constructs provide different data in the model.

4-2-4- Outer Loadings Evaluation

Threshold Rule:

As Hair et al. (2021) [45] state:

The indicators with a loading of 0.70 remain.

Loadings 0.40-0.70 can be maintained in case the AVE and CR are acceptable and have theoretical support.

Our Case:

NC(1) = 0.650

OC(4) = 0.687

Both are slightly below 0.70, but:

They already have thresholds of their construct reliability (a, CR, AVE).

The VIF values are low (<2).

Their elimination would give limited benefit and decreased theoretical coverage (i.e., indicators of cultural dimensions).

Conclusion: Retain NC(1) and OC(4) due to the fact that their contribution is still non-statistically and theoretically significant. Deviations less than 0.70 (minor deviations) are tolerable provided that other quality indicators are met [45, 53].

4-2-5- Assessment of the Text/Integrated Interpretation Paragraph

The measurement model was highly reliable and valid for all the constructs. Cronbach's alpha (0.724-0.849) was greater than the recommended alpha (0.70), whereas composite reliability values (ra, rc) were higher than 0.80, which is the reflection of internal consistency ([45, 51, 52]). The values of average variance extracted (AVE) were between 0.545 and 0.630, and this signifies strong convergent validity. Both the Fornell-Larcker criterion and HTMT analysis indicated discriminant validity, and all the square roots of AVE were higher than the inter-construct correlations, and the ratios of HTMT were below 0.90 [53]. The slight deviations (e.g., HTMT = 0.918 in the case of UR-JE) are explained by the fact that the two variables (university reputation and employability) are interrelated [50]. Additionally, the problem of multicollinearity could be excluded since all the VIFs were between 1.3 and 2.2, which is significantly lower than the critical value of 3.3 [45]. Even though some of the indicators (NC1 = 0.65 and OC4 = 0.687) showed a slight decline of the suggested loading (0.70), they were included because they were theoretically relevant, and the overall construct reliability was satisfactory.

Therefore, the measurement model is well-psychometric, which proves that all the constructs are reliable, valid, and can be used in the structural path analysis as shown in Figure 6.

The direct hypothesis analysis shows that most of the proposed relationships had strong support, as shown in Table 8. In particular, H1 (RS → TE), H2 (TE → AeL), H3 (AeL → SP), H4 (SP → SC), H5 (SC → UR), and H6 (UR → JE) were all significant with t-statistic and p-values equal to 0.000, which proved the sequential positive impact of readiness on job employment. Besides, the direct influences of policy support (Ps → TE) and training programs (TP → TE) were also important, which promotes their positions as influential predictors. Nonetheless, all moderation hypotheses were not accepted, such as H7 (OC × TE → AeL), H8 (NC × AeL → SP), H10 (Ps × RS → TE and TP × RS → TE), because their p-values were greater than 0.05, and their t-statistics were lower than the critical value. This implies that although there were strong direct relationships, the hypothesis moderating effects were not significant to the model.

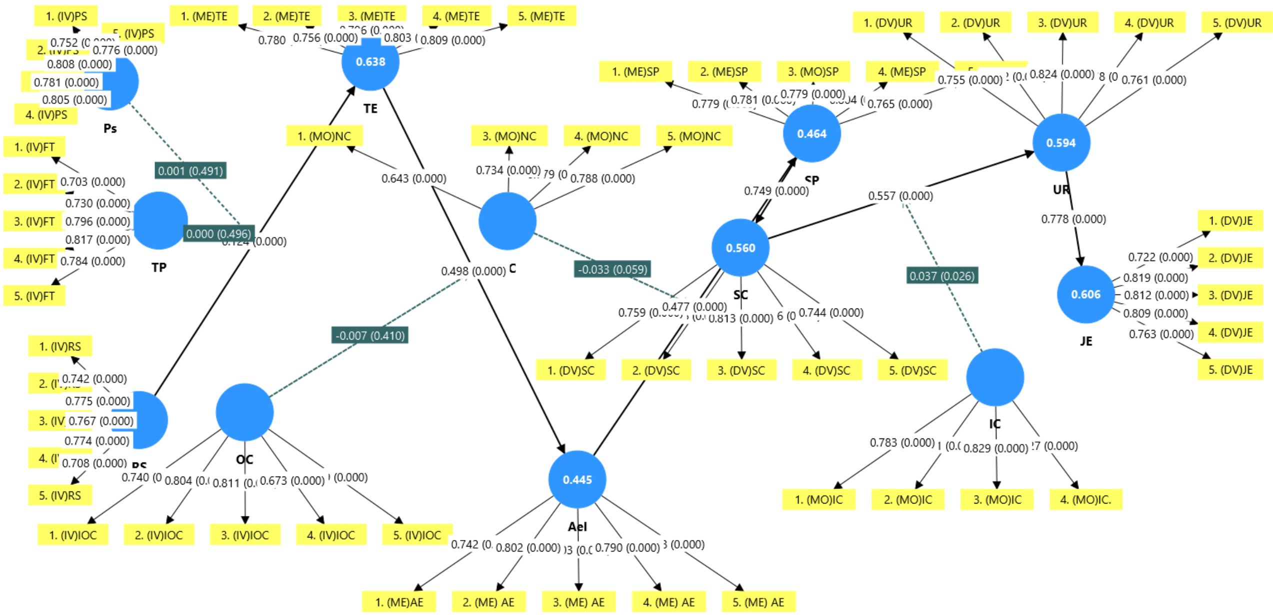


Figure 6. Conceptual Framework after validation

Table 8. Direct hypothesis analysis

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
Ael → SP	0.512	0.512	0.037	13.734	0.000
IC →UR	0.289	0.289	0.038	7.556	0.000
IC × SC →UR	0.035	0.034	0.016	2.171	0.015
NC →SP	0.280	0.282	0.036	7.777	0.000
NC × Ael →SP	-0.015	-0.016	0.018	0.862	0.194
OC →Ael	0.252	0.253	0.038	6.709	0.000
OC × TE →Ael	0.004	0.005	0.025	0.150	0.440
Ps →TE	0.380	0.382	0.048	7.914	0.000
Ps × RS →TE	0.003	0.003	0.044	0.078	0.469
RS →TE	0.131	0.130	0.036	3.649	0.000
SC →UR	0.581	0.582	0.036	16.134	0.000
SP →SC	0.789	0.790	0.020	39.855	0.000
TE →Ael	0.522	0.521	0.038	13.729	0.000
TP →TE	0.387	0.385	0.044	8.869	0.000
TP × RS →TE	-0.000	0.001	0.040	0.008	0.497
UR →JE	0.814	0.815	0.017	46.630	0.000

The result of the indirect hypothesis analysis, shown in Table 9, shows that most of the mediation pathways were significant, which showed strong sequential effects throughout the model. Particularly, the indirect relationships TP → TE → AeL, Ps → TE → AeL, and the extended chains, e.g., TP → TE → AeL → SP, Ps → TE → AeL → SP, and RS → TE → AeL → SP, were all significant with p-values of 0.000 and t-statistics significantly greater than 1.96. The more mediation paths, such as SP → SC → UR → JE, Ael → SP → SC → UR → JE, and TE → AeL → SP → SC → UR → JE, were proved very significant, which proved the cascading impact of teaching efficiency and adoption of e-learning on student performance and competence, university reputation, and job employment. Likewise, NC → SP → SC → UR and IC → UR → JE were also important, which confirmed the mediation functions of student competence and university reputation in cultural and institutional terms.

Table 9. Indirect hypothesis analysis

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
TP → TE → Ael	0.202	0.201	0.026	7.636	0.000
Ps × RS → TE → Ael	0.002	0.002	0.023	0.078	0.469
NC → SP → SC → UR	0.128	0.129	0.019	6.797	0.000
Ps → TE → Ael → SP → SC	0.080	0.080	0.015	5.455	0.000
SP → SC → UR → JE	0.373	0.374	0.030	12.407	0.000
Ael → SP → SC → UR → JE	0.191	0.192	0.022	8.599	0.000
Ps × RS → TE → Ael → SP → SC → UR → JE	0.000	0.000	0.004	0.077	0.469
TP → TE → Ael → SP → SC → UR	0.047	0.047	0.009	5.243	0.000
TP → TE → Ael → SP	0.103	0.103	0.017	6.201	0.000
RS → TE → Ael → SP	0.035	0.035	0.010	3.343	0.000
NC → SP → SC	0.221	0.222	0.029	7.622	0.000
OC × TE → Ael → SP → SC	0.001	0.002	0.010	0.150	0.440
TE → Ael → SP → SC → UR	0.122	0.123	0.018	6.848	0.000
TP → TE → Ael → SP → SC → UR → JE	0.039	0.039	0.008	5.060	0.000
TP × RS → TE → Ael → SP → SC → UR → JE	-0.000	0.000	0.004	0.008	0.497
TE → Ael → SP → SC → UR → JE	0.100	0.100	0.015	6.548	0.000
NC × Ael → SP → SC	-0.012	-0.012	0.014	0.867	0.193
TE → Ael → SP	0.267	0.267	0.031	8.554	0.000
TP × RS → TE → Ael → SP	-0.000	0.000	0.011	0.008	0.497
RS → TE → Ael → SP → SC → UR → JE	0.013	0.013	0.004	3.098	0.001
TP → TE → Ael → SP → SC	0.081	0.081	0.014	5.854	0.000
Ps → TE → Ael	0.198	0.199	0.030	6.519	0.000
Ps → TE → Ael → SP → SC → UR	0.047	0.047	0.009	5.190	0.000
Ps → TE → Ael → SP	0.101	0.102	0.018	5.583	0.000
TP × RS → TE → Ael	-0.000	0.000	0.021	0.008	0.497
OC × TE → Ael → SP → SC → UR → JE	0.001	0.001	0.005	0.150	0.440
TE → Ael → SP → SC	0.211	0.211	0.026	7.972	0.000
IC × SC → UR → JE	0.028	0.028	0.013	2.188	0.014
SP → SC → UR	0.459	0.460	0.033	13.822	0.000
NC × Ael → SP → SC → UR → JE	-0.006	-0.006	0.007	0.868	0.193
RS → TE → Ael → SP → SC → UR	0.016	0.016	0.005	3.144	0.001
Ps × RS → TE → Ael → SP	0.001	0.001	0.012	0.077	0.469
NC → SP → SC → UR → JE	0.104	0.105	0.016	6.608	0.000
TP × RS → TE → Ael → SP → SC → UR	-0.000	0.000	0.005	0.008	0.497
Ael → SP → SC	0.404	0.404	0.033	12.250	0.000
OC → Ael → SP → SC → UR	0.059	0.060	0.011	5.376	0.000
Ael → SP → SC → UR	0.235	0.235	0.026	9.183	0.000
Ps × RS → TE → Ael → SP → SC	0.001	0.001	0.009	0.077	0.469
OC × TE → Ael → SP → SC → UR	0.001	0.001	0.006	0.150	0.440
OC → Ael → SP	0.129	0.130	0.022	5.943	0.000
NC × Ael → SP → SC → UR	-0.007	-0.007	0.008	0.867	0.193
OC → Ael → SP → SC → UR → JE	0.048	0.049	0.009	5.249	0.000
Ps → TE → Ael → SP → SC → UR → JE	0.038	0.038	0.007	5.088	0.000
TP × RS → TE → Ael → SP → SC	-0.000	0.000	0.009	0.008	0.497
OC → Ael → SP → SC	0.102	0.102	0.017	5.864	0.000
Ps × RS → TE → Ael → SP → SC → UR	0.000	0.000	0.005	0.077	0.469
OC × TE → Ael → SP	0.002	0.002	0.013	0.150	0.440
RS → TE → Ael → SP → SC	0.028	0.027	0.008	3.288	0.001
IC → UR → JE	0.235	0.235	0.032	7.427	0.000
RS → TE → Ael	0.068	0.068	0.019	3.571	0.000
SC → UR → JE	0.473	0.474	0.032	14.580	0.000

But every one of the moderation effects was dismissed. All the paths that contained interaction terms like Ps × RS → TE → AeL, TP × RS → TE → AeL, OC × TE → AeL → SP, and NC × AeL → SP → SC were not significant and had p-values that were greater than 0.05 and t-statistics that were below the critical value of 0.05. It shows that the strength of the direct and mediated relationships is strong, but the hypothesized moderating effects were not significant in the indirect effect of the model.

Table 10 shows the Values of R-squared and Adjusted R-squared. This table shows the explanatory power of the model on each endogenous variable in terms of the percentage of explained variance of the endogenous variable. As an illustration, University Reputation (UR) R^2 is 0.594, which implies that 59.4% of its variation is modeled by Student Competence and Information Culture, revealing a good model fit to this path.

Table 10. Values of R-Squared and Adjusted R-Squared

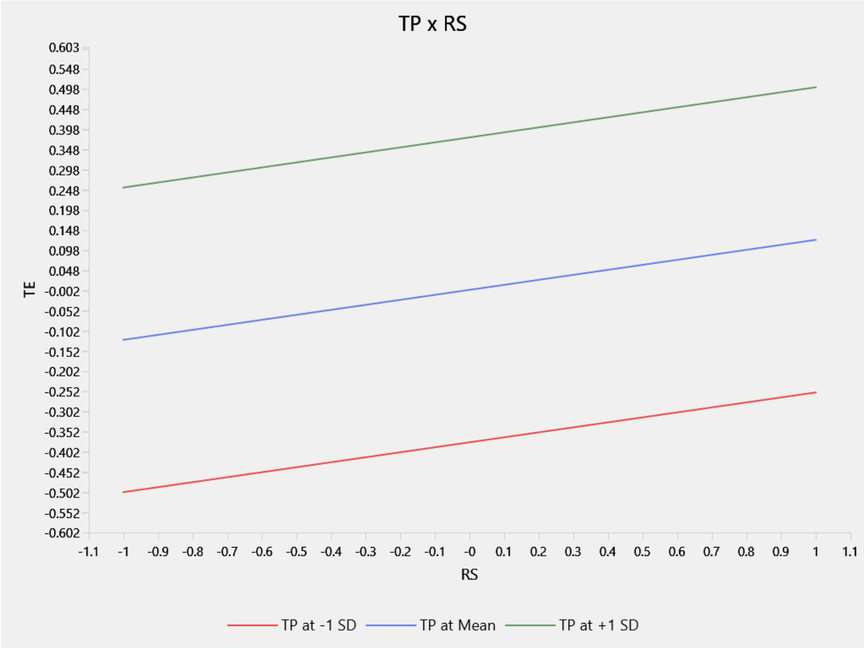
	R-square	R-square adjusted
Ael	0.445	0.443
JE	0.606	0.605
SC	0.560	0.560
SP	0.464	0.462
TE	0.638	0.635
UR	0.594	0.592

Table 11 displays the effect size (f^2) of each of the relationships, which gives an indication of the strength of the contribution of each of the predictors to a respective dependent variable. The presence of high f^2 values (e.g., UR-JE=1.536, SP-SC=1.274) indicates strong effects, and the low values of f^2 (e.g., OC × TE → Ael = 0.000) indicate the lack of a significant moderating effect.

Table 11. f-Square Effect Sizes

	f-square
Ael → SP	0.254
IC → UR	0.106
IC × SC → UR	0.006
NC → SP	0.081
NC × Ael → SP	0.004
OC → Ael	0.051
OC × TE → Ael	0.000
Ps → TE	0.132
Ps × RS → TE	0.000
RS → TE	0.021
SC → UR	0.405
SP → SC	1.274
TE → Ael	0.254
TP → TE	0.140
TP × RS → TE	0.000
UR → JE	1.536

Figure 7 demonstrates the relationship between readiness (RS) and training programs (TP) and predicting teaching efficiency (TE). The horizontal axis is the readiness, with a range of about -1.1 to +1.1, whereas the vertical axis is the efficiency in teaching, with a range of about -0.602 to 0.603. There are three, low (TP at -1 SD), average (TP at mean), and high (TP at +1 SD) lines showing various levels of training programs. The slopes of all lines are positive, which means that the more the readiness, the higher the teaching efficiency is. The moderating effect of training programs, however, is seen in the location of the lines. When the training programs are high, the efficiency in teaching remains constant throughout the readiness levels, as compared to the low and average training programs. This implies that training programs reinforce the positive correlation between preparedness and teaching efficiency as opposed to pushing the result in the uphill direction. The visual data substantiates the hypothesis that the effect of readiness on the efficiency of teaching is increased with the help of policy support and training programs, and the moderating role of training programs is important.



Note: H10: Policy Support (PS) and Training Programs (TP) combined enhance the RS → TE link. This graph specifically shows TP's role; if PS were included

Figure 7. The relationship between (RS), (TP), and (TE)

The relationship between teaching efficiency (TE) and the organizational culture (OC) in determining the adoption of e-learning (AeL) is depicted in Figure 8. The horizontal axis gives teaching efficiency between about -1.1 and +1.1, whereas the vertical axis gives the adoption of e-learning between about -0.828 and 0.772. Organizational culture is shown in three lines, indicating the low (OC at -1 SD), average (OC at mean), and high (OC at +1 SD) levels. The three lines' slopes are all positive, which means that the higher the teaching efficiency, the greater the adoption of e-learning.

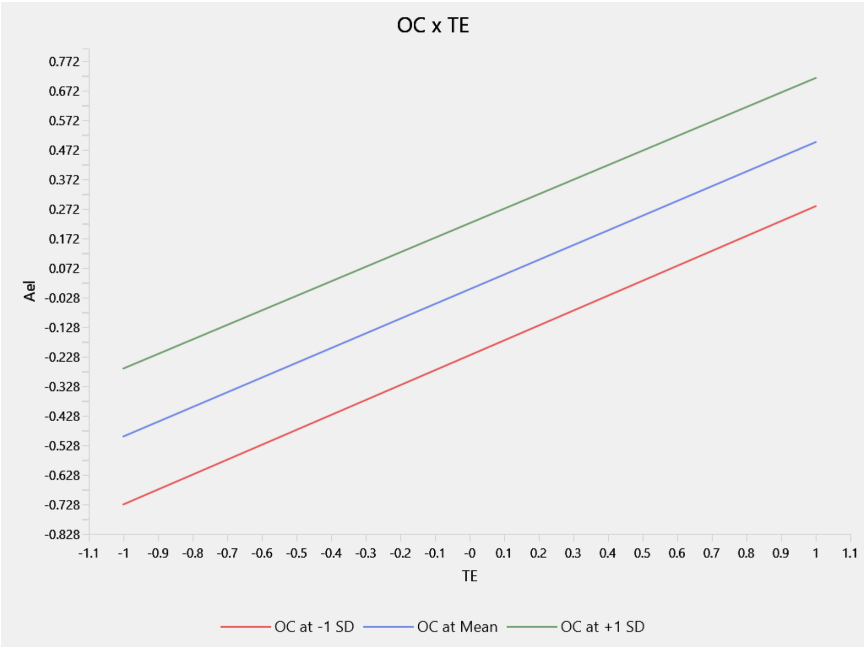


Figure 8. The relationship between (TE), (OC) in determining (AeL)

Organizational culture, when high, leads to a constant high e-learning adoption at all levels of teaching efficiency, on top of average and low organizational culture. This trend can validate the fact that organizational culture enhances the positive correlation between e-learning adoption and teaching efficiency. The graphical data directly confirm Hypothesis H7, according to which teaching efficiency and e-learning adoption are correlated by the moderation of the organizational culture.

Figure 9 shows how student competence (SC) and information culture (IC) interact in determining the university reputation (UR). The horizontal axis will have the competence of the students, and the vertical axis will be the reputation of the university. Three lines demonstrate the varying degrees of information culture: low (IC at -1 SD),average (IC at mean), and high (IC at +1 SD). All the slopes are upward, and this implies that as the competence of the students is high, the university's reputation is higher. The green line, which is the highly information-culture, is always above the others, hence it is clear that the information culture reinforces this relationship. This helps to prove Hypothesis H9, according to which information culture mediates the relationship between student competence and university reputation.

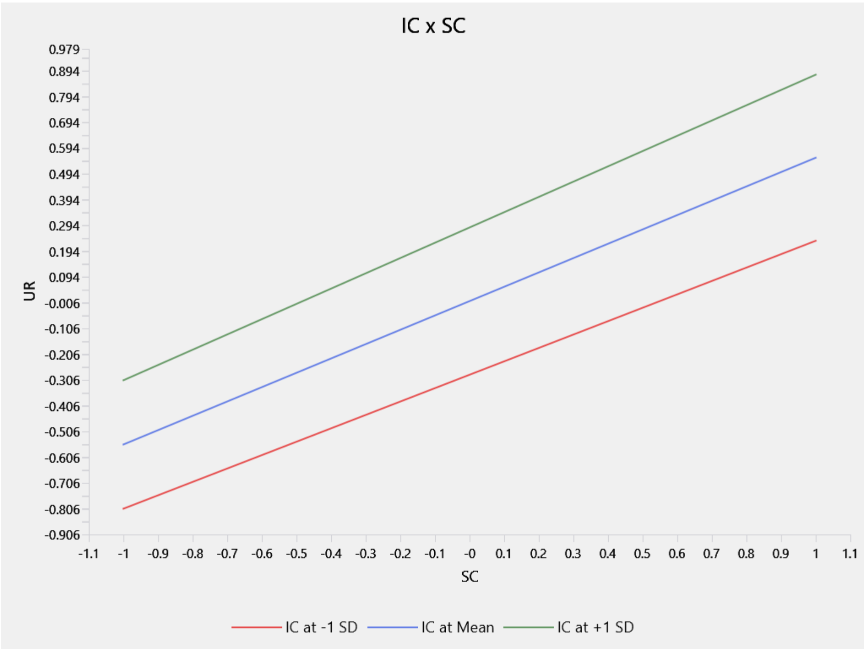


Figure 9. **Student competence (SC) and information culture (IC) interact to determine university reputation (UR)**

Figure 10 illustrates the relationship between readiness (RS) and policy support (PS) and predicts teaching efficiency (TE). The horizontal axis is the measure of readiness, and the vertical axis is the measure of teaching efficiency. There are three lines that show various levels of policy support: low (PS at -1 SD), average (PS at the mean), and high (PS at +1 SD). All the lines are upward-sloping, that is, as the readiness increases, the efficiency of teaching increases. The green line, which depicts the high policy support, always stays on top of the others, and this indicates that policy support enhances this relation. This confirms Hypothesis H10, according to which policy support and training programs have a positive impact on the relationship between readiness and teaching efficiency.

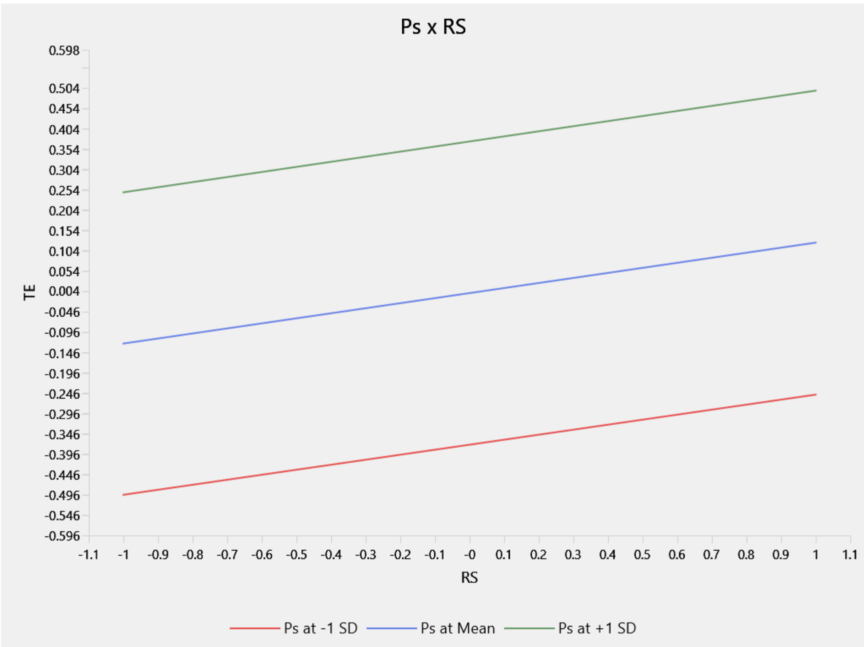


Figure 10. **The relationship between (RS) and (PS) predicts (TE)**

Figure 11 represents the relationship between e-learning (AeL), national culture (NC), and student performance (SP). The horizontal axis will be that of e-learning adoption, and the vertical axis will be student performance. There are three lines that represent the level of national culture as low (NC at -1 SD), average (NC at mean), and high (NC at +1 SD). Each of the lines has an upward slope, that is, as the adoption of e-learning goes on, the performance of the students improves. The green line, which symbolizes high national culture, is always on the upper end of the rest, indicating that national culture enhances this association. This confirms Hypothesis H8, which is that national culture mediates the relationship between e-learning adoption and student performance.

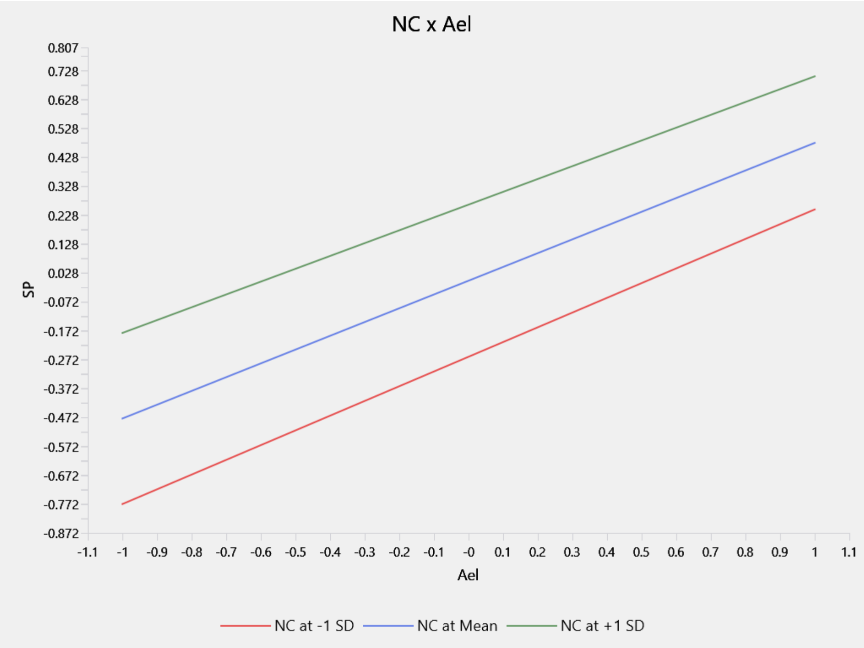


Figure 11. The relationship between (AeL), (NC), and (SP)

4-3- Direct Relationships

The analysis was able to confirm the presence of strong support for the majority of the direct hypotheses. H1 (RS → TE) was considered significant ($b = 0.131$, $t = 3.649$, $p < 0.001$), which means that institutional readiness has a positive impact on the efficiency of teaching. H2 (TE → AeL) presented a significant effect ($b = 0.522$, $t = 13.729$, $p < 0.001$), which verifies the idea that teaching efficiency is a key factor in the adoption of e-learning. Likewise, H3 (AeL → SP) was highly significant ($b = 0.512$, $t = 13.734$, $p < 0.001$), which proves that the adoption of e-learning improves the performance of students. The two following hypotheses (H4 (SP → SC) and H5 (SC → UR)) had the strongest path coefficient ($b = 0.789$ and $b = 0.581$, respectively; $p < 0.001$), which underlines the significant contribution of student competence to the process of building university reputation. Lastly, H6 (UR → JE) became the most robust in the model ($b = 0.814$, $t = 46.630$, $p < 0.001$), which supports the fact that institutional reputation is an important predictor of graduate employability.

The policy and training factors also influenced teaching efficiency in a significant positive way (Ps $b = 0.380$, $t = 7.914$; TP $b = 0.387$, $t = 8.869$; $p < 0.001$) and, therefore, they were important as operational enablers. Significant predictors were also the cultural factors, namely, the organizational culture (OC → AeL, $b = 0.252$, $t = 6.709$, $p < 0.001$) and in-formation culture (IC → UR, $b = 0.289$, $t = 7.556$, $p < 0.001$). Nonetheless, moderation hypotheses H7 (OC × TE → AeL): H8 (NC × AeL → SP): H10 (Ps × RS and TP × RS → TE) were dismissed because their p-values (> 0.05) were not significant, indicating that the latter do not influence the strength of the original relationships.

4-4- Indirect Relationships

The mediation analysis indicated that there were strong sequential effects throughout the ecosystem. The cascading effect of operational drivers on the long-term sustainability effects is confirmed by the indirect routes, TE → AeL → SP → SC → UR → JE ($b = 0.100$, $t = 6.548$, $p < 0.001$) and Ael → SP → SC → UR → JE ($b = 0.191$, $t = 8.599$, $p < 0.001$). The student competence and university reputation proved to be significant mediators, and the indirect effect of SP → SC → UR → JE is the largest ($b = 0.373$, $t = 12.407$, $p < 0.001$). The policy and training pro-grams had a secondary role through their instruction in efficiency and uptake of e-learning (TP → TE → AeL → SP → SC → UR → JE, $b = 0.039$, $t = 5.060$, $p < 0.001$), which, once again, supported their strategic role.

On the other hand, the indirect effects of moderation were non-significant, including OC × TE → AeL → SP and NC × AeL → SP → SC, and therefore, cultural and policy aspects do not significantly affect the mediated relationships. This implies that their impact is more organizational and facilitative as opposed to interactive.

5- Discussion

The results confirm the conceptual model given and support the idea that prepared-ness and teaching effectiveness are the principles of a sustainable e-learning system. The above operational drivers will trigger a series of effects that will lead to institutional reputation and employability, which is consistent with the long-term sustainability goals. The rejection of moderation hypotheses means that cultural and policy effects are facilitative and not dynamic moderators, but the significant mediation effects indicate the significance of competence and reputation as strategic consequences. These findings highlight the necessity of the institutions to emphasize preparedness, teaching effectiveness, and ability enhancement, and encourage a culture of information to, therefore, maintain e-learning programs.

Overall, as present in Table 12 the current research supports most of the fundamental relationships derived in earlier studies on e-learning, especially in the areas of preparedness, instructional effectiveness, adoption, and student achievement. It, however, builds upon earlier literature by incorporating these aspects into a holistic ecosystem context that has a clear tie between operational drivers and the long-term sustainability performance measures, which are the institutional reputation and graduate employability. In contrast to the previous research that focuses on the independent impacts, the results show that competence and reputation are important transmission channels by which e-learning creates long-term institutional and social value.

Table 12. Comparison of Present Study Results with Previous Studies by Almaqbali et al. [58]

Aspect / Relationship	Findings of the Present Study	Evidence from Previous Studies	Comparative Analysis / Contribution
Institutional Readiness → Teaching Efficiency	Positive and significant effect, confirming readiness as a key operational driver	Prior studies report readiness as essential for effective e-learning implementation, mainly focusing on adoption readiness	Confirms earlier findings and extends them by positioning readiness as the foundation of a sustainability-oriented ecosystem
Teaching Efficiency → E-learning Adoption	Strong positive effect, highlighting pedagogy as a central adoption mechanism	Consistent with studies emphasizing teaching quality and instructional design as drivers of e-learning success	Reinforces pedagogical centrality and embeds it within a long-term sustainability pathway
E-learning Adoption → Student Performance	Significant positive impact on student performance	Widely supported in prior literature focusing on short-term learning outcomes	Confirms convergence with prior studies while serving as a bridge to longer-term outcomes in the ecosystem
Student Performance → Student Competence	Very strong effect, indicating performance as a precursor to competence development	Prior studies often treat performance and competence separately	Extends literature by empirically linking performance to competence within one integrated model
Student Competence → University Reputation	Strong positive relationship	Limited empirical testing in prior e-learning studies	Novel contribution showing how learning outcomes translate into institutional reputation
University Reputation → Graduate Employability	Very strong and significant effect	Often discussed conceptually, rarely modeled empirically	Advances sustainability literature by statistically validating employability as a final ecosystem outcome
Cascading Indirect Effects (e.g., TE → AeL → SP → SC → UR → JE)	Multiple significant sequential effects confirming ecosystem behavior	Prior studies usually test partial or isolated mediation paths	Major contribution demonstrating how small upstream effects accumulate into strong sustainability outcomes
Policy Support & Training Programs	Significant direct effects on teaching efficiency; no moderation effects	Prior studies report policy and training as important enablers	Extends prior work by clarifying their role as structural enablers rather than interaction moderators
Organizational & National Culture (Moderation)	Moderation effects not supported	Mixed evidence in prior studies, often context- and task-specific	Suggests cultural effects operate through direct and mediated pathways in ecosystem-level models
Information Culture (Mediation)	Significant mediating role between competence and reputation	Knowledge-sharing and information culture highlighted in prior studies	Confirms and strengthens theory by empirically validating information culture as a key transmission mechanism
Overall Perspective	Holistic, sustainability-oriented e-learning ecosystem	Prior research largely adoption- or performance-focused	Extends the field by shifting focus from short-term adoption to long-term institutional and employability outcomes

6- Conclusion

The paper illustrates that the development of a sustainable e-learning ecosystem needs a solid operational base that is anchored on the preparedness and efficiency in teaching that directly affects the uptake of e-learning. The results establish that preparation regarding infrastructure, skills, and organizational backup increases the efficiency of teaching, which consequently prompts effective adoption and acquisition of e-learning. These operational drivers produce a ripple effect of results in a better performance and competence of the students. Notably, the competence of students is one of the key mechanisms by which the e-learning initiatives can be transformed into the larger institutional gains, such as the increased university reputation and the better employability of graduates. These direct and indirect relationships are what make sustainable e-learning go beyond technological implementation and realize a systemic process that brings together pedagogical quality and the growth of human capital. Though the influence of cultural factors and policy-related factors was considered as the moderators, the empirical findings show that they modulate their effects mostly in a supportive and not an interactional manner. Organizational culture, national culture, policy support, and training programs are directly correlated with the strengthening of teaching efficiency and e-learning effectiveness, but these factors do not dramatically change the strength of the basic structural relationships. Conversely, the mediating effect of information culture on the relationship between student competence and institutional reputation can be considered critical, as the significance of knowledge-sharing practices, transparency, and information-based decision-making in maintaining digital education programs. Taken together, the validated Sustainable E-Learning Ecosystem Framework provides a whole picture, combining technological, pedagogical, cultural, and policy aspects to clarify the short-term educational delivery and the long-term sustainability targets. The framework offers a pathway to a strategy of e-learning investment to higher education leaders and policymakers to align this investment with the outcome of institutional reputation building and employability, especially in the developing higher education systems in search of sustainable digital transformation.

7- Declarations

7-1- Author Contributions

Conceptualization, S.A. and B.S.; methodology, S.A.; software, BS; validation S.A. and B.S.; formal analysis, S.A. and B.S.; investigation, S.A. and B.S.; resources, S.A.; data curation, S.A.; writing—original draft preparation, S.A. and B.S.; writing—review and editing, S.A. and B.S.; visualization, B.S. and S.A.; supervision, B.S.; project administration, S.A. and B.S.; funding acquisition, S.A. All authors have read and agreed to the published version of the manuscript.

7-2- Data Availability Statement

The data presented in this study are available on request from the corresponding author.

7-3- Funding and Acknowledgments

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7-4- Institutional Review Board Statement

Not applicable.

7-5- Informed Consent Statement

Informed consent was obtained from all subjects involved in the study.

7-6- Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, and redundancies have been completely observed by the authors.

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