# An Integrated Model of Online Learning Success in Moroccan Higher Education: Evidence from PLS-SEM

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## ABSTRACT

**Online learning has played an essential role in education, underscoring the need to understand the factors that influence student satisfaction, continuity intention, and engagement. Building on a previous theoretical development of an integrated model of online learning success, this study empirically evaluates that model in the context of Moroccan higher education. Using a quantitative cross-sectional design, data were collected using a purpose sampling strategy from 207 students from Moroccan universities. To analyze the relationships between constructs conceptualized using multiple theoretical frameworks (TAM, ECM, D&M ISS, TTF, SRL, SDT, SCT, IDT, and CoI), data analysis was performed using Structural Equation Modeling via the Partial Least Squares approach (PLS-SEM), which is suitable for complex multi-theory models. The results showed that 8 of the 15 hypothesized relationships were statistically significant, with perceived ease of use and system, service, and information quality being significant predictors of student satisfaction. Satisfaction predicts continuity intention, task-technology fit and self-regulated learning predict perceived performance impact, and continuity intention also positively predicts performance. The relationships hypothesized through social/teaching presence, competence/autonomy/relatedness, and innovation attributes were not supported, suggesting a more complex or indirect influence in this context. These findings provide empirical support for key components of the integrated model and advance understanding of how established frameworks apply in a resource-constrained developing-country higher education context. Practically, the results underscore the importance for Moroccan institutions of prioritizing platform usability and quality, aligning technology with learning tasks, and fostering students' self-regulation skills to enhance satisfaction, continuity, and perceived performance in online learning.**

***Keywords-online learning; student satisfaction; continuity intention; performance impact; Moroccan higher education; integrated satisfaction model; PLS-SEM; technology adoption; self-regulated learning***

## I. INTRODUCTION

The integration of technology has changed the nature of education, particularly within online learning environments, creating opportunities and challenges. Building upon our earlier work [1], which introduced an integrated model that synthesizes existing frameworks, this study aimed to examine the complex dynamics of student satisfaction and continued engagement with online learning. This research evaluates this model in the context of Moroccan higher education.

The unique characteristics of the Moroccan higher education system present challenges not commonly encountered in more technologically advanced regions [2]. Morocco's higher education landscape is shaped by limited digital infrastructure—including uneven internet connectivity and limited institutional investment in e-learning platforms—alongside deeply rooted teacher-centered traditions that conflict with the self-directed nature of online learning [3]. In addition, high student-to-faculty ratios and socioeconomic disparities in device access further compound these barriers [4, 5]. These realities necessitate examination of satisfaction and continued use rather than relying on models validated in Western or East Asian contexts.

Previous studies on the satisfaction of online learning students have drawn from theories such as the Technology Acceptance Model (TAM), the Expectation Confirmation Model (ECM), the DeLone and McLean Information System Success Model (D&M ISS), Self-Regulated Learning (SRL), Task-Technology Fit (TTF), Self-Determination Theory (SDT), Innovation Diffusion Theory (IDT), Social Cognitive Theory (SCT), and the Community of Inquiry (CoI). As discussed in [1], these models provide insights into factors influencing student perception and behavior in online learning environments. Prior research demonstrates the influence of factors such as perceived usefulness [6, 7], ease of use [8], expectation confirmation [9, 10], system quality [11, 12], and social presence [13, 14] in predicting user satisfaction and continuity of use of online systems.

Beyond these theoretical contradictions, several contextual gaps remain unaddressed. First, TAM-based studies in online learning have been criticized for focusing narrowly on adoption intent and neglecting post-adoption behavior, satisfaction, and performance—gaps that ECM and D&M ISS partially address but rarely in combination [9, 11]. Second, while ECM has been validated in e-commerce and Western higher education contexts [9, 10], its applicability in teacher-centered, resource-constrained systems such as Morocco remains empirically unexamined. Third, although SRL has been identified as a predictor of academic success [15, 16], it is rarely tested alongside technological quality constructs (system, service, and information quality) in a single structural model, leaving unclear whether its effect on performance is independent of platform quality. Fourth, the findings on social presence (CoI) and its effect on satisfaction are contradictory, as some studies report significant direct effects [17, 18] and others suggest that these relationships are mediated by basic psychological needs [19] or disappear in asynchronous and low-bandwidth environments that are common in Morocco.

Further gaps remain. First, most integrated online learning models have been validated in high-resource contexts (e.g., the United States, China, South Korea), where infrastructure reliability and learner digital literacy cannot be assumed to be comparable to the Moroccan setting. Second, no prior study has simultaneously integrated TAM, ECM, D&M ISS, TTF, SRL, SDT, IDT, SCT, and CoI within a single model to examine their combined explanatory power in a Francophone African higher education context. Third, the interplay between psychological constructs and technological quality perceptions remains underexplored in resource-constrained environments. Finally, empirical evidence on how cultural norms around instructor authority and community dynamics (CoI) moderate online learning success in Morocco is virtually absent from the literature. Addressing these gaps is important for several reasons. First, it advances understanding of student success determinants in the Moroccan context. Second, it supports contextually relevant strategies to improve engagement and outcomes. Third, it contributes to theory by extending the validation of integrated IS-education models beyond Western contexts and by clarifying the relative predictive weight of psychological constructs (particularly SRL) versus system-level factors (SSI, TTF) within a single unified model. Finally, the findings guide Moroccan institutions in prioritizing platform investments and learner support.

While each of these theories offers valuable insights individually, relying on any single framework would yield an incomplete picture: TAM explains initial acceptance but not post-adoption satisfaction or performance; ECM captures confirmation and satisfaction but ignores system quality and task alignment; D&M ISS addresses quality dimensions but neglects psychological and motivational factors; TTF explains performance through fit but does not account for social or self-regulatory dimensions; and SRL, SDT, SCT, and CoI address learner psychology and social dynamics but lack the technological acceptance and quality components needed to explain platform-level outcomes. Their integration is therefore complementary, as each theory compensates for the blind spots of the others.

In mobile banking, researchers have successfully combined TAM with TTF [20, 21] and TAM with SDT to explain adoption and continued use beyond what either model predicts alone. In e-learning, integrated models combining TAM and ECM [10], TAM and D&M ISS [12], and ECM with SRL [16] outperformed single-theory approaches. This study extends this tradition by bringing together a broader set of complementary frameworks-TAM, ECM, D&M ISS, TTF, SRL, SDT, IDT, SCT, and CoI-within a single model, responding to calls for more comprehensive, context-sensitive frameworks.

Drawing on these gaps, this study aimed to answer the following research questions:

1. RQ1: To what extent do technological factors (perceived ease of use, system quality, service quality, information quality) influence student satisfaction with online learning platforms in Moroccan higher education?
2. RQ2: Does TTF mediate or contribute to performance impact beyond quality and usability perceptions?
3. RQ3: Does satisfaction mediate the relationship between system perceptions and continuity intention, and does continuity intention predict perceived performance impact?

Together, these questions reflect the coherence between the Moroccan contextual problem (infrastructure constraints, cultural norms and self-directed learning challenges) and the theoretical lenses selected: TAM and D&M ISS address system and quality perceptions; ECM captures expectation confirmation and satisfaction; TTF and SRL address the fit between tasks and learner agency; SDT, SCT, CoI, and IDT account for motivational, social, and adoption dimensions. This alignment ensures that the integrated model is theoretically grounded and practically relevant to the Moroccan setting.

This study aimed to improve online learning design and outcomes for Moroccan students. Its main objectives were to (i) validate the proposed integrated model of student satisfaction in Moroccan higher education, (ii) identify key factors influencing satisfaction and continued use, and (iii) provide recommendations for improving online learning practices in Morocco.

### A. *Theoretical Model and Hypotheses Development*

This study proposes and tests an integrated model of student satisfaction and continuity of use of online learning platforms in Moroccan higher education, shown in Figure 1. The relationship between the theoretical constructs developed from the models (CoI, STD, TAM, ECM, IDT, D&M ISS, TTF, SRL) relies on the following theoretical rationale:

- Social and Teaching Presence (STP) in online learning increases support and sense of community, resulting in greater student satisfaction [17, 18]. We hypothesized that Social and teaching presence positively affect student satisfaction (H1).
- SDT suggests that competence, autonomy, and relatedness are central to intrinsic motivation and satisfaction. These factors should enhance the satisfaction of the students in the online learning process [19, 22]. Thus, H2: Competence, autonomy, and relatedness positively affect student satisfaction.
- TAM also suggests that Perceived Ease Of Use (PEOU) influences perceived usefulness [6, 8]. If a platform is easy to use, students will perceive it as useful for learning. Thus, we hypothesized that PEOU positively affects perceived usefulness (H3).
- Continuity of use may lead to improved performance [23, 24]. Thus, H4: Continuity intention positively affects performance impact.
- As the TAM would maintain, perceived usefulness (PU) is among the strongest determinants of acceptance and satisfaction towards technology [7, 25]. Students who believe that online platforms enhance their learning will be more satisfied [26]. Therefore, H5: perceived usefulness positively affects student satisfaction.
- TAM suggests that perceived usefulness is an excellent predictor of continuity intention. If students find a platform useful, then they're likely to use it over and over again [9]. Therefore, H6: Perceived usefulness positively affects continuity intention.
- IDT suggests that if something is better, easy to try out, visible, compatible, and not too complex, it will be adopted [27, 28]. Therefore, H7: Relative advantages, trialability, observability, and compatibility positively affect continuity intention, while complexity negatively affects continuity intention.
- The D&M ISS model identifies system, service, and information quality as essential to user satisfaction. Better quality leads to greater satisfaction [11, 12]. Therefore, H8: System, service, and information quality positively affect student satisfaction.

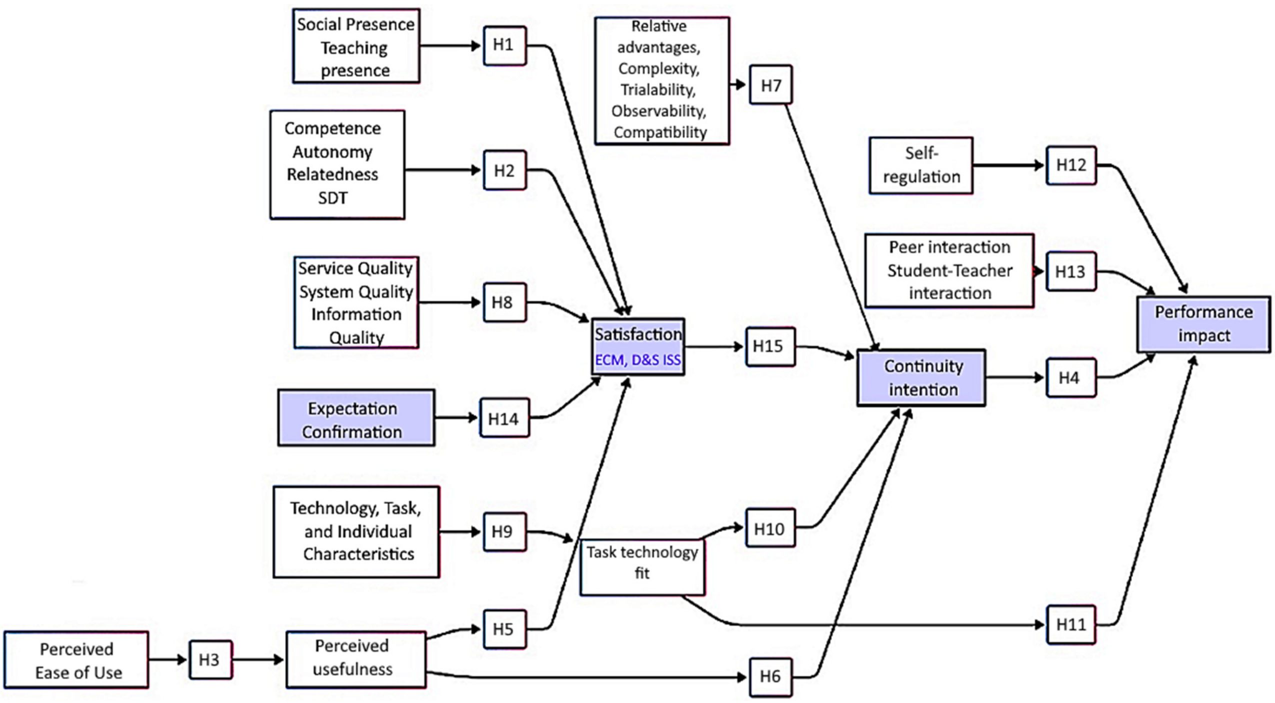


Fig. 1. Integrated model of student satisfaction and continuity of use of online learning platforms

- TTF gets higher when technology matches task needs and individual skills. Technology, task, and individual characteristics contribute to this fit [29]. Hence, H9: Technology, task, and individual characteristics positively affect TTF.
- Where technology is adequately matched with the task, users are more likely to continue using it [20, 21]. Hence, H10: TTF positively affects continuity intention.
- A proper fit between technology and task should improve performance [30]. Therefore, H11: TTF positively affects performance impact.
- Self-regulated learners are more effective, and this should improve performance [15, 16]. Therefore, H12: Self-regulated learning positively influences performance impact.
- Social interaction can improve learning and performance [31, 32]. Thus, H13: Peer interactions and teacher-student interactions positively influence performance impact.
- If expectations are met, satisfaction will increase [23, 33]. Therefore, H14: Expectation confirmation positively influences student satisfaction.
- Satisfied students are more likely to use the platform again [24]. Thus, H15: Student satisfaction positively affects continuity intention.

Figure 1 describes all the hypotheses for the relationships between the different factors. These hypotheses are the foundation for data analysis and are relevant to justifying the proposed model in the particular context of online higher education. The aim is to offer empirical justification of the effectiveness of the proposed conceptual model through rigorous examination of these hypotheses.

## II. METHODOLOGY

This study was conducted in accordance with the ethical principles that govern research involving human participants. The survey was distributed anonymously; no personally identifiable information was collected at any stage. Participation was entirely voluntary, and the completion of the questionnaire was taken as implicit informed consent. Participants were informed of the purpose of the study and their right to withdraw at any time without consequence. As the study involved anonymous survey data without clinical procedures or sensitive personal information, formal ethics committee approval was not required.

### *A. Research Design*

This study adopted a quantitative method to test the hypotheses derived from the integrated model of student satisfaction. A cross-sectional survey design was used to analyze the relationships between the key constructs. The data employed in this study were collected using an online questionnaire (Tables I and II). Questionnaire item responses were measured on a five-point Likert scale, where 1 denotes strongly disagree and 5 strongly agree. Participant demographics such as age, gender, and field of study were also collected using the questionnaire. Table I presents the independent variables with their corresponding codes. Dependent variables were expectation confirmation, student satisfaction, and intention to continue using online learning platforms, as shown in Table II.

TABLE I. INDEPENDENT VARIABLES WITH THEIR CORRESPONDING CODES

| Factors | Code factors |
|---|---|
| Social and teaching presence | STP |
| competence, autonomy, and relatedness | CAR |
| Perceived ease of use | PAU |
| Perceived usefulness | PAF |
| Relative advantages, trialability, observability and compatibility, complexity | ATO |
| System, service, and information quality | SSI |
| Technology, task, and individual characteristics | TIC |
| Task-technology fit | TTF |
| Self-regulation learning | SRL |
| Peer interactions and teacher-student interactions | PIT |

TABLE II. DEPENDENT VARIABLES WITH THEIR CORRESPONDING CODES

| Factors | Code Factors |
|---|---|
| Expectation confirmation | EPC |
| Students' satisfaction | SSF |
| Continuity intention | CTI |
| Performance Impact | PI |

### *B. Participants (Sampling Method, Sample Size, Demographics)*

The participants were recruited through an online convenience sample. The questionnaire was developed and distributed via Google Forms through online forums and email lists targeting students from Moroccan higher universities. The survey remained open for a period of two months, from January to February 2026. The questionnaire was administered in French. The first question served as a screening item, requiring respondents to confirm their participation in hybrid or online courses; those who did not meet this criterion were directed to exit the survey and were not included in the dataset.

A total of 207 valid responses were received, yielding a response rate of 100%. As all questionnaire items were set as mandatory, no data were missing, ensuring complete responses from all participants. Outlier sensitivity was mitigated by the use of Partial Least Squares Structural Equation Modeling (PLS-SEM), which is known to be robust to non-normality and less sensitive to outliers than covariance-based SEM approaches. The final sample differed in age, level of education, and field of study. Figures 2-5 summarize the main demographic characteristics of the sample, including age distribution, gender, level of education, and self-perceived digital competence. It should be noted that the use of purposive and convenience sampling introduces potential selection bias, as participants were self-selected and recruited through online forums and institutional email lists. This may over-represent digitally engaged or motivated students, and caution should be exercised when generalizing these findings to the broader Moroccan student population or to other national contexts with different infrastructure and cultural profiles.

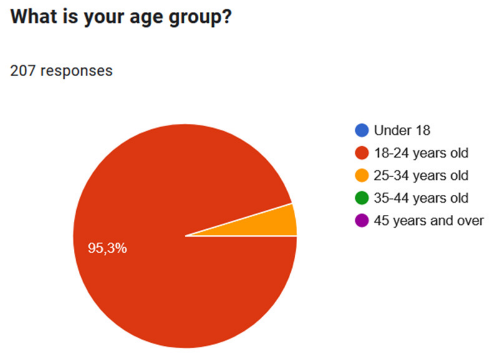


Fig. 2. Age distribution of participants.

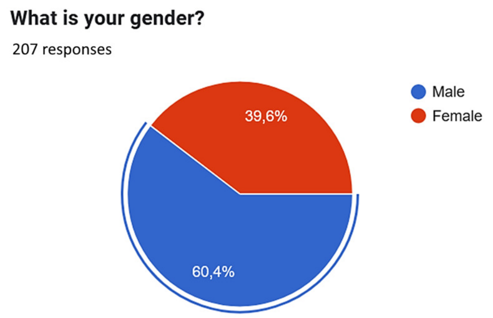


Fig. 3. Gender distribution of participants.

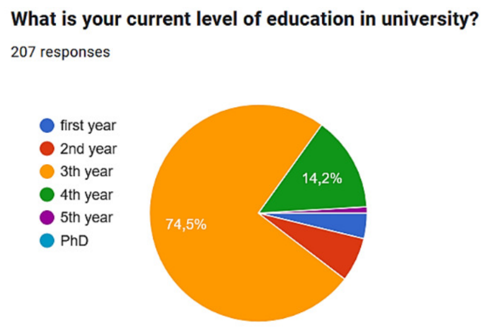


Fig. 4. Educational level of participants.

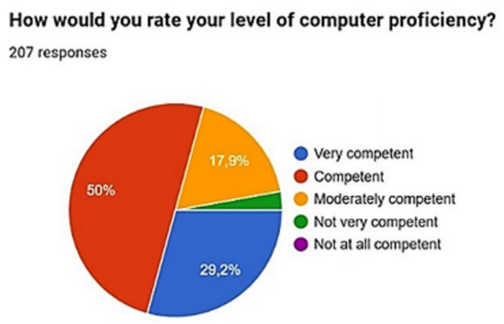


Fig. 5. Self-reported digital competence of participants.

## *C. Common Method Bias*

To assess the potential threat of common method bias, Harman's single-factor test was conducted using SPSS. All study constructs were subjected to an exploratory factor analysis with extraction forced to a single factor. The single factor accounted for 39.9% of the total variance, which is well below the 50% threshold commonly used as an indicator of problematic common method bias. These results suggest that common method bias is unlikely to be a serious concern in this study.

## *D. Data Analysis Techniques*

The data gathered were analyzed using statistical techniques, namely Structural Equation Modeling (SEM) [34] to examine relationships between observed variables and latent constructs, using SmartPLS v4 and SPSS v30 to test the strength of the relationships among the various factors. Both reliability testing and validity testing were employed. Reliability was assessed using Cronbach's alpha [35] and Composite Reliability (CR) to estimate the internal consistency of the scales. A value of $\alpha < 0.5$ indicates unacceptable internal consistency [36]. Composite or construct validity, which assesses the extent to which a measure accurately reflects the underlying concept it is intended to measure [37], was evaluated using factor loadings and Average Variance Extracted (AVE). Specifically, factor loadings were examined to ensure that each item loaded strongly on its intended construct [38]; a factor loading less than 0.40 indicates a poor relation to the construct. AVE then measured the extent to which the constructs were distinct from one another [39]; an AVE < 0.50 is problematic, indicating that the construct explains less variance in its indicators than is due to measurement error, as well as a CR < 0.70 indicating unsatisfactory internal consistency.

Variance Inflation Factor (VIF) values were examined to assess potential multicollinearity among predictor constructs. All inner VIF values ranged from 1.000 to 3.302, well below the recommended threshold of 5.0, confirming the absence of multicollinearity concerns. Table III presents the VIF values for all predictor-target construct relationships.

TABLE III. INNER VIF VALUES FOR COLLINEARITY ASSESSMENT

| Predictor | Target Construct | VIF |
|---|---|---|
| ATO | CTI | 3.181 |
| CAR | SSF | 2.056 |
| CTI | PI | 1.668 |
| EPC | SSF | 2.205 |
| PAF | CTI | 3.302 |
| PAF | SSF | 2.235 |
| PAU | PAF | 1.000 |
| PIT | PI | 2.317 |
| SRL | PI | 2.186 |
| SSF | CTI | 2.121 |
| SSI | SSF | 1.990 |
| STP | SSF | 1.526 |
| TIC | TTF | 1.000 |
| TTF | CTI | 2.055 |
| TTF | PI | 2.096 |

## *E. Validity and Reliability Measures*

Both reliability and validity testing were conducted, with their results presented in Table IV. The Cronbach's alpha values indicated all the results from the tests for each of the constructs in the model. Most constructs exhibited acceptable to good internal consistency, with Cronbach's alpha values ranging from 0.571 to 0.852. Most factor loadings were above the recommended cut-off value of 0.50, indicating the items to be highly related to their corresponding constructs. CR ranged from 0.770 to 0.924, indicating good to acceptable internal consistency. AVE values ranged from 0.588 to 0.859, indicating good convergent validity for most constructs.

TABLE IV. RELIABILITY AND VALIDITY RESULTS

| Factor | $\alpha$ | Factor loading | CR | AVE |
|---|---|---|---|---|
| STP | 0.695 | 0.725 | 0.831 | 0.622 |
| | | 0.783 | | |
| | | 0.852 | | |
| CAR | 0.71 | 0.666 | 0.837 | 0.635 |
| | | 0.844 | | |
| | | 0.865 | | |
| PAF | 0.852 | 0.827 | 0.901 | 0.695 |
| | | 0.800 | | |
| | | 0.845 | | |
| | | 0.861 | | |
| PAU | 0.602 | 0.791 | 0.770 | 0.626 |
| | | 0.791 | | |
| ATO | 0.807 | 0.856 | 0.874 | 0.588 |
| | | 0.876 | | |
| | | 0.807 | | |
| | | 0.730 | | |
| | | 0.505 | | |
| SSI | 0.535 | 0.896 | 0.891 | 0.803 |
| | | 0.896 | | |
| TIC | 0.805 | 0.819 | 0.885 | 0.720 |
| | | 0.873 | | |
| | | 0.852 | | |
| TTF | 0.766 | 0.844 | 0.865 | 0.681 |
| | | 0.846 | | |
| | | 0.785 | | |
| SRL | 0.742 | 0.892 | 0.886 | 0.796 |
| | | 0.892 | | |
| PIT | 0.836 | 0.927 | 0.924 | 0.859 |
| | | 0.927 | | |
| EPC | 0.571 | 0.809 | 0.791 | 0.654 |
| | | 0.809 | | |
| SSF | 0.809 | 0.917 | 0.914 | 0.841 |
| | | 0.917 | | |
| CTI | 0.746 | 0.893 | 0.887 | 0.797 |
| | | 0.893 | | |

# III. RESULTS

This section presents the results of the SEM analysis, conducted using SmartPLS v4 to examine the relationships among the constructs in the proposed integrated model. The analysis was designed to examine the hypothesized direct effects among the factors influencing student satisfaction, continuity intention, and hence the Performance Impact (PI) in online learning within the Moroccan higher education context.

## A. *Structural Equation Model (SEM)*

The integrated model, shown in Figure 6, was analyzed using the PLS-SEM approach. This method was chosen because of its suitability for the research objectives and data characteristics. PLS-SEM is a variance-based approach primarily focused on maximizing the variance explained in the dependent variables, which aligns with the goal of identifying factors that predict student satisfaction, continuity intention, and performance impact in online learning. In addition, PLS-SEM is robust to deviations from data normality and can effectively handle complex models with our sample size. Unlike covariance-based SEM approaches such as AMOS (CB-SEM), which require large samples, multivariate normality, and well-established theoretical models, PLS-SEM is better suited for exploratory research involving complex models with multiple constructs and theoretical frameworks. Given that this model integrates 9 theories with 15 hypothesized paths and a sample of 207 students, PLS-SEM offers superior handling of model complexity without imposing restrictive distributional assumptions. Furthermore, PLS-SEM is widely recommended in educational technology and information systems research when the primary goal is predictive relevance and theory extension rather than confirmatory model fit.

Although the NFI value falls slightly below the conventional 0.90 threshold, this is expected given the complexity of the integrated model and the sample size (N=207). In PLS-SEM, particularly for exploratory multi-theory models, NFI values above 0.80 are generally considered indicative of adequate fit.

## B. *Presentation of Key Findings (Hypotheses Examination)*

The relationships between the latent variables were evaluated by examining the path coefficients $\beta$, $t$-statistics, and $p$-values for each hypothesized path.

Path coefficient $\beta$: This number tells us how strong the connection is between two factors and in what direction. A positive number shows that as one factor goes up, so does the other. A negative number shows that as one factor goes up, the other one goes down. The larger the number (positive or negative), the stronger the connection.

$t$-statistic: This value helps us look at whether the relationship found within the sample is probably going to happen in the overall population. The greater the $t$-statistic, the stronger it suggests that the relationship is probably going to be real and not just due to chance within our sample.

$p$-value: A low $p$-value (typically less than 0.05) means that there's little chance the result is just by chance, making it reasonably certain that there is a genuine relationship. If the $p$-value is more than 0.05, there is not enough evidence to say there is a genuine relationship based on the data.

Table V presents a summary of the hypothesis test results. Hypotheses were considered supported if the $p$-value was less than 0.05, that is, indicating a statistically significant relationship. Bootstrapping was performed with 5,000 subsamples using a two-tailed test at a 95% confidence level to assess the significance of path coefficients.

The analysis of the structural model revealed that 8 out of the 15 hypothesized paths were statistically significant at $p < 0.05$.

- H3: Perceived ease of use (PAU) positively affects perceived usefulness (PAF) (Support: $\beta = 0.534$, $t = 8.010$, $p = 0.000$).

- H4: Continuity intention (CTI) positively affects performance Impact (PI) (Support: $\beta$ = 0.070, $t$ = 2.064, $p$ = 0.039).
- H5: Perceived usefulness (PAF) positively affects student satisfaction (SSF) (Support: $\beta$ = 0.413, $t$ = 5.337, $p$ = 0.000).
- H8: System, service, and information quality (SSI) positively affects Students' satisfaction (SSF) (Support: $\beta$ = 0.232, $t$ = 2.783, $p$ = 0.005).
- H9: Technology, task, and individual characteristics (TIC) positively affect TTF (Support: $\beta$= 0.658, $t$ = 12.438, $p$ = 0.000).

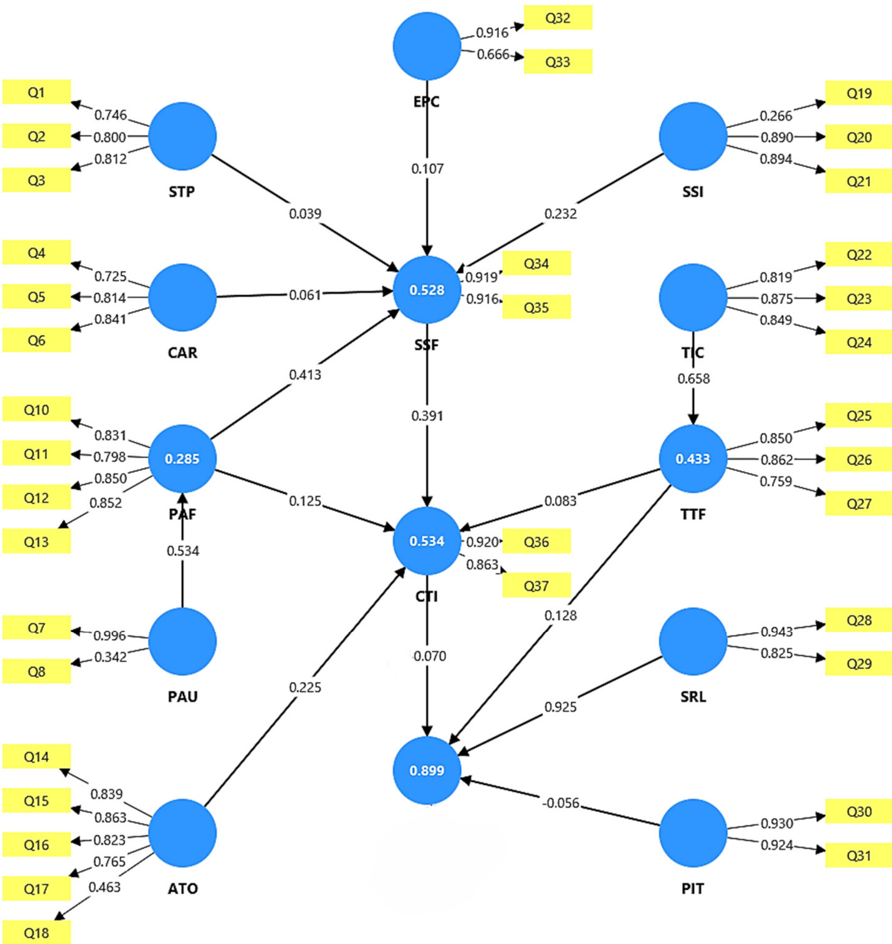


Fig. 6. Estimated structural model (with standardized path coefficients).

TABLE V. SUMMARY OF HYPOTHESIS TESTING RESULTS

| | Hypothesis | $\beta$ coefficient | *t*-statistic | *p*-value | 2.5% CI | 97.5% CI | Yes/no |
|---|---|---|---|---|---|---|---|
| H1 | STP→SSF | 0.039 | 0.725 | 0.468 | - | - | No |
| H2 | CAR→SSF | 0.061 | 0.677 | 0.498 | - | - | No |
| H3 | PAU→PAF | 0.534 | 8.010 | 0.000 | 0.396 | 0.661 | Yes |
| H4 | CTI→PI | 0.070 | 2.064 | 0.039 | 0.106 | 0.140 | Yes |
| H5 | PAF→SSF | 0.413 | 5.337 | 0.000 | 0.258 | 0.558 | Yes |
| H6 | PAF→CTI | 0.125 | 1.328 | 0.184 | - | - | No |
| H7 | ATO→CTI | 0.225 | 1.802 | 0.072 | - | - | No |
| H8 | SSI→SSF | 0.232 | 2.783 | 0.005 | 0.062 | 0.396 | Yes |
| H9 | TIC→TTF | 0.658 | 12.438 | 0.000 | 0.547 | 0.756 | Yes |
| H10 | TTF→CTI | 0.038 | 0.942 | 0.346 | - | - | No |
| H11 | TTF→PI | 0.128 | 3.020 | 0.003 | 0.040 | 0.203 | Yes |
| H12 | SRL→PI | 0.925 | 36.413 | 0.000 | 0.875 | 0.976 | Yes |
| H13 | PIT→PI | -0.056 | 1.554 | 0.120 | - | - | No |
| H14 | EPC→SSF | 0.107 | 1.184 | 0.236 | - | - | No |
| H15 | SSF→CTI | 0.391 | 4.995 | 0.000 | 0.237 | 0.548 | Yes |

- H11: TTF positively affects performance impact (PI) (Support: $\beta = 0.128$, $t = 3.020$, $p = 0.003$).
- H12: Self-regulated learning (SRL) positively affects performance impact (PI) (Support: $\beta = 0.925$, $t = 36.413$, $p = 0.000$).
- H15: Student satisfaction (SSF) positively affects continuity intention (CTI) (Support: $\beta = 0.391$, $t = 4.995$, $p = 0.000$).

Following the results from the SEM analysis, Figure 7 presents a refined model diagram, illustrating relationships between the constructs, including only those paths that were statistically significant at the 0.05 significance level. Unsupported paths, as well as their corresponding hypothesis labels from the full theoretical model (Figure 1), have been excluded for brevity and to graphically emphasize the key findings of this study.

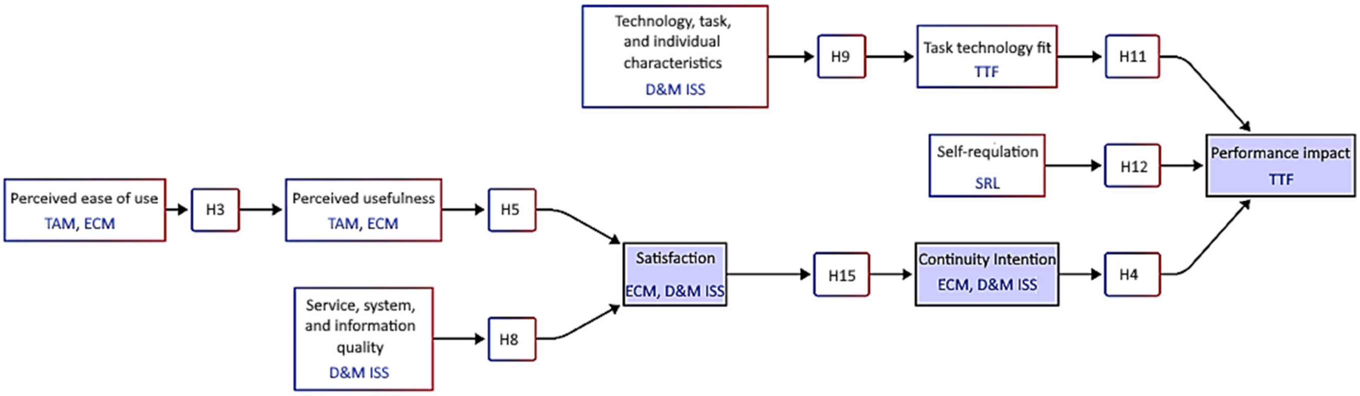


Fig. 7. Refined approach

## IV. DISCUSSION

This section discusses the findings of the SEM analysis, compares them to the literature and theoretical perspectives, explores the theoretical and practical implications, and determines the limitations of this study. This analysis aimed to validate an integrated model of student satisfaction and continuity intention in online learning in the context of higher education in Morocco. Figure 7 shows the refined structural model, showing only the statistically significant paths. The SEM analysis indicated that 8 of the 15 hypothesized relationships were significant at the 0.05 level, which was important for understanding the factors that influenced the online learning experiences of students in this context and offering partial support for the proposed integrated framework. The significant paths highlight the key drivers of student satisfaction, continuity intention, and performance impact within the context of Moroccan higher education.

### A. *Interpretation of Supported Hypotheses*

Hypothesis H3, proposing that perceived ease of use (PAU) would be positively related to perceived usefulness (PAF), was strongly supported ($\beta = 0.534$, $t = 8.010$, $p = 0.000$). This finding is highly consistent with the major tenets associated with the TAM [40]; the original model hypothesized that users are likely to consider it useful if they consider it easy to use [25]. The result in this study is consistent with earlier research in online learning that has found a significant positive link between ease of use and perceived usefulness [6].

Hypothesis H4, which states that continuity intention (CTI) positively influences performance impact (PI), was supported ($\beta = 0.070$, $t = 2.064$, $p = 0.039$). This finding suggests that in this sample, greater intention to continue using online platforms was associated with slightly greater perceived performance impact. This would be expected, as those who intended to continue using online resources would also be likely to have greater perceived academic success through their continued engagement with the online learning resources. Although the positive effect was small, the statistical significance suggested that even a small increase in students' intention to continue using online platforms can have a positive influence on their perceived performance. This finding is consistent with studies that suggest a link between technology use or intention to use and performance in educational settings [41, 42]. However, the effect of continuity intention appears to be relatively minor. Findings indicate that intention to continue is positively correlated with perceived performance, but also indicate that other factors, especially student ability to self-regulate, are far more impactful on driving perceived academic success in this particular online learning context.

Hypothesis H5, which posited that perceived usefulness (PAF) positively affects student satisfaction (SSF), was also strongly supported ($\beta = 0.413$, $t = 5.337$, $p = 0.000$). This finding aligns with both TAM and the ECM [43], where perceived usefulness is a strong predictor of satisfaction. This result is in agreement with previous research that has demonstrated a significant positive relationship between perceived usefulness and student satisfaction in online learning environments [26, 44]. The significant path coefficient suggests that when students find online learning platforms useful for their studies, their overall satisfaction with the learning experience is significantly enhanced [45].

Hypothesis H8 is also supported, demonstrating that system, service, and information quality (SSI) are significantly impacting student satisfaction (SSF) ($\beta = 0.232$, $t = 2.783$,

$p$ = 0.005. This finding aligns with D&M ISS [46], which identifies system, service, and information system quality as a primary influence on user satisfaction, and previous studies that have applied the D&M ISS model to online learning and found system, service, and information quality to be significant for predicting student satisfaction [47, 48].

In examining the factors leading to TTF, hypothesis H9, which proposed that technology, task, and individual characteristics (TIC) positively affect TTF, was very strongly supported ($\beta$ = 0.658, $t$ = 12.438, $p$ = 0.000). This substantial path coefficient underlines the critical role of the alignment between the features of the online technology, the demands of the learning tasks, and the skills and preferences of individual students in determining how well the technology facilitates their academic work. This finding strongly supports the TTF theory [29] and is consistent with previous research that indicated that a good fit between these variables is essential for effective use of technology [49, 50].

Moving to performance impact, hypothesis H11, proposing that TTF positively impacts performance impact (PI), was supported ($\beta$ = 0.128, $t$ = 3.020, $p$ = 0.003). This finding indicates that when online learning technology is considered to fit the tasks the students need to accomplish, it leads to a perceived improvement in their academic performance. This emphasizes the importance of selecting and implementing online tools for the specific learning activities and students' capabilities, in keeping with the core proposition of the TTF model [29] when discussing the fit-performance relationship. This result aligns with studies that have found a positive relationship between TTF and various measures of performance in online contexts [51].

Hypothesis H12, suggesting that self-regulated learning (SRL) has a positive effect on performance impact (PI), was extremely strongly supported ($\beta$ = 0.925, $t$ = 36.413, $p$ = 0.000). This finding provided the most robust correlation in the model and demonstrates that the capacity of students to have control over their own learning process—setting personal learning goals, monitoring their understanding, and adapting their strategies—is a very strong predictor of how they would perceive the impact on their performance in an online learning environment. This is significant in terms of SRL theory [52] as well as representative of a large body of research that supports SRL as a necessity for academic success [53, 54], especially in learning environments where learning is less structured, such as online learning.

Lastly, Hypothesis H15, which proposed that student satisfaction (SSF) positively affects continuity intention (CTI), was strongly supported ($\beta$ = 0.391, $t$ = 4.995, $p$ = 0.000). This result is consistent with the ECM [41], where satisfaction is a key driver of continued system use. Students who are satisfied with their online learning experiences in Morocco are significantly more likely to continue using online platforms for their studies. The finding is well supported in the literature on technology adoption and technology continuity [55, 56], confirming that positive experiences lead to sustained engagement. For institutions in Morocco, this suggests that student satisfaction should be a primary focus as a means to encourage continued use of online learning resources.

### *B. Interpretation of Unsupported Hypotheses*

Even though not all hypothesized relationships achieved statistical significance, these non-supported relationships are still a meaningful contribution to the subtlety of the integrated model in the Moroccan context, as well as providing areas of the direct effects that could be weaker or mediated. Hypotheses H1 (STP → SSF), and H2 (CAR → SSF), drawing from CoI and SDT, respectively, were not supported, suggesting that while social presence, teaching presence, competence, autonomy, and relatedness are theoretically important, their direct influence on overall student satisfaction in Moroccan universities may not be statistically significant in this context ($\beta$ = 0.039, $p$ = 0.468 and $\beta$ = 0.061, $p$ = 0.498, respectively). This contrasts with some previous studies that found direct effects of these constructs on satisfaction [57, 58]. However, other studies have suggested that these relationships can be complex or mediated by other factors [19, 59], indicating that the relationship between presence and satisfaction is mediated by basic psychological needs such as motivation. It is plausible that the effects of social and teaching presence and competence/autonomy/ relatedness on satisfaction are mediated by other variables not included in this direct path model, suggesting a more complex indirect relationship that warrants further investigation.

The link of perceived usefulness (PAF) and continuity intention (CTI) (H6) was also not supported ($\beta$ = 0.125, $t$ = 1.328, $p$ = 0.184). While TAM typically suggests a direct link from perceived usefulness to behavioral intention [40], our findings in the Moroccan context do not support this direct relationship. However, this model does suggest that student satisfaction (SSF) was more strongly impacted by perceived usefulness (H5) and will ultimately predict continuation intention (H15). This suggests an indirect mediation effect, through student satisfaction, such that perceived usefulness predicts continuation intention insofar as it impacts student satisfaction. In other words, realizing that a platform is useful is unlikely to sustain continued use of the platform without the student being satisfied with their experiences overall, partially derived from usefulness.

Similarly, Hypothesis H7, based on IDT, which posited a positive relationship between relative advantage, trialability, observability, compatibility (ATO), and continuity intention (CTI), was also not supported ($\beta$ = 0.225, $t$ = 1.802, $p$ = 0.072). While IDT makes the case that ATO influences understanding and diffusion of innovation [60], no direct impact was found on the intention to continue using an online learning platform to be statistically significant within our context. This finding contrasts with some studies that used IDT in the context of online learning and found some of the ATO variables to be useful predictors of continuity intention in substantial terms [61, 62]. It is possible that in the context of compulsory or common online learning platforms in Moroccan universities, perceived advantages or facilitation of trying/observing the platform are less significant drivers of intention to continue using the platform than factors associated with immediate satisfaction based on perceived usefulness. Similar to H6, this relationship may have been mediated by other model factors such as satisfaction or perceived impact on performance.

The path between TTF and continuity intention (CTI) (H10) was also not statistically significant ($\beta$ = 0.038, $t$ = 0.942, $p$ = 0.346). The TTF theory states that a good fit will occur with TTF and lead to technology use [19, 63]; however, this study did not find evidence to support a direct path from TTF to intention to continue to use online platforms. This is opposite to certain studies, which have revealed a direct, positive link between TTF and continuity intention [64]. However, our results show that TTF significantly influences Performance Impact (H11), and Continuity Intention is strongly predicted by Student Satisfaction (H15). This suggests that the influence of TTF on continuity intention might be indirect, potentially mediated by perceived performance impact or satisfaction. The students might be more inclined to continue using a platform because it helps them achieve better performance, or they are satisfied, rather than solely based on the fit itself.

Hypothesis H13, which examined the relationship between peer interactions and teacher-student interactions (PIT) and performance impact (PI), was not statistically significant ($\beta$ = -0.056, $t$ = 1.554, $p$ = 0.120). Interaction is considered important for learning outcomes [41, 65], but our findings did not reveal a demonstrably significant relationship in this model. This is in contrast to some studies that have shown that interaction can have a positive impact on performance in online contexts. There may be some reasons for the non-significance in the Moroccan context, including the type or frequency of interaction that took place in the online courses surveyed, or the relationship between interaction and performance may be dependent on other cognitive or other motivational factors, such as the SRL, which in our results was found to be a very strong predictor of performance impact (H12).

Finally, Hypothesis H14, claiming that expectation confirmation (EPC) has a positive effect on student satisfaction (SSF), was rejected ($\beta$ = 0.107, $t$ = 1.184, $p$ = 0.236). While ECM posits that expectation confirmation is a precursor to satisfaction [43], the direct path in our model was not statistically significant. Many studies have identified a direct positive relationship between expectation confirmation and satisfaction in the context of technology use and online learning [66]. This could mean that in this specific context, initial expectations matter in the learning process; however, their direct confirmation or disconfirmation might have a less direct impact on overall student satisfaction compared to the perceived usefulness or quality of the platform. It is possible that other factors in our integrated model are stronger direct drivers of satisfaction or that the effect of expectation confirmation is indirect.

### *C. Theoretical Contributions*

This study expands the existing literature on online learning success by empirically corroborating an integrated model that combines elements from several key information systems and education theories in the under-researched context of Moroccan higher education. The findings offer several important theoretical implications. First, the strong support for the relationships derived from fundamental models such as TAM (PAU → PAF, PAF → SSF), D&M ISS (SSI → SSF), and TTF (TIC → TTF, TTF → PI) in the Moroccan online learning context confirms the generalizability of these prominent frameworks across a developing country setting. This is significant as is much of the existing research on these theories. Moreover, this research demonstrates that key concepts like perceived ease of use, perceived usefulness, system quality, and task-technology fit are key mechanisms that drive student satisfaction and perceived performance in this region concerning the online learning experience.

Second, the integration of these theories offered a more holistic perspective than relying on a single theory. The results show how technology, psychological, and task factors overlap and combine to affect the online learning experience. For example, the significant relationships of TIC on TTF show how technology and its design and characteristics interact with tasks and users to generate a fit perception that either positively or negatively affects performance. Similar to the significant paths leading to student satisfaction (from PAF and SSI), we emphasize the perceived value of the system in relation to learning tasks and the true quality of the system.

Third, supported and unsupported hypotheses provide important concepts on theory in general and implications of some theoretical links in this specific context. The absence of direct significant relationships from CoI (STP → SSF), SDT (CAR → SSF), and some components of IDT (ATO → CTI) to their theorized outcomes (satisfaction or continuity intention) suggests that the nature of influence from social/teaching presence, competence/autonomy/relatedness, and perceived attributes of innovations may differ between contexts, and may be more complex or indirect. Further theoretical refinement and investigation of potential mediating or moderating variables that might explain how these factors ultimately impact student outcomes in this context are warranted. For example, the potential mediation roles of satisfaction or perceived performance highlighted in the discussion of unsupported hypotheses (H6, H10, H13, H14) warrant further exploration in future theoretical models. This indicates that simple direct causal paths from certain theoretical constructs may not accurately represent aspects of the learning context and characteristics of the learning experience in all contexts. Ultimately, this study supported the positive association between student satisfaction (SSF) and continuity intention (CTI), which supports the ECM, supporting the strength of a central concept. Although the correlation between CTI and performance impact was small but positive (H4), the considerable link between self-regulation learning (SRL) and performance impact (H12) demonstrates the theoretical significance of learner characteristics; namely, self-regulation skills can be seen as important predictors of perceived success in online learning. This indicates that although system and design factors are important, the student's capacity for self-management may be an even stronger determinant of online learning outcomes.

Overall, this research contributes to theory by verifying key components of integrated models in a new environment, emphasizing the robustness of certain theoretical relationships, and revealing the areas where theoretical links can be more complex or indirect, particularly in the context of Morocco's online learning environment.

### *D. Practical Implications*

The findings have practical implications for those developing and delivering online learning in Moroccan universities. The support for PAU→PAF→SSF highlights usability as a priority. Institutions should invest in intuitive platform design, reliable infrastructure, and accessible technical support. Furthermore, student onboarding on online tools is also recommended. Second, SSI significantly predicts satisfaction, which requires investment in platform reliability, support services, and content quality. Third, the TIC→TTF→PI chain highlights the need to align technology with tasks and student capabilities. Instructors should select technology based on learning outcomes, student digital literacy, and task requirements. Fourth, and perhaps most importantly, the very strong positive relationship of SRL on perceived performance (PI) indicates the important role of developing and facilitating self-regulatory skills in students. Institutions and educators should employ strategies in the design of online courses to help students build their ability to set goals, plan for learning, manage time, monitor understanding, and adapt their learning strategies. This might include direct instruction on SRL strategies, tools to self-evaluate and track progress, and purposeful independent learning assignments that encourage reflection. Considering the strength of the relationship, interventions that focus on SRL could have a major impact on student performance and success in online courses.

In summary, the supported relationship between student satisfaction (SSF) and intention to continue in the course (CTI) supports the notion that student satisfaction is an antecedent of continued use. Although student satisfaction is paramount, this will ultimately drive students to continue using resources such as online learning, which the findings suggest can facilitate perceived performance improvement. It must also be noted that non-significant paths do not imply irrelevance. For example, social presence (STP) was not found to be a direct factor influencing satisfaction, nor was peer interaction (PIT) found to have a direct impact on performance; this does not mean institutions should disregard their potential indirect influences or that they are unimportant to other aspects of the online learning experience.

Beyond institutional-level actions, the findings carry national policy implications. The Digital Morocco 2030 strategy (launched September 2024, with a budget of approximately 11 billion dirhams) explicitly targets digital infrastructure expansion and the training of 100,000 digital talents annually—goals that directly intersect with this study's findings. H8 supports prioritizing national investment in e-learning infrastructure. Similarly, the dominant effect of SRL on performance (H12) points to the need to embed SRL development into national pedagogical frameworks and teacher training programs, in alignment with the emphasis of ESRI 2030 PACT on student autonomy. These findings suggest that Morocco's digital education agenda will be most impactful when platform investments, pedagogical reform, and learner support are developed in coordination.

## V. LIMITATIONS AND FUTURE RESEARCH DIRECTIONS

Despite its contributions, this study has limitations that should be considered. First, the use of purposive and convenience sampling may over-represent digitally engaged students, limiting generalizability to the broader Moroccan student population. Future studies should employ stratified random sampling across multiple institutions and disciplines. Second, the cross-sectional design prevents causal inference; longitudinal studies would provide stronger evidence of causal relationships, particularly for continuity intention and performance impact. Third, the exclusive reliance on quantitative self-reported data limits the depth of interpretation, especially for non-significant paths. A mixed-methods approach, combining surveys with interviews, would provide richer contextual insight. Finally, the model was tested in a single Moroccan national context; replication in other Francophone African or developing-country settings would help establish whether the supported and unsupported paths generalize beyond this specific cultural and infrastructural environment.

## VI. CONCLUSION

This study empirically validated an integrated model of online learning success in Moroccan higher education by combining nine theoretical frameworks, TAM, ECM, D&M ISS, TTF, SRL, SDT, IDT, SCT, and CoI, within a single PLS-SEM model. Eight of the 15 hypothesized relationships were supported. Perceived ease of use and system, service, and information quality emerged as significant predictors of student satisfaction, which in turn drove continuity intention. Task-technology fit and, most prominently, SRL were the strongest predictors of perceived performance impact, with self-regulation yielding the largest path coefficient in the entire model. Continuity intention also exerted a small but statistically significant effect on performance. The constructs drawn from CoI, SDT, and IDT did not produce significant direct effects, suggesting that their influence in this context may operate through mediating mechanisms not captured in the current model.

These findings confirm the cross-cultural applicability of foundational IS and education theories in a resource-constrained, Francophone African setting, highlighting self-regulation as a particularly critical lever for academic success in online environments. For Moroccan institutions and policymakers, the results point to clear priorities: investing in platform usability and quality, aligning technology with pedagogical tasks, and actively developing students' self-regulatory capacities. Taken together, this study contributes empirical grounding for the design of contextually appropriate online learning strategies in Moroccan higher education and lays the foundation for future comparative and longitudinal research in similar contexts in developing countries.

## CONFLICT OF INTEREST

The authors declare that they have no known conflicts of interest that could have appeared to influence the work reported in this paper.

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## AVAILABILITY OF DATA AND MATERIALS

The dataset generated and analyzed during this study is available from the corresponding author upon reasonable request.

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