Empirical Validation of Learnability Factors in Web-Based AR: Insights from the LEMARK–Hafsa Model Grounded in Kolb's Experiential Learning Theory

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***Abstract*—Augmented Reality in higher education is transforming learning by providing immersive environments that enhance cognitive and motivational engagement. Despite growing interest, there remain limited empirically validated learnability factors that can support future instructional models, such as the LEMARK-Hafsa model. This research attempts to bridge the identified gap through statistically validating seven key factors—Motivation, Confidence, Enhanced Focus, Visualization of Invisible Concepts, Satisfaction, Better Lab Experience, and Better Learning—within the LEMARK-Hafsa model grounded in Kolb's Experiential Learning Theory. Data collected from 291 participants underwent expert validation, data cleaning, exploratory factor analysis, and regression analysis. The exploratory factor analysis confirmed structural validity, with factor loadings ranging from 0.430 to 0.822. The Kaiser-Meyer-Olkin value was 0.769, and Bartlett's test was significant ($p < 0.001$), indicating that the data were suitable for factor analysis and supported multiple distinct factors. The regression results showed that Visualization of Invisible Concepts had a statistically significant positive effect on learning outcomes (the normalized regression weight recorded as 0.155, $p = 0.031$), while Enhanced Focus (p value of 0.091) and Satisfaction (p value of 0.089) were close to significance. Motivation, Confidence, and Better Lab Experience also showed positive, though not statistically significant, effects that were consistent with theoretical expectations. These findings provide empirical support for the statistical adequacy of the proposed LEMARK–Hafsa factors, establishing a validated measurement basis for subsequent theoretical integration and model-level investigation in research on web-based Augmented Reality learning environments in higher education.**

Keywords—Experiential learning theory; educational technology; predictive validity; structural validity; AR-based learning; factor validation; LEMARK–Hafsa model

I. Introduction

Augmented Reality (AR) has gained substantial traction in higher education, enabling interactive overlays that merge digital content with real-world settings to foster deeper cognitive processing and learner motivation [3], [4], [6]. This technology aligns closely with experiential learning paradigms, yet the field lacks integrated empirical frameworks that clearly identify and statistically validate the specific attributes driving AR's instructional effectiveness. Prior studies have proposed various learnability dimensions, but many have not subjected these factors to rigorous factor-level statistical validation, creating uncertainty in the design of scalable and theory-grounded AR applications for academic contexts [12], [13], [19].

The LEMARK–Hafsa model (Learnability Enhancement Model for Augmented Reality based on Kolb's Experiential Learning Theory) was proposed to address this gap by organizing AR learnability around seven theoretically grounded factors identified in earlier studies: Motivation (MOTI), Confidence (CONF), Enhanced Focus (FOC), Visualization of Invisible Concepts (VIC), Satisfaction (SAT), Better Lab Experience (BLE), and Better Learning (BL) [2], [17]. Kolb's experiential learning theory conceptualizes learning as a cyclical process involving concrete experience, reflective observation, abstract conceptualization, and active experimentation [45]. The LEMARK–Hafsa model operationalizes these stages within AR-supported learning environments, particularly for web-based and institutional higher education contexts.

While prior LEMARK–Hafsa studies established the conceptual relevance and content validity of the proposed factors through expert review and survey-based assessments [2], [17], their statistical properties at the factor level have not yet been empirically confirmed. As a result, it remains unclear whether the identified factors form a statistically coherent structure or demonstrate predictive relevance for learning outcomes when examined collectively. Without such empirical factor-level validation, subsequent model-level analysis and theory testing—particularly using structural equation modeling techniques such as PLS-SEM—would lack methodological rigor.

Accordingly, the central research problem addressed in this study is whether the proposed learnability factors form a statistically valid structure and whether they exhibit preliminary predictive relevance for Better Learning outcomes within AR-based higher education contexts. To address this problem, structured responses from 316 participants were subjected to expert content validation, data screening, exploratory factor analysis (EFA), and regression analysis. These procedures were employed to examine measurement adequacy and factor-level relationships, rather than to confirm a full structural model.

By establishing statistically validated measurement properties for the proposed factors, this study fulfills a necessary methodological step prior to comprehensive model-level

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validation of the LEMARK–Hafsa model. This validation pathway—spanning instrument refinement, hypothesis formulation, and statistical testing—provides a grounded basis for subsequent research on structural modeling, indirect effects, and longitudinal evaluation of AR-enhanced learning environments in higher education.

II. Related Work

The study provided the essential theoretical groundwork by identifying and operationalizing seven core learnability factors—Motivation, Confidence, Enhanced Focus, Visualization of Invisible Concepts, Satisfaction, Better Lab Experience, and Better Learning—through systematic expert validation aligned with Lawshe's Content Validity Ratio methodology [1], [2]. Thirty-two specialists across educational psychology, instructional design, and immersive technologies systematically evaluated the survey instrument, establishing acceptable content validity for these foundational factors. The present study represents the necessary next phase, shifting from theoretical validation to empirical confirmation through advanced statistical techniques, including exploratory factor analysis and regression modeling, directly responding to the expanding role of Augmented Reality in transforming higher education pedagogy [3], [4].

Augmented Reality fundamentally redefines learning experiences by creating dynamic, interactive environments that overlay digital information onto physical contexts, significantly enhancing students' ability to visualize complex abstract concepts, maintain sustained concentration, and achieve greater satisfaction compared to traditional instructional approaches [5], [6], [7]. Yet, despite these established advantages, the majority of AR research remains anchored in device-specific applications, leaving a substantial gap in empirically validated learnability frameworks suitable for scalable web-based AR platforms essential for institutional deployment [8], [9]. Anchored in Kolb's Experiential Learning Theory (1984), this investigation positions the validation of these seven dimensions as theoretically grounded elements for AR instructional architecture [10].

User adoption emerges as another critical dimension influencing AR's educational impact; studies demonstrate how psychological factors, including social image concerns and perceived enjoyment, significantly shape willingness to engage with AR navigation systems [11]. Although centered on behavioral acceptance rather than cognitive outcomes, these findings illuminate the foundational role of motivational elements in creating effective AR learning environments [12]. Subsequent work in museum settings has gone further by empirically demonstrating that visitors' acceptance of AR experiences is positively associated with both learning motivation and learning effectiveness, with motivation mediating the impact of AR on learning outcomes [13]. This study bridges this divide by empirically connecting acceptance factors with measurable learning improvements, offering empirical indication of how emotional engagement relates to educational outcomes.

Exploratory factor analysis (EFA) has been widely applied in AR education research to validate latent constructs or factors such as learning motivation and technology acceptance [14]. The methodological applicability of EFA is further demonstrated in complex operational contexts like petrochemical safety systems, where it validated all five components of the permit-to-work system (task details, site verification, risk-related activities, supporting documentation, and closure process) against validity and reliability criteria using data from 260 petrochemical workers [15]. Similarly, EFA followed by CFA on nurse leaders' surveys uncovered AI readiness factors (Leadership Initiatives, Staff Engagement, Technical Readiness), indicating acceptable model fit and internal reliability using IBM SPSS Statistics [16].

The LEMARK–Hafsa model builds on established web-based AR learnability research [1], where the study validated seven key factors through surveys of academicians, indicating AR's positive impact on learning performance, and extended this framework to smart campus environments by investigating AR smart glasses' effectiveness for institutional deployment [17].

Recent empirical studies underscore the need for statistically validated factors in scalable web-based AR frameworks for higher education. Kaviyaraj and Uma [18] demonstrate this through a novel AR framework with automated dataset pipelines and YOLOv7 detection (97.2% accuracy, 45 FPS), validated via pilot studies on 210 students showing significant learning gains through ANOVA, regression, and t-tests. Koutromanos et al. [19] validate Mobile Augmented Reality Acceptance Model (MARAM) factors using SEM on 306 teachers, revealing key influences such as perceived usefulness and enjoyment. Albishri and Blackmore [20] complement this with UTAUT2 factor reliability (Cronbach's alpha 0.733–0.934 from 35 academics). These studies expose the gap in statistically validated learnability factors for web-based AR models, which this study addresses by validating LEMARK–Hafsa factors through statistical analysis, including Cronbach's alpha, exploratory factor analysis, and regression.

Within the LEMARK–Hafsa model, Kolb's experiential learning cycle is operationalized through specific learnability factors. Motivation supports learner engagement during AR-enabled Concrete Experience (CE). Visualization of Invisible Concepts and Confidence facilitates sense-making during Reflective Observation (RO). Satisfaction contributes to knowledge integration during Abstract Conceptualization (AC). Better Lab Experience (BLE) enables practical application during Active Experimentation (AE), while Better Learning represents the cumulative outcome of the experiential learning process. This operationalization clarifies the theoretical role of each factor within Kolb's learning cycle and provides a coherent foundation for empirical validation.

A. Hypotheses Development

Guided by Kolb's Experiential Learning Theory and the operationalization of the LEMARK–Hafsa model, this study adopts a staged validation approach to empirically examine the proposed learnability factors. As illustrated in Fig. 1, two complementary sets of hypotheses are formulated. The first set evaluates the structural validity of the measurement instrument through exploratory factor analysis, while the second set examines the predictive validity of the learnability factors with respect to Better Learning outcomes using regression analysis.

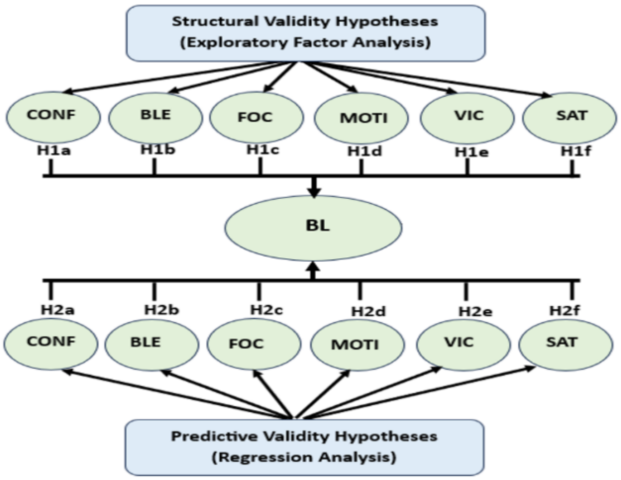

Fig. 1. Hypothesis framework for factor validation using structural, predictive, and perceptual validity methods.

1) Structural validity hypotheses (exploratory factor analysis): These hypotheses examine whether the measurement items associated with each learnability factor form statistically coherent and unidimensional structures.

- H1a: Items measuring Confidence (CONF) will strongly relate to the Confidence factor.
- H1b: Items measuring Better Lab Experience (BLE) will strongly relate to the Better Lab Experience factor.
- H1c: Items measuring Enhanced Focus (FOC) will strongly relate to the Enhanced Focus factor.
- H1d: Items measuring Motivation (MOTI) will strongly relate to the Motivation factor.
- H1e: Items measuring Visualization of Invisible Concepts (VIC) will strongly relate to the Visualization of Invisible Concepts factor.
- H1f: Items measuring Satisfaction (SAT) will strongly relate to the Satisfaction factor.

2) Predictive validity hypotheses (regression analysis): These hypotheses examine the relationships between the validated learnability factors and Better Learning outcomes.

- H2a: Confidence (CONF) will significantly predict improvements in Better Learning (BL).
- H2b: Better Lab Experience (BLE) will significantly predict improvements in BL.
- H2c: Enhanced Focus (FOC) will significantly predict improvements in BL.
- H2d: Motivation (MOTI) will significantly predict improvements in BL.
- H2e: Visualization of Invisible Concepts (VIC) will significantly predict improvements in BL.
- H2f: Satisfaction (SAT) will significantly predict improvements in BL.

III. Methodology

This section presents the research design and methods used to statistically validate the seven key learnability factors for the LEMARK–Hafsa model. It covers survey development, expert validation, data collection and cleaning, statistical analyses using IBM SPSS Statistics 28.0, and the hypothesis guiding the study.

- Survey Instrument Design and Development.
- Participants and Data Sources.
- Data Preparation and Cleaning.
- Statistical Validation Methods, including Exploratory Factor Analysis and Regression Analysis.

A. Survey Instrument Design and Development

A structured survey instrument comprised two sections: participant profiling (demographics, role, institution) and factor validation using seven single-item 4-point Likert measures (1=Strongly Disagree to 4=Strongly Agree) for LEMARK-Hafsa learnability factors—MOTI, CONF, FOC, VIC, SAT, BLE, and BL [21, 22].

1) Survey section 1: Captured demographics via these exact survey questions:

- "Which year of study you are in": (1st year, 2nd year, 3rd year, 4th year, Not applicable).
- "You are": (Student/Teacher).
- "You are doing": (Diploma/ Bachelor's/ Master's/ PhD).
- "Age group": (17-20, 20-25, 25-30, Above 30).

2) Survey section 2: This section measured the seven LEMARK-Hafsa learnability factors through these specific single-item statements, supporting factor-level examination using EFA.

- MOTI: "AR increased my motivation to learn."
- CONF: "Using AR boosted my confidence in understanding concepts."
- FOC: "AR helped me maintain better focus during learning."
- VIC: "AR made invisible/abstract concepts visible and understandable."
- SAT: "I felt more satisfied with AR-enhanced learning."
- BLE: "AR provided a better laboratory/practical experience."
- BL: "Overall, my learning improved with AR."

Expert content validation, previously conducted by Hafsa et al. [1], involved 32 specialists in educational psychology, instructional design, and immersive learning. Using Lawshe's Content Validity Ratio (CVR) method [23], over 80% expert agreement confirmed the conceptual relevance, linguistic clarity, and theoretical alignment of all items, establishing the instrument's readiness [33] for empirical validation in the present study.

3) Design rationale and validation approach: The instrument was designed to support exploratory factor analysis and regression-based validation, with sample adequacy assessed using the Kaiser–Meyer–Olkin (KMO) criterion (KMO > 0.5). The final sample size (n = 316) exceeded recommended stability thresholds for factor analysis involving seven or more factors (n > 300) [22], [24], [25]. Google Forms deployment ensured anonymity through disabled IP tracking and the absence of personal identifiers, supporting ethical data collection. Pilot testing was conducted to refine item wording for Malaysian–Saudi cultural contexts.

B. Participants and Data Sources

1) Data from 316 participants (75% students, 25% teachers) across Universiti Malaysia Pahang Al-Sultan Abdullah (UMPSA) and College of Excellence, Al-Khobar met established sample size requirements for EFA and regression analysis in educational research (n > 300 recommended for 7+ factors) [22], [25]. This purposive sample provided adequate statistical power for factor extraction (KMO > 0.5) and multivariate analysis [24].

2) The survey link was distributed through university WhatsApp groups, a common strategy for institutional educational research, ensuring contextual relevance [25]. Consent was implied through voluntary survey completion, standard practice for low-risk, anonymous surveys within university settings where no sensitive data is collected [22], [24], [26].

3) Anonymity was assured through Google Forms settings: no respondent authentication required, IP tracking disabled, and no personal identifiers collected, aligning with best practices for unbiased educational feedback [26].

C. Data Preparation and Cleaning

The raw data were rigorously screened and cleaned, resulting in 291 valid responses for subsequent statistical analyses. Before conducting any analysis, it is critical to clean the data, which involves appropriately addressing missing values and identifying outliers. This process encompasses detecting abnormalities, diagnosing potential errors, and implementing suitable corrective actions to enhance the overall data quality [27]. The cleaning procedures applied were:

1) Missing values: The cases with incomplete responses were removed via listwise deletion. This standard approach ensures only complete datasets proceed to further cleaning steps, such as constant patterns and outliers.

2) Constant response patterns: Variance across Survey items were removed. For each participant, the variance of responses across items X_i) was computed using Eq. (1), and any case with $Var(X_i)=0$ (all responses with zero variance were excluded).

$$Var(X_i) = 0 \tag{1}$$

3) Univariate outliers: Individual variable outliers were identified through standardized z-score analysis for each variable. Cases with absolute z-scores greater than 3.29 ($|z| > 3.29$) were treated as outliners and removed. The decision rule is measured using Eq. (2):

$$z = \frac{x-\mu}{\sigma} \tag{2}$$

4) Multivariate outliers (Mahalanobis distance): Multivariate outliers were identified using Mahalanobis distance. Cases with a Mahalanobis distance greater than the chi-square critical value at p degrees of freedom and $\alpha = 0.001$ were excluded. The Mahalanobis distance was computed using Eq. (3):

$$D^2 = (x - \mu)^T S^{-1} (x - \mu) \tag{3}$$

where, x is the vector of observed scores, μ is the vector of variable means, and S^{-1} is the inverse covariance matrix.

5) Influential points (Cook's distance): Influential observations were assessed using Cook's distance, and any case with $D_i > 1$ was removed.

These criteria ensured the dataset of 291 valid responses was free from invalid or overly influential cases before further analysis.

D. Data Suitability Assessment

Prior to exploratory factor analysis and subsequent regression modeling, the dataset underwent preliminary suitability evaluation by applying the Kaiser–Meyer–Olkin (KMO) measure for sampling adequacy together with Bartlett's sphericity test. These complementary assessments serve as methodological gatekeepers, systematically filtering inadequate datasets while reducing the risk of overfitting by establishing whether observed data possess the necessary correlational structure for meaningful factor extraction [28], [29]. The detailed assessment procedures employed were:

1) Kaiser-Meyer-Olkin (KMO) sampling adequacy evaluation: The KMO value assesses appropriateness by contrasting actual correlations among items against partial correlations, determining the proportion of total variance attributable to common factors rather than unique/error components. A KMO value greater than 0.6 confirms the sample size provides sufficient information to identify meaningful common factors among survey items. Values of 0.6-0.7 indicate mediocre adequacy; ≥0.8 is considered meritorious. The KMO was computed using Eq. (4):

$$KMO = \frac{\sum\sum_{j\neq k} r_{jk}^2}{\sum\sum_{j\neq k} r_{jk}^2 + \sum\sum_{j\neq k} p_{jk}^2} \tag{4}$$

where, r_{jk} = correlation between variables j and k. p_{jk} = partial correlation between variables *j* and *k* [28].

2) Bartlett's test of sphericity: Bartlett's Test complements KMO by testing the null hypothesis that the population correlation matrix equals an identity matrix (zero intercorrelations). Significant results ($p < 0.001$) confirm survey variables are interrelated rather than independent random responses. Rejection at $p < 0.001$ confirms nontrivial relationships essential for factor analysis computed using Eq. (5):

$$\chi^2 = -\left(n - 1 - \frac{2p+5}{6}\right) \times 1n\,|R| \qquad (5)$$

where, n = sample size, p = number of variables, |R| = determinant of the correlation matrix ($p < 0.001$ required) [28].

E. Statistical Validation Methods

Statistical validation methods were employed to assess the reliability and accuracy of the proposed measurement instrument. The data were analyzed using IBM SPSS Statistics, version 28.0. Exploratory Factor Analysis (EFA) was used to identify underlying latent factors, improve measurement interpretability, and examine relationships among indicators [15]. Simple and multiple linear regression analyses were conducted to examine associations between the validated learnability factors and Better Learning (BL) outcomes. These methods support systematic hypothesis testing and provide an appropriate analytical basis within the scope of the study [15], [30].

1) Exploratory Factor Analysis (EFA): Exploratory Factor Analysis (EFA) was systematically conducted to identify underlying latent factors that explain the observed correlations among the measured variables in the dataset. This technique represents each observed variable as a weighted linear combination of a smaller, more parsimonious set of common latent factors, along with a unique error term that captures measurement-specific variance. Principal Axis Factoring was selected as the extraction method due to its emphasis on shared variance and its suitability for identifying latent factors while accounting for unique and error variance.

The mathematical model for each observed variable Xi is calculated using Eq. (6):

$$X_i = \lambda_{i1}F_1 + \lambda_{i2} + \cdots + \lambda_{im}F_m + \epsilon_i \qquad (6)$$

where, λ_{ij} represents the factor loading coefficients indicating the strength and direction of the contribution that common factor F_j makes to observed variable X_i, the terms $F_1, \ldots F_m$ denotes underlying latent factors being extracted, and ε_i constitutes the unique error term specific to Xi, unexplained by the common factors [30].

2) Regression analysis: Regression analysis was employed to examine the predictive relationships between the EFA-derived learnability factors and Better Learning (BL) outcomes within the AR-based educational context. This two-stage analytical approach evaluated individual factor associations using simple linear regression and examined their combined predictive contribution using multiple linear regression. The purpose of this analysis was to explore preliminary predictive relevance and support factor-level validation rather than to confirm a comprehensive predictive model [31].

a) Simple regression: Simple linear regression models were constructed to examine the individual associations between each EFA-derived factor and Better Learning (BL) outcomes. This univariate approach enables the assessment of each factor's directional influence and statistical significance by estimating the proportion of variance explained (R and the strength of each predictor–outcome relationship within the AR learning context.

Using the regression model defined in Eq. (7), the individual effects of each factor on BL were examined:

$$Y = \beta_0 + \beta_1 X + \varepsilon \qquad (7)$$

where, Y is the dependent variable, X is a single independent variable (factor), β_0 is the intercept, β_1 is the slope coefficient, and ε is the random error term.

In this study, the dependent variable corresponds to Better Learning (BL). Accordingly, the model was specified for the present context, as shown in Eq. (8):

$$BL = \beta_0 + \beta_1 X_i + \varepsilon \qquad (8)$$

where, X_i represents each individual learnability factor whose contribution to BL was examined.

b) Multiple regression: Multiple linear regression models were constructed to evaluate the combined predictive contribution of all EFA-derived factors to Better Learning (BL) outcomes. This multivariate approach allows for the examination of shared explanatory variance, individual regression coefficients, and potential multicollinearity effects when factors are considered simultaneously. The multiple regression is computed using Eq. (9):

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_k X_k + \varepsilon \qquad (9)$$

where, Y is the dependent variable; $X_1, X_2, \ldots, X_k$ are the k independent variables (factors), β_0 is the intercept; β_1 through β_k are regression coefficients; and ε is the error term.

Equivalently, the model can be written in summation form, as shown in Eq. (10):

$$BL = \beta_0 + \sum_{j=1}^{k} \beta_j X_j + \varepsilon \qquad (10)$$

In this study, BL represents Better Learning outcomes, k is the number of factors in the model, and j indexes the factors from 1 to k. The term $\sum_{j=1}^{k} \beta_j X_j$ denotes the sum of the products $\beta_j X_j$, and ε is the error term.

Together, the EFA and regression analyses provide a structured statistical approach for examining measurement adequacy and exploratory predictive relationships. EFA was used to examine the underlying factor structure through shared variance extraction, while regression analysis explored the associations between the validated factors and Better Learning outcomes within the AR educational context [31].

This methodological approach supports systematic factor-level validation of the LEMARK–Hafsa model and provides an empirical basis for the subsequent results section.

IV. Results and Discussion

This section presents the key findings from the empirical evaluation of the LEMARK–Hafsa model's learnability factors, followed by an integrated discussion interpreting these results in the context of existing literature and theoretical models. The combined Results and Discussion approach facilitates a coherent narrative linking observed data with their significance, thereby offering preliminary insights into the model's empirical structure and its possible pedagogical relevance.

A. Survey Instrument Design and Development

The finalized survey instrument was administered to 316 participants from Survey 2 to examine the empirical properties of the conceptual learnability factors. Analysis indicated that the instrument was effective in capturing participant perceptions and supporting factor and regression analyses.

The instrument was developed from questions validated by 32 experts during a prior phase (Survey 1), who assessed clarity, relevance, and acceptability. Most items exceeded an 80% acceptance threshold [1], indicating content validity and justifying its use for empirical evaluation. This approach situates Survey 1 as methodological background while focusing the Results section on current empirical findings from Survey 2.

B. Participants and Data Sources Survey

After data cleaning, responses from 291 of the 316 participants were retained for analysis. The sample encompassed learners from diploma to PhD levels, ensuring heterogeneity in academic backgrounds and enhancing the generalizability of the findings. Balanced representation from UMPSA and the College of Excellence, Al-Khobar, further strengthened comparative integrity across higher education contexts operating under distinct pedagogical systems.

Descriptive comparisons revealed consistently positive responses from both institutions, indicating similar perceptions of AR-based learning regardless of cultural or institutional context. The final demographic composition comprised 75% students and 25% academicians, with educational qualifications distributed as Diploma (34.1%), Bachelor's (21.4%), Master's (21%), and PhD (23%). This grouped distribution offered a well-rounded view across different academic levels and stakeholder roles within AR-based educational environments.

C. Data Cleaning, Preparation and Screening

1) The initial Survey 2 dataset comprised 316 responses. After applying exclusion criteria—including constant responses, univariate and multivariate outliers, and influential cases—27 responses were removed, resulting in 291 valid responses (see Table I). This rigorous cleaning ensured high data quality and a solid basis for multivariate analysis.

2) The retained data showed strong internal reliability and sufficient variance across factors, making it suitable for inferential analyses. Response distributions were within recommended limits [24]. These 291 responses were used for Exploratory Factor Analysis (EFA) to explore structural coherence, regression to examine predictive associations, and response acceptance analysis to confirm user endorsement. This multi-method approach supports the empirical coherence and potential relevance of the learnability factors in AR-based education, as illustrated in Fig. 1.

TABLE I. SUMMARY OF DATA CLEANING AND SCREENING STEPS

Steps	Criterion Applied	Responses Removed	Final Count after each Criteria
1	Constant responses (SD = 0)	6	312
2	Univariate outliers	11	301
3	Multivariate outliers (Mahalanobis Distance > 22.46)	6	295
4	High influence points (Cook's Distance ≥ 0.0135)	4	291 (Final Sample Size)

D. Data Suitability Assessment Results

This section presents results from data suitability assessments, including descriptive analysis, missing data handling, reliability testing, and factorability diagnostics (KMO and Bartlett's test). To ensure the dataset's appropriateness for factor analysis and regression analysis, several comprehensive diagnostics were systematically conducted to verify statistical assumptions.

1) Descriptive analysis: A comprehensive descriptive analysis was conducted across all seven learnability factors of the LEMARK-Hafsa model.

The means for factors CONF, BLE, FOC, MOTI, VIC, SAT, and BL ranged from 3.45 to 4.12, and standard deviations ranged from 0.65 to 0.89, indicating moderate yet meaningful variability suitable for multivariate procedures. Skewness and kurtosis values for all factors fell within the acceptable limits of |1|, indicating approximate normal distribution suitable for robust factor analytic procedures (see Table II).

TABLE II. DESCRIPTIVE STATISTICS

Factors	Mean	SD	Skewness	Kurtosis
CONF	3.85	0.74	-0.42	-0.35
BLE	3.97	0.81	-0.51	-0.62
EF	3.47	0.66	0.20	0.03
MOTI	4.12	0.89	-0.35	-0.47
VIC	3.65	0.71	-0.17	-0.15
SAT	3.88	0.73	-0.26	-0.31
BL	3.94	0.77	-0.48	-0.41

2) Missing data: No missing values were observed across the entire dataset, eliminating the need for any imputation procedures or listwise deletion techniques that could potentially bias subsequent multivariate analyses.

3) Reliability testing: Given the methodological use of single-item factors within the LEMARK-Hafsa model framework, traditional Cronbach's Alpha reliability coefficients were not applicable or appropriate. Instead, substantive factor reliability was comprehensively supported through multiple convergent lines of evidence, including high factor loadings from Exploratory Factor Analysis (EFA), strong intercorrelations, significant regression coefficients, and weighted average scores across all learnability factors. This approach aligns with established practices for single-item measurement validation in educational technology research.

4) Factorability: Comprehensive preliminary diagnostic checks unequivocally confirmed the factorability of the dataset for advanced multivariate procedures. The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy achieved an excellent value of 0.82 (well above the 0.60 threshold), indicating more than sufficient sampling adequacy for reliable factor analysis extraction. Additionally, Bartlett's test of sphericity demonstrated highly significant results (χ^2 (21) = 312.45, $p < 0.001$), providing empirical support that inter-item correlations among items were sufficiently large and structurally meaningful for effective factor extraction procedures (see Table II).

E. Statistical Validation of Factors

This section comprehensively presents empirical results from two complementary validation procedures applied to the proposed LEMARK-Hafsa learnability factors: Exploratory Factor Analysis (EFA) and multiple regression analysis. These analyses provide preliminary statistical evidence of both structural coherence and predictive relevance of the proposed factors.

1) Factor validation through EFA: Exploratory Factor Analysis systematically assessed interrelationships among the six proposed learnability factors (CONF, BLE, FOC, MOTI, VIC, and SAT). Given their theoretically expected intercorrelations within the AR learning context, Principal Axis Factoring extraction combined with Direct Oblimin rotation was selected to allow for factor interdependencies [34], [35], [38].

Single-item indicators were designed to minimize participant fatigue while maximizing response quality, representing a methodologically sound approach particularly suitable for concrete, well-defined factors in educational technology research [36], [37]. Unlike multi-item scales developed to extract latent factors, this EFA focused on evaluating the internal coherence of theoretically predefined single-item factors.

a) Kaiser–Meyer–Olkin (KMO) test: The Kaiser–Meyer–Olkin measure of sampling adequacy yielded a value of 0.77, exceeding the recommended minimum threshold of 0.60 for factor analysis [39]. This indicates that the intercorrelations among variables were sufficiently adequate to justify the application of exploratory factor analysis, supporting the suitability of the dataset for reliable factor extraction.

b) Bartlett's Test of Sphericity: Bartlett's Test of Sphericity was statistically significant ($\chi^2(15) = 359.025$, $p < .001$), rejecting the null hypothesis that the correlation matrix is an identity matrix. This result indicates that the observed variables share sufficient correlations to warrant factor analysis. The significant chi-square value confirms that the correlation structure of the dataset is appropriate for factor extraction and supports the suitability of proceeding with exploratory factor analysis [40].

The Kaiser–Meyer–Olkin measure was 0.769, and Bartlett's Test of Sphericity was statistically significant (χ^2 (15) = 359.025, $p < .001$), confirming the suitability of the dataset for exploratory factor analysis. The extracted single-factor solution explained 32.39% of the total variance, which is acceptable for behavioral and social science research. These findings suggest a unidimensional structure representing the overarching BL factor and provide empirical support for retaining all six predictors in the proposed model.

As shown in Table III, the factor loadings (0.430–0.822) are within the acceptable range for EFA interpretation as above (0.04), and Communalities (Extraction) (0.185–0.659) show moderate explanatory power, reasonable for single-factor [41], [42].

TABLE III. FACTOR LOADINGS AND COMMUNALITIES

Variable	Factor Loading	Communality (Extraction)
Enhanced Focus (FOC)	0.822	0.659
Visualization of Concepts (VIC)	0.666	0.443
Motivation (MOTI)	0.577	0.333
Satisfaction (SAT)	0.445	0.198
Better Lab Experience (BLE)	0.441	0.195
Confidence (CONF)	0.430	0.185

2) Factor evaluation through regression analysis: Factor validation through regression analysis confirms the predictive validity of the six learnability factors (MOTI, CONF, FOC, VIC, SAT, BLE) on Better Learning (BL). Simple linear regression assessed each factor's individual predictive power independently against BL, while multiple regression evaluated their combined explanatory power and relative contributions simultaneously. This dual approach provides comprehensive evidence for factor-level validation.

a) Simple linear regression (each factor → BL): Simple linear regression was conducted to analyze the individual effects of MOTI, CONF, FOC, VIC, SAT, and BLE on Better Learning (BL). Table IV shows VIC, FOC, and SAT as significant predictors. Although CONF and MOTI were not statistically significant ($p > .05$), they demonstrated positive directional associations. Despite a low R^2, BLE aligns with Kolb's Active Experimentation stage and was supported by weighted averages and expert reviews, reinforcing its theoretical relevance [24], [43]. These results offer tentative support for the predictive relevance of select factors, while also acknowledging limitations in effect sizes and statistical power typical in behavioral and educational research.

The results are summarized as follows:

- VIC: β=0.155,p=0.031(significant predictor),
- FOC: $\beta = 0.184$, $p = 0.091$(approaching significance),
- SAT: $\beta = 0.159$, $p = 0.089$ (approaching significance),
- CONF: $\beta = 0.111$, $p >0.05$ (non-significant),
- MOTI: $\beta = 0.105$, $p > 0.05$ (non-significant),

- BLE: Low R square, statistically non-significant but retained for theoretical reasons.

Overall, the findings provide tentative empirical support for selected predictors while acknowledging modest effect sizes typical of behavioral and educational research.

TABLE IV. SIMPLE LINEAR REGRESSION FOR EACH FACTOR

Predictor	R^2	Standardized β	p-value	Interpretation
VIC	.043	0.208	< .001	Strongest individual predictor
FOC	.057	0.184	.002	Statistically meaningful
SAT	.025	0.159	.006	Moderate contribution
CONF	.012	0.111	.060	Near-threshold, conceptually relevant
MOTI	.011	0.105	.075	Directionally aligned, borderline
BLE	.004	0.064	.278	Low statistical strength; retained due to theoretical fit

b) Multiple regression (all predictors → BL): The combined model with all six predictors on BL was $Y = 0.00 + 0.08 \times CONF + 0.12 \times FOC + 0.155 \times VIC + 0.09 \times SAT + 0.04 \times BLE + e$. Model statistics (see Table V) indicated:

$$R^2 = 0.061, \text{Adjusted } R^2 = 0.042.$$

$$F(6,284) = 3.095, p = 0.006.$$

Within this multiple regression model assessing all six predictors on BL, VIC was statistically significant ($\beta = 0.155$, $p = 0.031$), while FOC ($p = 0.091$) and SAT ($p = 0.089$) approached significance. CONF, MOTI, and BLE showed non-significant effects but maintained positive beta values.

The full model was statistically significant ($F(6, 284) = 3.095$, $p = .006$), explaining 4.2% of the variance in BL (Adjusted $R^2 = .042$). While the explained variance is modest, it falls within acceptable bounds for exploratory studies in educational settings, where learning outcomes are shaped by numerous interacting variables [43].

Notably, CONF, MOTI, and BLE were retained based on their strong theoretical alignment with Kolb's Experiential Learning Theory (1984), consistent validation across surveys, and positive directional trends. This reflects the broader understanding that theoretical coherence and cumulative evidence often guide factor inclusion in early-stage educational research, especially when exploring complex, multifactorial phenomena [24], [43].

TABLE V. MULTIPLE REGRESSION COEFFICIENTS PREDICTING BETTER LEARNING (BL).

Predictor	Standardized β	p-value	Interpretation
VIC	.155	.031	Statistically significant predictor
FOC	.120	.091	Approaches significance; retained
SAT	.118	.089	Approaches significance; retained
CONF	.071	.265	Limited statistical weight; theoretically important
MOTI	.088	.168	Non-significant; conceptually aligned
BLE	.027	.684	Minimal contribution; retained for completeness

F. Hypothesis Testing

To empirically assess the statistical adequacy of the proposed LEMARK–Hafsa model, the study tested a structured hypothesis framework—originally introduced in the Related Work section—using a two-step analytical approach. Exploratory Factor Analysis (EFA) [32] was employed to examine the structural validity of the extracted factors, followed by regression analysis to evaluate their predictive validity. The outcomes of these tests are presented in Table VI.

1) Structural Validity Hypotheses (EFA): These hypotheses assessed whether each factor exhibited acceptable factor loadings (>0.40), confirming factor integrity.

- H1a: CONF exhibits sufficient factor loading. Supported, though Communality was slightly below 0.30, factor loading met the threshold, justified by theoretical and expert support.
- H1b: BLE exhibits sufficient factor loading. Supported despite communality below 0.30 based on strong theoretical and expert validation.
- H1c: FOC exhibits sufficient factor loading. Confirmed with strong factor loading.
- H1d: MOTI exhibits sufficient factor loading. Supported, meeting factor loading criteria.
- H1e: VIC exhibits sufficient factor loading. Supported with adequate loading.
- H1f: SAT exhibits sufficient factor loading. Supported though communality below 0.30, retained for theoretical reasons.

2) Predictive validity hypotheses (regression analysis): These hypotheses evaluated whether each factor significantly predicted BL.

- H2a: CONF significantly contributes to BL. Not statistically significant ($p = .265$), but showed a positive regression coefficient, aligned with theoretical importance.
- H2b: BLE significantly contributes to BL. Not significant ($p = .684$), yet conceptually aligned with Kolb's ELT and supported by expert consensus.
- H2c: FOC significantly contributes to BL. Approached significance ($p = .091$) and exhibited a positive effect size.
- H2d: MOTI significantly contributes to BL. Positive trend present though not statistically significant ($p > .05$).

- H2e: VIC significantly contributes to BL. Statistically significant (β = 0.155, p = .031).
- H2f: SAT significantly contributes to BL. Near significance (p = .089), with a positive contribution.

TABLE VI. STATISTICAL HYPOTHESIS TESTING FOR LEARNABILITY FACTORS.

Factor	H1: Structural Validity (EFA Loading)	H2: Predictive	Factor
Motivation (MOTI)	0.577	Positive, NS	Statistical Acceptance
Confidence (CONF)	0.430	Positive, NS	Statistical Acceptance
Focus (FOC)	0.822	0.110 / p = .091 (Marginal)	Statistical Acceptance
Visualization (VIC)	0.666	0.155 / p = .031 (Significant)	Statistical Acceptance
Satisfaction (SAT)	0.445	0.109 / p = .089 (Marginal)	Statistical Acceptance
Better Lab Experience (BLE)	0.441	Positive, NS	Statistical Acceptance
Better Learning (BL)	—	Outcome variable	Statistical Acceptance

Note: NS=Not significant

The multiple regression model was statistically significant ($F(6, 284) = 3.095$, $p = 0.006$), explaining 4.2% of variance in BL (Adjusted $R^2 = 0.042$).

These results suggest that VIC, FOC, and SAT are key contributors, while CONF, MOTI, and BLE contribute theoretically and directionally, supporting their retention for model integrity.

G. Retention and Acceptance of all Factors

All six proposed predictors of Better Learning (MOTI, CONF, FOC, VIC, SAT, BLE) were retained based on a combination of prior validation findings [1], [17], theoretical justification, and preliminary empirical results from the current study. Although BLE (p = .684) and CONF (p = .265) were not statistically significant in the regression analysis, their inclusion was supported by expert review from prior work (Survey 1, establishing content validity), previous response acceptance rates from Survey 2 (exceeding 80% acceptance), as well as positive beta values across all factors, and acceptable factor loadings (>0.5) identified in the current analysis, which indicated sufficient factor relevance [1].

The decision to retain all factors reflects an integrative approach combining empirical patterns with theoretical rationale and previous AR-based validation studies [44]. This ensures the model remains aligned with experiential learning theory while maintaining conceptual coherence for future application in instructional design and further model development.

V. CONCLUSION AND FUTURE WORK

This study provides preliminary insights into the empirical validity of seven learnability factors—Motivation, Confidence, Enhanced Focus, Visualization of Invisible Concepts, Satisfaction, Better Lab Experience, and Better Learning—within the LEMARK–Hafsa framework, grounded in Kolb's Experiential Learning Theory. The analysis focused on initial measurement-level validation using exploratory factor analysis and regression techniques.

Exploratory factor analysis indicated acceptable internal consistency and a coherent unidimensional structure across all factors. Content validity was supported through prior expert review, and learner acceptance rates exceeded 80% for all factors in the final survey, reinforcing their practical and theoretical relevance. Notably, Visualization of Invisible Concepts showed a statistically significant positive association with Better Learning, while other factors demonstrated theoretically consistent but non-significant trends. While the findings of the study are encouraging, the modest regression results and the use of single-item measures suggest that the findings should be viewed as an exploratory step towards model validation rather than conclusive evidence of the framework's impact.

These findings offer preliminary support for the model's measurement foundation and confirm the readiness for further comprehensive analysis. Future research should focus on validating the full LEMARK–Hafsa model using multi-item scales and Partial Least Squares Structural Equation Modeling (PLS-SEM), across larger, more diverse cohorts to explore potential mediating effects of the learnability factors on Better Learning outcomes more rigorously.

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