Research Tool

Indian Journal of Extension Education
Vol. 62, No. 1 (January–March), 2026, (159-165)

ISSN 0537-1996 (Print)
ISSN 2454-552X (Online)

# Advancing Digital Extension Education: Development and Validation of Digital Learning Engagement Scale

Yamini Pakala[1]* and Sunitha Guniganti[2]

[1]Research Scholar, [2]Associate Professor, Department of Management Studies, National Institute of Technology, Warangal, Telangana, India
*Corresponding author email id: yaminip@student.nitw.ac.in

## HIGHLIGHTS

- Developed an 18-item Digital Learning Engagement Scale (DLES) measuring behavioural, emotional, cognitive, and psychological engagement, essential for modern digital education.
- Established a robust four-factor structure of digital learning engagement with strong reliability, model fit and validity.
- DLES effectively diagnoses engagement to improve learning outcomes in digital extension education and is a unique scale tailored for asynchronous and self-directed professional learning

ARTICLE INFO

**Keywords:** Digital learning engagement, Scale development, Behavioural engagement, Cognitive engagement, Emotional engagement, Psychological engagement, Digital extension education.

https://doi.org/10.48165/IJEE.2026.621RT04

**Citation:** Pakala, Y., & Guniganti, S. (2026). Advancing digital extension education: Development and validation of digital learning engagement scale. *Indian Journal of Extension Education*, *62*(1), 159-165. https://doi.org/10.48165/IJEE.2026.621RT04

## ABSTRACT

Digital transformation has revolutionized extension education and professional upskilling, revealing significant gaps in learning engagement assessment within digital contexts. Conventional classroom-based scales fail to capture multifaceted digital engagement in AI-augmented, asynchronous environments, overlooking self-regulation difficulties, learner isolation, and adaptive interactions. This hampers organizations and extension practitioners from identifying disengagement early and designing evidence-based interventions. Addressing this, an 18-item Digital Learning Engagement Scale (DLES) was developed through robust psychometric evaluation, content validation by eight experts. Data was collected from 461 digital learning platform users. Exploratory factor analysis (n=227) using principal axis factoring is chosen to handle correlated engagement dimensions, identified a stable four-factor structure (behavioural, emotional, cognitive and psychological engagement) explaining 66.93 per cent of variance (KMO=0.937, Bartlett's $p < 0.001$). Confirmatory factor analysis confirmed excellent model fit ($\chi^2$//df = 1.34, CFI = 0.945, TLI = 0.935, RMSEA = 0.065, SRMR = 0.057) with strong internal consistency ($\alpha$ = 0.86 -0.91), composite reliability (CR = 0.87- 0.91), convergent and discriminant validity. The DLES enables extension professionals, educators, and organizations to assess engagement, identify barriers, and implement targeted data-driven interventions, improving retention and learning effectiveness.

## INTRODUCTION

The Integration of digital technologies like extension Massive Open Online Courses (MOOCS) (National Institute of Agricultural Extension Management, 2024), mobile applications, Artificial Intelligence (AI), gamification, augmented and virtual reality has transformed extension education and professional training (Roy et al., 2025). This digital transition complements in-person outreach and skill development activities (Ziaulhaq Haqyar et al., 2025) by enhancing flexibility, scalability, and inclusivity for geographically dispersed agricultural practitioners and extension personnel (Gao et al., 2024). Extension education increasingly occurs in asynchronous, self-paced formats, and learners face distinct

Received 14-11-2025; Accepted 09-12-2025

engagement challenges such as limited real time interaction, learner isolation (Xue et al., 2025) motivational and self-regulation difficulties that impede effective learning and knowledge application (Malavika et al., 2025). As the digital learning environments become more adaptive and personalized through AI (Gupta & Anusha, 2020), conventional engagement metrics are insufficient to capture complex multidimensional patterns of engagement in hybrid and fully digital contexts.

Existing classroom-based engagement instruments (Kahu et al., 2018) and voluntary MOOC scales (Deng et al., 2020) have become outdated amid AI driven adaptive systems that deliver personalized learning pathways and real time feedback. These tools lack psychometric sensitivity for assessing engagement among workplace and remote extension learners balancing demanding occupational workloads (Gupta & Vatta, 2025). Although learning analytics, effectively track usage patterns and behavioural engagement through activity logs, clickstreams, and learning durations, fall short in capturing emotional, cognitive and psychological engagement dimensions that impact course completion rates and learning outcomes (Wong & Liem, 2022). These gaps reveal critical need for a psychometrically robust, context specific, multidimensional engagement scale (Greenhow et al., 2022).

Addressing this gap, this study develops and validates Digital Learning Engagement Scale (DLES) for digital extension education and workplace upskilling.

Grounded in modern engagement theory (Halverson & Graham, 2019) and foundational engagement frameworks (Appleton et al., 2006; Fredricks et al., 2004), Digital Learning Engagement (DLE) is conceptualized as a multidimensional construct comprising four distinct dimensions. Behavioural Learning Engagement (BLE) reflects active participation, effective time management, commitment and persistence. Emotional learning engagement (ELE) encompasses affective attachment to learning, including motivation, sense of belonging, and alignment with professional goals and organizational mission. Cognitive learning engagement (CLE) represents strategic mental effort in planning, monitoring, and evaluating learning tasks reflecting deep intellectual effort and reflective thinking. Psychological learning engagement (PLE) distinguished as separate dimension in extension and workplace contexts, constitutes motivational and social-psychological influences including supervisor and peer support, perceived learning benefits, and emotional factors that extend beyond individual emotion and cognition.

The DLES is developed through rigorous, multistage psychometric process, including systematic item generation with expert content validation for relevance and clarity, Exploratory Factor Analysis (EFA) to identify latent factorial structure; Confirmatory Factor Analysis (CFA) to verify model fit; and assessments of reliability, convergent and discriminant validity to establish scale robustness. DLES acts as a diagnostic tool for extension institutions, organizations, educators, trainers, and researchers to identify engagement barriers, measure engagement, refine adaptive learning pathways and implement targeted interventions to enhance motivation, participation, retention and learning outcomes.

## METHODOLOGY

A cross-sectional survey design was employed to enable efficient large sample data collection and split sample validation (EFA and CFA) avoiding confounding effects of repeated measurements. After pilot testing the instrument with 100 respondents to refine the instrument, the final questionnaire was distributed to digital learning platform users in India, through online Google forms and offline questionnaires, yielding 461 valid responses. All respondents provided informed consent and participated voluntarily with guaranteed anonymity. Demographic information includes gender, age, education, and income for sample description and subgroup exploration.

An initial pool of 38 items (BLE - 6 items, ELE - 8 items, CLE -13 items, PLE - 11 items) were generated drawing from literature review, existing scales and theoretical frameworks. The items comprised elements of behavioural, emotional, cognitive, and psychological dimensions and learning interventions such as gamification, micro learning, and AI personalization. Items were validated by panel of eight experts for relevance, clarity, and adequacy. Sixteen items that are redundant, overly context specific and reverse worded were removed after content validity. Data integrity was checked through means, standard deviations, skewness and kurtosis. Missing data is handled with listwise deletion. Total sample was randomly split into two independent subsets for EFA ($n = 227$) and CFA ($n = 234$).

To examine the factor structure, EFA using Principal Axis Factoring (PAF) with oblimin rotation was selected, as engagement subdimensions are theoretically correlated and self-report data often deviates from normality. PAF suits scale development over Principal Component analysis (PCA) to extract latent constructs via shared variance (excluding unique/ error variance) permitting correlated factors for realistic psychological modelling (Fabrigar et al., 1999). Sampling adequacy and sphericity were supported by Kaiser Meyer Olkin (KMO) and Bartlett's test. Factor retention followed eigenvalue > 1.0 and scree plot inspection. Items were retained if the factor loading was $\geq .50$ with minimal cross-loadings resulting in a four-factor structure consistent with theoretical subdimensions BLE, ELE, CLE, and PLE. CFA was conducted to validate the proposed four-factor model using Maximum Likelihood estimation. Model fit was assessed through chi square ratio ($\chi^2/df$), Comparative Fit Index (CFI), Tucker-Lewis Index (TLI), Root Mean Square Error of Approximation (RMSEA), and Standardized Root Mean Square Residual (SRMR) using goodness of fit thresholds (CFI/TLI $\geq .90$; RMSEA/SRMR $\leq .08$, preferably $\leq .06$). 18 items with factor loadings greater than 0.70 and statistically significant were retained.

Reliability was evaluated using Cronbach alpha, Composite Reliability (CR) and corrected item-total correlations, indicating internal consistency. Convergent validity was established through Average Variance Extracted (AVE) exceeding 0.50, CR above 0 .80 and significant factor loadings. For transparency regarding scale length, average inter-item correlation (r) (back-calculated from $\alpha$ and k) and Spearman–Brown projections, illustrating reliability changes for $k\pm1$ items are done. Fornell–Larcker and Heterotrait Monotrait ratio were used to assess Discriminant validity. This rigorous methodology ensures psychometric robustness of DLES. The scale development and validation process following structured multistage approach is depicted in Figure 1.

## RESULTS

### Demographic characteristics and mean scores of digital learning engagement dimensions

Table 1 presents the demographic profile and engagement scores of four hundred and sixty-one participants within DLES. The sample predominantly consisted of males (65.1%) and millennials/Generation Y (81.6%). The age distribution is substantially skewed, reflecting real-world dominance of millennials among digital learners in workplace learning and extension education contexts. Mean scores across all engagement dimensions ranged from 3.77 to 4.19, indicating moderate to high engagement. Spearman's correlation between gender and engagement ($\rho = 0.025$), age and engagement ($\rho = -0.032$) were low, indicating no association. In contrast modest correlations of engagement with education ($\rho = 0.081$) and income ($\rho = 0.023$). The respondents with higher academic degrees, such as PhDs, reported greater engagement across the four dimensions. This can be most likely due to their enhanced meta cognitive capacity, better self-regulatory learning capacities, increased awareness of learning opportunities related to career development, and less difficulty in adapting to technology. Income correlations ranged from $\rho = 0.021$ to 0.028. 6-10 lakh annual income cohorts have higher engagement compared to lower income brackets driven by resource availability for sustained learning without competing financial pressures. Behavioural learning engagement has greater variability (SD = 0.89). Cognitive learning engagement exhibited higher consistency across subgroups (Mean = 4.19, SD = 0.72). These findings suggest that the DLES effectively differentiates engagement levels across demographic subgroups, highlighting opportunities for targeted workforce development interventions.

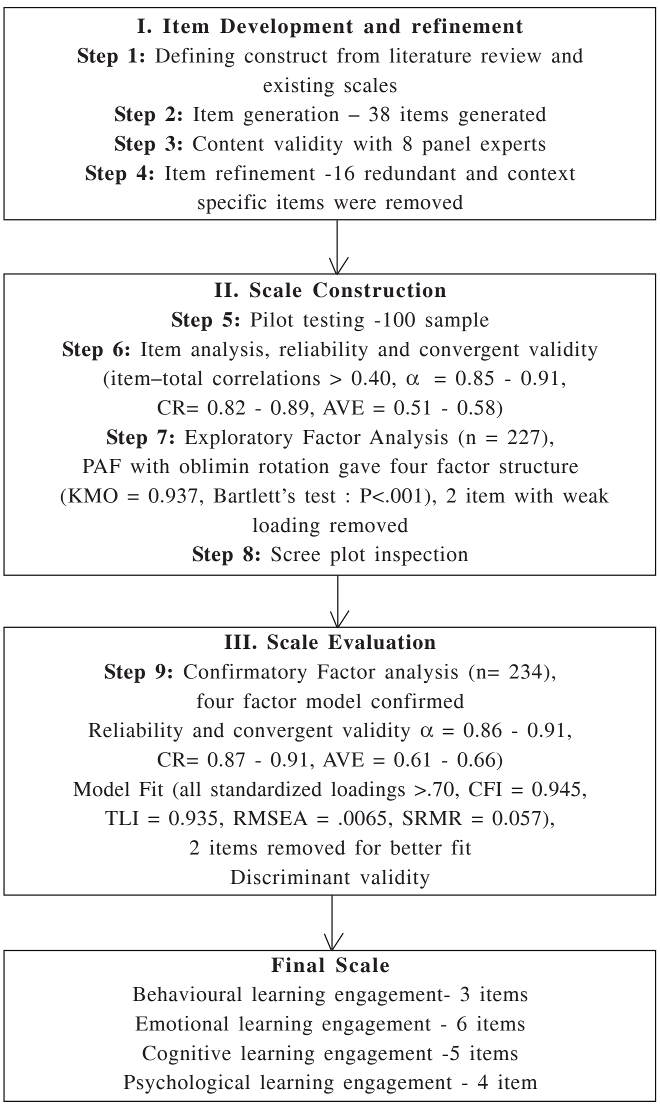


**Figure 1.** Sequential Scale Development and Validation Process of DLES

### Item analysis, reliability and convergent validity

Table 2 presents reliability and convergent validity for each subscale of digital learning engagement. All corrected item–total correlations exceeded 0.40, supporting the item adequacy. The DLE scale demonstrated excellent internal consistency (Cronbach's $\alpha$ = 0.91), with subscales Cronbach's alphas ranging from 0.85 to 0.91, exceeding the established threshold of 0.70 for scale reliability. The ELE exhibited highest reliability ($\alpha = 0.91$), followed by the CLE ($\alpha = 0.87$), PLE ($\alpha = 0.85$), and BLE ($\alpha = 0.85$). Mean inter-item correlations ($r \approx .61$ –.68) indicated an appropriate conceptual focus within each subscale, reflecting related yet distinct facets of engagement without redundancy. Composite reliability coefficients (CR= 0.82 -0.89) and average variance extracted (AVE = 0.51 – 0.58) met and exceeded established psychometric benchmarks of CR $\geq$ 0.70 and AVE $\geq$ 0.50, confirming internal consistency and convergent validity.

### Exploratory factor analysis

To examine the multidimensional latent structure of digital learning engagement, exploratory factor analysis was conducted. Sampling adequacy was tested using Kaiser-Meyer Olkin (KMO). The KMO value of 0.937, exceeded 0.60 threshold indicating good inter-item correlation for meaningful factor extraction. Bartlett's test of sphericity achieved statistical significance ($p < .001$), indicating correlation sufficiency among variables and suitability of data for factor analysis. Principal Axis Factoring (PAF) with oblimin rotation ($\delta = 0$) is chosen for factor extraction as it aligns with the conceptual expectation that sub dimensions of digital learning engagement are interrelated. PAF extracted four factors with eigenvalues > 1.0, collectively explaining 66.93 % of the total variance. Each factor aligned with the theoretical frameworks of the behavioural (BLE), emotional (ELE), cognitive (CLE), and psychological (PLE) engagement dimensions collectively represents the multifaceted nature of engagement in a digital learning environment. Table 3 presents detailed results of the pattern-matrix, and Figure 2 displays the scree plot of eigenvalues, showing a clear elbow after the fourth factor, confirming four-factor solution.

The sharp inflection after the fourth factor supports the four-factor model. EFA results confirmed that the DLE scale captures four coherent latent dimensions, explaining 66.93 % of the variance,

**Table 1.** Demographic characteristics, mean scores of digital learning engagement dimensions

| Variable | n(%) | BLE (ρ) Mean±SD | ELE (ρ) Mean± SD | CLE (ρ) Mean ±SD | PLE (ρ) Mean ±SD | Total DLE (ρ) Mean ±SD |
|---|---|---|---|---|---|---|
| Gender | | 0.028 | 0.039 | 0.024 | 0.017 | 0.025 |
| Male | 300 (65.1) | 3.91±0.85 | 4.06±0.79 | 4.18±0.71 | 4.05±0.82 | 4.05±0.67 |
| Female | 161 (34.9) | 3.92±0.97 | 4.12±0.79 | 4.20±0.75 | 4.09±0.79 | 4.08±0.71 |
| Age group | | -0.035 | -0.034 | 0.009 | 0.018 | -0.032 |
| Gen X | 48 (10.4) | 3.78±0.92 | 4.01±0.72 | 4.10±0.70 | 4.04±0.74 | 3.98±0.66 |
| Gen Y | 376 (81.6) | 3.93±0.91 | 4.08±0.82 | 4.21±0.74 | 4.07±0.84 | 4.07±0.71 |
| Gen Z | 37 (8.0) | 3.97±0.59 | 4.13±0.57 | 4.11±0.50 | 3.99±0.62 | 4.05±0.48 |
| Education | | 0.071 | 0.066 | 0.06 | 0.054 | 0.081 |
| Graduate | 240 (52.1) | 3.88±0.86 | 4.05±0.74 | 4.17±0.69 | 4.05±0.74 | 4.04±0.62 |
| Post-Graduate | 189 (41.0) | 3.95±0.91 | 4.11±0.83 | 4.20±0.75 | 4.08±0.87 | 4.09±0.73 |
| PhD | 32 (6.9) | 4.02±1.01 | 4.12±0.90 | 4.28±0.77 | 4.05±1.01 | 4.12±0.86 |
| Annual Income (Rs. LPA) | | 0.028 | 0.028 | 0.027 | 0.021 | 0.023 |
| 0–3 | 91 (19.7) | 3.95±0.84 | 4.09±0.76 | 4.24±0.64 | 4.07±0.86 | 4.08±0.67 |
| 3–6 | 94 (20.4) | 3.77±0.92 | 4.04±0.74 | 4.05±0.80 | 3.88±0.89 | 3.94±0.69 |
| 6–10 | 117 (25.4) | 4.00±0.92 | 4.09±0.86 | 4.24±0.73 | 4.18±0.74 | 4.13±0.71 |
| > 10 | 159 (34.5) | 3.93±0.88 | 4.10±0.79 | 4.21±0.71 | 4.08±0.78 | 4.08±0.67 |

*Note (S):* ρ = Spearman's rho correlation coefficient. All correlations are not significant (p > .05). BLE = Behavioural Learning Engagement, ELE = Emotional Learning Engagement, CLE = Cognitive Learning engagement, PLE = Psychological Learning Engagement, DLE = Digital Learning Engagement.

**Table 2.** Item analysis, reliability, and convergent-validity summary

| Dimension | Number Items | Item-Total r Range | α | CR | AVE | r (Inter-item) | α if Item deleted (min–max) |
|---|---|---|---|---|---|---|---|
| BLE | 4 | 0.59 – 0.73 | 0.88 | 0.85 | 0.54 | 0.62 | 0.85 – 0.89 |
| ELE | 8 | 0.66 – 0.80 | 0.91 | 0.89 | 0.58 | 0.68 | 0.89 – 0.92 |
| CLE | 5 | 0.66 – 0.73 | 0.87 | 0.82 | 0.53 | 0.65 | 0.84 – 0.89 |
| PLE | 5 | 0.53 – 0.74 | 0.85 | 0.84 | 0.51 | 0.61 | 0.82 – 0.87 |

aligning with the theoretical conceptualization of DLE. BLE 1and PLE 5 were removed due to weak loadings. due All items loaded saliently on their intended constructs, with minimal cross-loadings, validating the theoretical separation of the behavioural, emotional, cognitive, and psychological facets of DLE. These findings provide an empirical foundation for subsequent CFA and structural model validation.

### Confirmatory Factor Analysis (CFA)

To validate the factor structure derived from the EFA, confirmatory factor analysis was performed on an independent sample (n = 234) to verify model's stability and fit. Maximum Likelihood estimation with oblique (correlated) factors is used. The four-factor DLES measurement model achieved a strong global fit and validity across indices. ELE 1 and ELE 7 with standard loadings (<0.60) and conceptual overlaps with psychological items were removed to improve model parsimony and psychometric strength of the ELE subscale. All standardized loadings exceeded 0.70 ($p < .001$), with clear indicator reliability and moderate inter-factor correlations consistent with related but distinct dimensions. The goodness-of-fit statistics indicated an excellent model fit. Chi-square ratio $\chi^2$/df= 1.34 is below the cutoff of 2.0, indicating an excellent fit. The Comparative Fit Index (CFI) and Tucker-Lewis Index (TLI = 0.935) both surpassed the acceptable cutoff of 0.90. The root mean square error of approximation (RMSEA =0.065) and the standardized root mean square residual (SRMR = 0.057) were below their recommended cutoffs (RMSEA < 0.06 and SRMR < 0.08), suggesting a low discrepancy between the proposed model and observed data.

### Discriminant Validity

Upon establishing convergent validity and model fit, discriminant validity was assessed through Fornell–Larker criterion and the Heterotrait–Monotrait (HTMT) ratio. As shown in Table 5, the square root of AVE of all four dimensions BLE, ELE, CLE, and PLE exceeded its correlations with other constructs, confirming that each construct shares more variance with its own indicators than with others. The HTMT ratio was used to further validate the empirical distinctiveness of each dimension. HTMT values ranged from 0.81 to 0.88 all well below the threshold of 0.90 (Henseler et al., 2015), indicating that the four engagement factors were reliably separable within the measurement model. The slightly higher HTMT value between ELE and PLE is theoretically expected due to their shared motivational elements. Results from both discriminant validity tests confirm that the four dimensions behavioural, emotional, cognitive, and psychological are conceptually related in theory, yet distinct facets of engagement in practice, supporting the multidimensional structure of DLE.

**Table 3.** Exploratory Factor Analysis Results

| Dimension/ Subscale | Factor loading | Eigen value | % Variance | Cumulative % |
|---|---|---|---|---|
| Behavioural Learning Engagement | | 8.930 | 44.902 | 44.902 |
| BLE1 | 0.592 | | | |
| BLE2 | 0.632 | | | |
| BLE3 | 0.734 | | | |
| BLE4 | 0.696 | | | |
| Emotional Learning Engagement | | 2.057 | 10.342 | 55.244 |
| ELE1 | 0.660 | | | |
| ELE2 | 0.798 | | | |
| ELE3 | 0.741 | | | |
| ELE4 | 0.790 | | | |
| ELE5 | 0.777 | | | |
| ELE6 | 0.739 | | | |
| ELE7 | 0.663 | | | |
| ELE8 | 0.713 | | | |
| Cognitive Learning Engagement | | 1.310 | 6.588 | 61.832 |
| CLE1 | 0.661 | | | |
| CLE2 | 0.680 | | | |
| CLE3 | 0.693 | | | |
| CLE4 | 0.733 | | | |
| CLE5 | 0.714 | | | |
| Psychological Learning Engagement | | 1.014 | 5.096 | 66.928 |
| PLE1 | 0.718 | | | |
| PLE2 | 0.660 | | | |
| PLE3 | 0.739 | | | |
| PLE4 | 0.726 | | | |
| PLE5 | 0.527 | | | |

*Note (s):* The rotation converged in 11 iterations. Only primary loadings ≥ .50 are reported for clarity purposes.

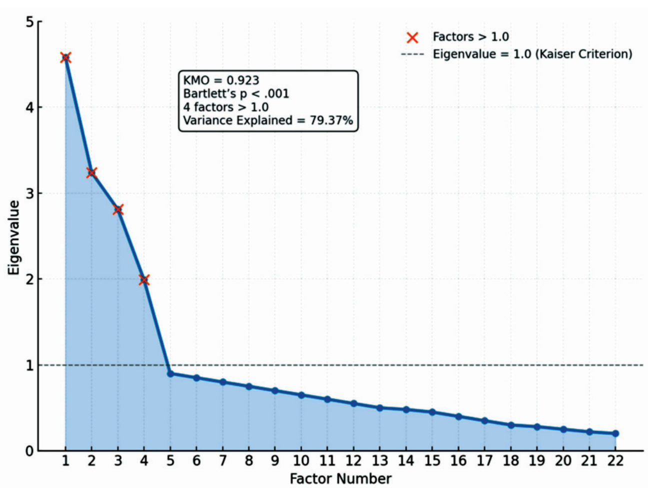


**Figure 2.** Scree Plot of Eigenvalues for DLE Scale

**Table 5.** Model fit indices summary

| Fit Index | Recommended | Obtained | Interpretation |
|---|---|---|---|
| $\chi^2$/df | <3.00 | 1.34 | Excellent fit |
| CFI | ≥ 0.90 | 0.945 | Good fit |
| TLI | ≥ 0.90 | 0.935 | Good fit |
| RMSEA | ≤ 0.06 | 0.065 | Good fit |
| SRMR | ≤ 0.08 | 0.057 | Good fit |

**Table 6.** Fornell–Larcker criterion results for discriminant validity

| Dimension | √AVE | BLE | ELE | CLE | PLE |
|---|---|---|---|---|---|
| BLE | 0.752 | — | *0.79* | *0.73* | *0.76* |
| ELE | 0.812 | 0.79 | — | *0.77* | *0.82* |
| CLE | 0.732 | 0.73 | 0.77 | — | *0.74* |
| PLE | 0.793 | 0.76 | 0.82 | 0.74 | — |

## DISCUSSION

The digital learning engagement scale (DLES) is the first validated instrument designed for asynchronous, AI-augmented workplace and extension learning environments. Unlike prior scales developed for face-to-face classrooms (Kahu et al., 2018), voluntary MOOCS (Deng et al., 2020), DLES treats psychological engagement as distinct dimension rather than merging with emotional factors. DLES items were developed considering realities of occupational constraints, contemporary challenges such as limited peer interaction, real time facilitation, learner isolation and algorithmic personalization that are absent in previous instruments.

Results affirm a stable four-factor structure, indicating engagement's distinct yet interrelated sub dimensions in digital contexts. The developed scale exhibits robust psychometrics including high internal consistency, strong validity, and good model fit positioning DLES as a theoretically grounded tool for measuring engagement.

Demographic findings revealed significant shift in engagement determinants. Negligible correlations between age, gender and DLE scores indicate that modern learning platforms with user friendly interactive interfaces, with personalized content have effectively mitigated technology adoption challenges and use (Du Plooy et al., 2024). These findings emphasize the shift from technology barriers to psychological and motivational barriers like disengagement, learner isolation, and information overload (Feroz et al., 2022). Higher educational levels like post-graduation and PhD are linked to increased engagement due to psychological factors like self-regulation, intrinsic motivation and goal orientation.

The findings indicate that digital learning engagement is much more than participation, cognitive strategies, and emotional commitment. Behavioural engagement measured by proactive

**Table 4.** Confirmatory factor analysis – convergent validity, reliability

| Dimension | Items (k) | Loading Range | AVE | CR | α | Inter-Factor (Range) r |
|---|---|---|---|---|---|---|
| BLE | 3 | 0.79–0.82 | 0.66 | 0.87 | 0.86 | 0.58–0.65 |
| ELE | 6 | 0.78–0.87 | 0.61 | 0.91 | 0.91 | 0.62–0.71 |
| CLE | 5 | 0.79–0.86 | 0.63 | 0.89 | 0.90 | 0.64–0.72 |
| PLE | 4 | 0.76–0.82 | 0.62 | 0.88 | 0.88 | 0.59–0.70 |
| Overall DLE | 18 | 0.76–0.87 | 0.62 | 0.93 | 0.93 | - |

*Note(s):* k = No. of items, AVE = Average Variance Extracted, CR = Composite Reliability, α = Cronbach alpha, r = latent factor correlations.

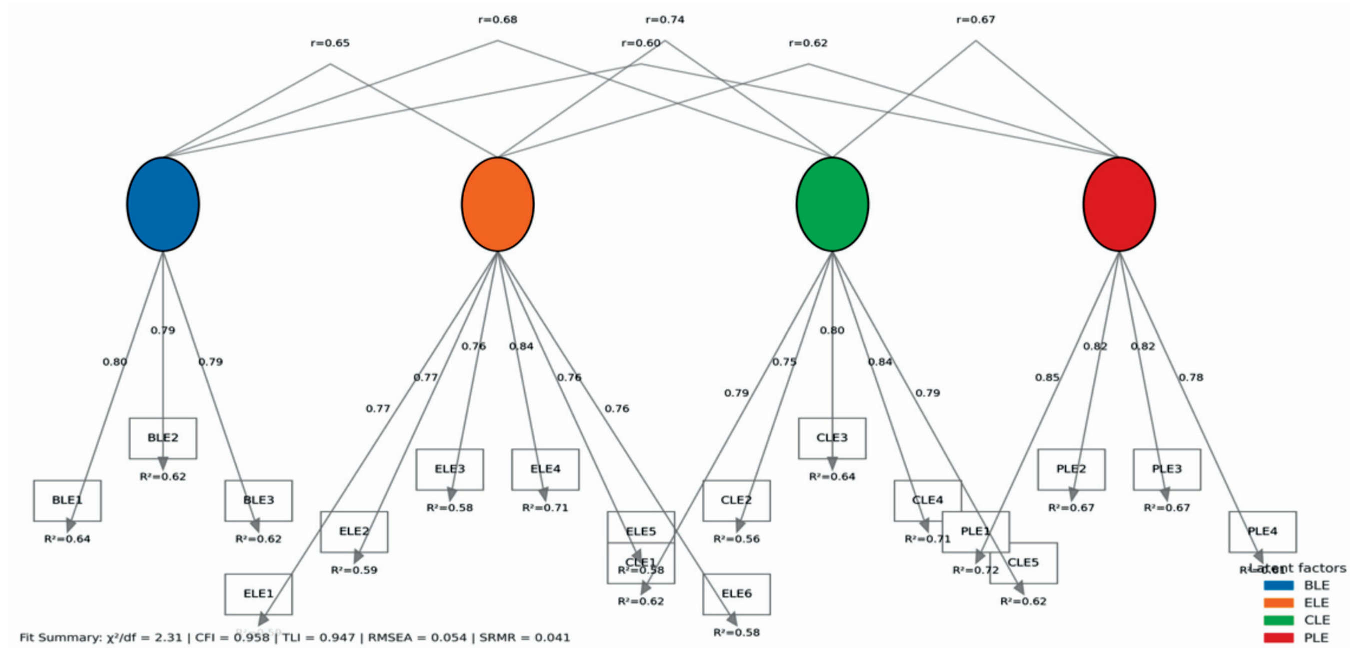


**Figure 3.** Standardized estimates and $R^2$ values of digital learning engagement

actions such as course completion, interaction in discussion forums aligns with technology driven asynchronous workplace learning. Emotional engagement as a critical indicator explains the affective experiences of learners, such as satisfaction, enthusiasm, and positive feelings in the learning process, maintaining motivation (Parekkadan House & Roy, 2025). Cognitive engagement is reflected through mental effort, persistence, and deep processing strategies resonating with self-regulated learning models (Das & Jha, 2025). Psychological engagement as a unique construct highlights social and psychological factors that motivate and influence engagement beyond cognitive efforts.

Following the best practices in scale development, this study performed both exploratory analysis and confirmatory factor analysis on independent samples to identify and validate the latent factor structure of digital learning engagement. Principal axis factoring with oblimin rotation, uncovered four distinct factors explaining major proportion of variance and consistent with theoretical framework. This enhances generalizability and reliability of the instrument minimizing overfit or underfit concerns in scale development. Reliability analysis further demonstrated that removal of any single item would have negligible effect on total consistency, highlighting robustness and precision of DLES. Convergent and discriminant validity results show that each sub dimension measures unique yet related aspects of digital learning engagement.

Although DLES demonstrated strong psychometrics, limitations include non-probability sampling, self-report biases, cross-sectional design within Indian professional contexts, limiting generalizability. Criterion validity could not be established due to absence of benchmarks for digital engagement. Future research should test predictive validity against outcomes like learning performance and retention, examine nomological networks, and adopt longitudinal designs to track engagement trajectories and validate DLES across diverse cultures, sectors and educational contexts. The DLES advances engagement measurement by introducing a context specific instrument tailored for adult professional learners. By emphasizing psychological resources and self-regulation abilities, the scale addresses the unique motivational profile of autonomous learners in professional learning. This scale serves as a diagnostic tool for identifying engagement gaps and predicting learner disengagement, enabling timely interventions. The DLES is theoretically grounded and empirically tested, thus adding literature on contemporary engagement research in complex digital learning environments.

## CONCLUSION

The study successfully developed an eighteen item, multidimensional Digital Learning Engagement Scale (DLES) comprising behavioural, emotional, cognitive, and psychological engagement dimensions critical for professional digital learning. DLES with robust psychometric properties filled significant gaps by focusing on asynchronous and AI augmented learning contexts. DLES has beneficial implications for distance education and organizational learning to monitor and enhance learning engagement, personalizing instructional design, and support activities through targeted interventions. DLES engagement metrics insights support in improving course relevance, completion rates across diverse professional contexts. Future studies should validate and refine DLES across various sectors and extend the scale's generalizability, and utility.

## DECLARATIONS

Ethics approval and informed consent: All respondents provided informed consent and participated voluntarily with guaranteed anonymity

Conflict of interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

The authors declare that during the preparation of this work, they thoroughly reviewed, revised, and edited the content as needed. The authors take full responsibility for the final content of this publication.

Publisher's note: All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organisation, or those of the publisher, the editors, and the reviewers. Any product/process or technology that may be evaluated in this article, or a claim that may be made by its manufacturer, is not guaranteed or endorsed by the publisher.

## REFERENCES


Appleton, J. J., Christenson, S. L., Kim, D., & Reschly, A. L. (2006). Measuring cognitive and psychological engagement: Validation of the Student Engagement Instrument. *Journal of School Psychology, 44*(5), 427–445. https://doi.org/10.1016/j.jsp.2006.04.002

Chakraborty, J., Das, R., & Jha, K. K. (2025). The Role of Cognitive Style in Academic Achievements and Creative Thinking among Students. *Indian Journal of Extension Education*, *61*(3), 69-74. https://doi.org/10.48165/IJEE.2025.61313

Cotton, R., Johnson, M., Hanks, J., & McGill, D. (2025). Is a virtual learning environment effective for mid-career agricultural extensionists' cross-cultural learning? *The Journal of Agricultural Education and Extension, 1*–24. https://doi.org/10.1080/1389224X.2025.2513265

Deng, R., Benckendorff, P., & Gannaway, D. (2020). Learner engagement in MOOCs: Scale development and validation. *British Journal of Educational Technology, 51*(1), 245–262. https://doi.org/10.1111/bjet.12810

Du Plooy, E., Casteleijn, D., & Franzsen, D. (2024). Personalized adaptive learning in higher education: A scoping review of key characteristics and impact on academic performance and engagement. *Heliyon*, *10*(21), e39630. https://doi.org/10.1016/j.heliyon.2024.e39630

Fabrigar, L. R., Wegener, D. T., MacCallum, R. C., & Strahan, E. J. (1999). Evaluating the use of exploratory factor analysis in psychological research. *Psychological Methods, 4*(3), 272–299. https://doi.org/10.1037/1082-989X.4.3.272

Feroz, H. M. B., Zulfiqar, S., Noor, S., & Huo, C. (2022). Examining multiple engagements and their impact on students' knowledge acquisition: The moderating role of information overload. *Journal of Applied Research in Higher Education*, *14*(1), 366–393. https://doi.org/10.1108/JARHE-11-2020-0422

Fredricks, J. A., Blumenfeld, P. C., & Paris, A. H. (2004). School engagement: Potential of the concept, state of the evidence. *Review of Educational Research*, *74*(1), 59–109. https://www.jstor.org/stable/3516061

Gao, T., Lu, Q., Feng, H., & Zhang, Y. (2024). Does farmers' cognition enhance their enthusiasm for adopting sustainable digital agricultural extension services? Evidence from rural China. *Sustainability*, *16*(10), 3972. https://doi.org/10.3390/su16103972

Greenhow, C., Graham, C. R., & Koehler, M. J. (2022). Foundations of online learning: Challenges and opportunities. *Educational Psychologist, 57*(3), 131–147. https://doi.org/10.1080/00461520.2022.2090364

Gupta, R. M., & Anusha. (2020). Determinants of successful integration of e-learning into higher education. *Indian Journal of Extension Education*, *56*(4), 37-42.

Gupta, R., & Vatta, L. (2025). Disruptions in lifestyle due to escalating screen time: A behavioural perspective. *Indian Journal of Extension Education*, *61*(4), 14–18. https://doi.org/10.48165/IJEE.2025.61403

Halverson, L. R., & Graham, C. R. (2019). Learner engagement in blended learning environments: A conceptual framework. *Online Learning, 23*(2), 145–178. https://doi.org/10.24059/olj.v23i2.1450

Haqyar, Z., Rohila, A. K., Malik, J. S., & Kumar, A. (2025). Usage pattern of information and communication Technology tools among university faculty members. *Indian Journal of Extension Education*, *61*(1), 108-112. https://doi.org/10.48165/IJEE.2025.611RN03

Kahu, E. R., Nelson, K., & Picton, C. (2018). The development and validation of the Higher Education Student Engagement Scale (HESES). *Review of Higher Education, 41*(3), 413–435. https://doi.org/10.1353/rhe.2018.0011

Malavika, G., Shamsa, F., Allan, A. T., Thara, S., Meethal, S. V. K., Sownthariya, S., & Thomas, A. (2025). Time management and procrastination patterns among undergraduate agriculture students. *Indian Journal of Extension Education*, *61*(4), 128–133. https://doi.org/10.48165/IJEE.2025.61421

National Institute of Agricultural Extension Management. (2024). Extension MOOCs: Online platform for extension functionaries. https://www.manage.gov.in/moodleafa/

Parekkadan House, P. J. S., & Roy, D. (2025). Attainment of Student Engagement in Secondary Schools in Kerala: An Empirical Investigation. *Indian Journal of Extension Education*, *61*(2), 8-13. https://doi.org/10.48165/IJEE.2025.61202

Roy, S., Mukherjee, S., BM, Y., Singh, G., Kalaiselvi, P., Raj, R., Balo, S., & Diwakar, N. (2025). From field to future: The evolution of agricultural extension in the digital age for sustainable and revitalized rural economies. *International Journal of Agriculture Extension and Social Development, 8*(11), 530–540.

Wong, Z. Y., & Liem, G. A. D. (2022). Student engagement: Current state of the construct, conceptual refinement, and future research directions. *Educational Psychology Review, 34*(1), 107–138. https://doi.org/10.1007/s10648-021-09628-3

Xue, Y., Khalid, F., & Karim, A. A. (2025). Cognitive and behavioural engagement challenges open and distance learning and potential solutions from artificial intelligence. *Frontiers in Education*, 10, Article 1610148. https://doi.org/10.3389/feduc.2025.1610148