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Exploring Adaptive Learning Dimensions Through EFA and CFA Validation

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ABSTRACT

The increasing demand for adaptive learning in vocational education highlights the need for valid instruments to measure its key constructs. Despite growing research on adaptive assessment, adaptive gamification, personalized feedback, and self-regulated learning (SRL), these constructs are commonly examined separately. This study addresses this gap by developing and validating an SRL based adaptive learning instrument that integrates them within a unified measurement framework. The instrument was constructed from four theoretical constructs: adaptive assessment, adaptive gamification, personalized feedback, and self-regulated learning. A total of 507 students participated in the study. Data were analyzed using Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA). From the initial 24 items, nine items with inadequate psychometric properties were removed during the validation process, resulting in 15 valid items. The EFA results revealed four latent factors, namely feedback awareness, self-regulation, regulation deficit, and adaptive motivation. CFA confirmed a good model fit (CFI = 0.98, TLI = 0.97, RMSEA = 0.051, SRMR = 0.038) and acceptable composite reliability. The findings indicate that adaptive learning is perceived as an integrated process across SRL phases. This study provides a validated instrument and a conceptual basis for future research in adaptive learning.

1. Introduction

In the global agenda of Technical and Vocational Education and Training (TVET), meaningful, inclusive, and quality-oriented learning places assessment no longer merely as a tool to measure learning outcomes, but as a mechanism that actively directs the learning process of students (UNESCO, 2022). This orientation is also reflected in educational policies that emphasize assessment as an integral part of

the learning cycle, particularly through the utilization of formative assessment to support the continuous development of student competencies (Halim et al., 2024). In vocational education, assessment quality is closely linked to graduates' competency readiness because assessment provides evidence of competency mastery and supports alignment between learning outcomes and workplace demands (Yusop et al., 2022).

As an education system oriented toward workforce readiness, vocational education has the mandate to produce graduates with competencies that can be demonstrated through performance and skills relevant to the needs of industry and the labor market. In achieving this goal, assessment plays a strategic role in supporting the learning process and facilitating the development of student competencies (Sandal, 2023; Yusop et al., 2022). However, in practice, students' abilities are heterogeneous and develop at different rates. Some students require timely scaffolding, whereas others need greater challenges to remain engaged (Baartman & Gulikers, 2025; Welsandt et al., 2024). In such situations, assessment that functions solely as an evaluation of final outcomes may fail to capture the ongoing dynamics of students' competency development. As a result, instructional interventions become less precise and do not always occur at the appropriate time (Xu et al., 2024).

In response to these challenges, more adaptive and learner-centered approaches are needed to ensure that assessment can accommodate the diverse learning trajectories of students. In this context, approaches such as adaptive assessment (AA), adaptive gamification (AG), and personalized feedback (PF) offer promising solutions to support more personalized and responsive learning environments. Adaptive assessment adjusts question difficulty to students' abilities, adaptive gamification personalizes game elements to enhance engagement, and personalized feedback provides contextual guidance for learning improvement (Cuéllar et al., 2025; Ihichr et al., 2024; Xiao & Hew, 2024).

However, the literature indicates that these three approaches are generally still studied separately and are often treated as standalone learning strategies. In practice, the integration of adaptive assessment, adaptive gamification, and personalized feedback also tends to be partial. For instance, in computer-based adaptive assessment systems, adaptivity often focuses solely on adjusting the difficulty level of questions without providing adequate diagnostic support for students' conceptual misconceptions or procedural errors (Ebenbeck et al., 2024). On the other hand, the implementation of static gamification, such as providing the same rewards to all students, may increase engagement in the initial stages but risks losing effectiveness in the long term when it is not aligned with individual motivational characteristics (Cigdem et al., 2024; Gini et al., 2025). In addition, when feedback is only provided after the learning process is completed, students lose the opportunity to reflect during the learning process. In fact, the effectiveness of feedback is highly influenced by its source and the timeliness of its delivery (Weidlich et al., 2025). This fragmentation may hinder adaptive learning support and limit students' engagement in the SRL cycle of goal setting, monitoring, and reflection.

Theoretically, this need is aligned with the Self-Regulated Learning (SRL) framework, which emphasizes that effective learning involves processes of goal setting, monitoring learning progress, and reflecting on the learning strategies employed (Hemmler & Ifenthaler, 2024; Pintrich, 2004; Zimmerman, 2002). However, in many previous studies, SRL is more often positioned as an outcome of learning rather than as an analytical framework that explains the mechanisms of interaction among various components within adaptive learning systems (Oportus-Torres et al., 2024; Wu et al., 2023). As a result, the relationship between adaptive mechanisms such as AA, AG, and PF and students' self-regulation processes has not been widely examined in an integrated manner.

In addition, most studies examining components of adaptive assessment, adaptive gamification, personalized feedback, and self-regulated learning generally employ survey instruments developed contextually without undergoing adequate construct validation processes. In survey-based research, however, the validity and reliability of instruments are crucial aspects to ensure that each indicator truly represents the construct being measured. In psychometric studies, Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA) are often used sequentially to identify and confirm the factor structure of an instrument (Korkmaz et al., 2017). EFA explores latent factor structures, whereas CFA evaluates model fit using goodness of fit indices. Nevertheless, studies that systematically validate constructs representing the integration of adaptive assessment, adaptive gamification, personalized feedback, and SRL remain relatively limited. Most research tends to focus on testing the effectiveness of learning interventions without first ensuring that the instruments used possess valid and reliable factor structures. This condition indicates a methodological gap in research on adaptive learning, particularly in ensuring that the constructs employed truly reflect the conceptual dimensions intended to be measured.

Based on these gaps, this study aims to examine the construct structure representing adaptive assessment, adaptive gamification, personalized feedback, and SRL through a factor analysis approach. Specifically, this study employs EFA to identify the factor structure formed from the developed indicators, as well as CFA to confirm the fit of the resulting measurement model. Thus, this study is expected to produce a valid and reliable measurement instrument to examine adaptive mechanisms in digital learning within the context of vocational education. Based on these research objectives, the research questions in this study are formulated as follows.

1. How is the factor structure formed from the indicators of adaptive assessment, adaptive gamification, personalized feedback, and SRL based on the results of EFA?
 2. Can the factor structure obtained from EFA be confirmed through CFA?
 3. What are the levels of validity and reliability of the constructs representing adaptive assessment, adaptive gamification, personalized feedback, and SRL in the resulting measurement model?
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2. Methodology

This study employed a Design-Based Research (DBR) approach aimed at developing and validating an adaptive learning instrument within the context of vocational education. The DBR approach was selected because it supports a systematic process of design, testing, evaluation, and refinement, allowing the resulting instrument to be both theoretically grounded and empirically validated. The study focused on four theoretical constructs frequently discussed in adaptive learning literature, namely adaptive assessment (AA), adaptive gamification (AG), personalized feedback (PF), and Self-Regulated Learning (SRL). Through an iterative development process, the instrument was designed to capture students' perceptions of adaptive learning mechanisms and their relationship with self-regulation processes. The overall validation process involved instrument development, empirical testing, and psychometric evaluation using Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA) to ensure the quality of the measurement model.

Instrument

The questionnaire instrument was developed based on a comprehensive review of literature related to adaptive assessment, adaptive gamification, personalized feedback, and self-regulated learning in digital learning environments. Four theoretical constructs were identified and subsequently operationalized into measurable indicators, resulting in a total of 24 questionnaire items. The instrument development process began with identifying relevant constructs and indicators from previous studies that have examined adaptive learning and technology-enhanced educational environments. Each construct was then translated into measurable indicators and questionnaire statements designed to capture students' perceptions and experiences regarding adaptive learning practices. To ensure adequate coverage of the theoretical dimensions, multiple indicators were developed for each construct. The resulting instrument was intended to provide a comprehensive representation of adaptive learning dimensions and their relationship with self-regulated learning. The distribution of items across the four constructs is presented in Table 1.

Table 1. Distribution of Items Across Constructs

No	Construct	Items
1	Adaptive Assessment	AA1_1, AA1_2, AA1_3, AA2_1, AA2_2, AA2_3
2	Adaptive Gamification	GA1_1, GA1_2, GA1_3, GA2_1, GA2_2, GA2_3
3	Personalized Feedback	PF1_1, PF1_2, PF1_3, PF2_1, PF2_2, PF2_3
4	Self-Regulated Learning	SRL1_1, SRL1_2, SRL2_1, SRL2_2, SRL3_1, SRL3_2

Following the development stage, the instrument underwent empirical validation through factor analysis procedures to evaluate its construct validity and reliability. The quality of the instrument was assessed using factor loading values, Composite Reliability (CR), and Average Variance Extracted (AVE). Exploratory Factor Analysis (EFA) was conducted to identify the underlying factor structure of the instrument, while Confirmatory Factor Analysis (CFA) was performed to verify the

factor structure and evaluate model fit. These procedures were carried out to ensure that the developed instrument accurately measured the intended constructs and demonstrated acceptable psychometric properties. The overall process of instrument development and validation adopted in this study is illustrated in Figure 1, which outlines the stages from literature review and item development to EFA and CFA validation.

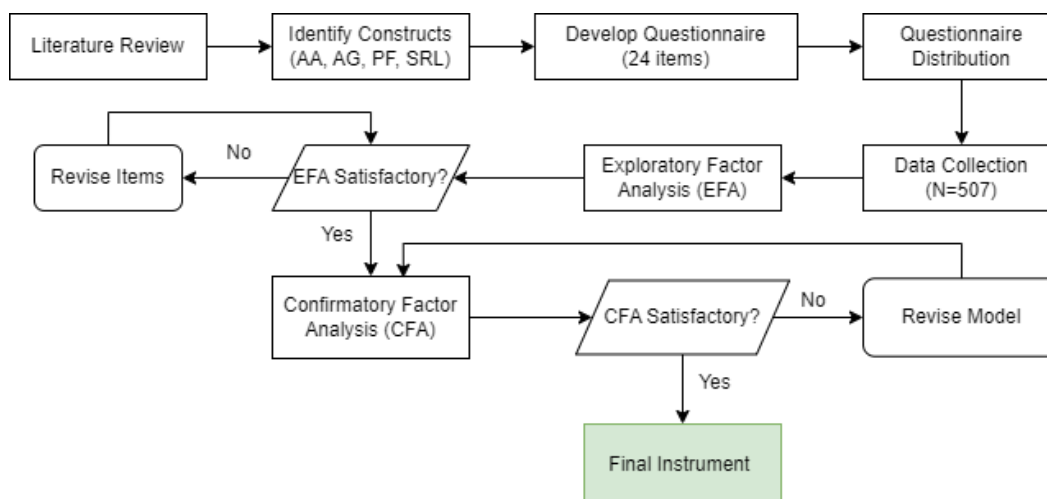


Figure 1. Flowchart of the Instrument Development and Validation Process

Data Collection

The developed instrument was distributed to respondents through both online and offline survey administration. The participants consisted of 507 active undergraduate students from Universitas Pendidikan Indonesia who voluntarily participated in the study. Data collection was conducted after the instrument development stage had been completed and all questionnaire items had been reviewed for clarity and relevance. Respondents were asked to provide responses based on their perceptions and experiences related to adaptive learning practices in digital learning environments. Prior to analysis, the collected responses were screened to ensure completeness and suitability for factor analysis procedures. All responses were compiled into a single dataset and prepared for subsequent statistical analysis.

Data Analysis

The collected data were analyzed using a factor analysis approach to examine the construct validity and reliability of the developed instrument. Prior to conducting factor analysis, data screening procedures were performed to identify missing values, assess normality assumptions, and examine potential multicollinearity among indicators. Exploratory Factor Analysis (EFA) was employed as the initial stage to identify the latent factor structure underlying the developed items. Sample adequacy was evaluated using the Kaiser Meyer Olkin (KMO) measure and

Bartlett's Test of Sphericity, while Promax rotation was applied to obtain a clearer factor solution. Subsequently, Confirmatory Factor Analysis (CFA) was conducted to verify the factor structure identified through EFA and to evaluate the fit of the measurement model. Model fit was assessed using chi-square/df, Comparative Fit Index (CFI), Tucker Lewis Index (TLI), Standardized Root Mean Square Residual (SRMR), and Root Mean Square Error of Approximation (RMSEA). In addition, Composite Reliability (CR) and Average Variance Extracted (AVE) were calculated to assess construct reliability and convergent validity.

3. Results and Discussion

Based on the initial analysis results, no missing data were identified during the data screening process. The skewness values for all items ranged from -1.35 to -0.22, while the kurtosis values ranged from -0.77 to 1.29. These values fall within the acceptable absolute range of ± 1.5 , indicating that the assumption of normality was satisfied. In addition, Pearson correlation analysis showed that the correlations among items ranged from 0.10 to 0.71, all below the recommended threshold of 0.80, suggesting the absence of multicollinearity issues. Therefore, the dataset was considered appropriate for further Exploratory Factor Analysis (EFA). Table 2 presents the descriptive statistics of all measurement items, including the mean, standard deviation, skewness, and kurtosis values.

Table 2. Descriptive Statistics of Measurement Items

Item	Mean	Std. Deviation	Skewness	Kurtosis
AA1_1	3.890	1.061	-0.824	0.147
AA1_2	3.519	1.178	-0.438	-0.593
AA1_3	4.059	1.071	-1.175	0.866
AA2_1	3.742	1.271	-0.736	-0.552
AA2_2	4.179	1.041	-1.345	1.289
AA2_3	3.990	1.026	-0.971	0.587
GA1_1	3.895	0.990	-0.797	0.273
GA1_2	3.501	1.177	-0.561	-0.335
GA1_3	4.010	0.931	-0.874	0.545
GA2_1	3.318	1.166	-0.309	-0.621
GA2_2	3.822	1.029	-0.829	0.394
GA2_3	4.012	0.960	-1.007	0.932
PF1_1	4.105	0.990	-0.887	0.014
PF1_2	3.769	1.264	-0.804	-0.457
PF1_3	4.032	1.076	-1.134	0.711
PF2_1	3.726	1.220	-0.729	-0.445
PF2_2	4.075	1.072	-1.204	0.924
PF2_3	3.974	1.030	-0.973	0.523
SRL1_1	3.467	1.190	-0.385	-0.675
SRL1_2	4.002	1.013	-1.035	0.805
SRL2_1	3.300	1.187	-0.226	-0.720
SRL2_2	3.746	1.065	-0.582	-0.227
SRL3_1	4.032	0.978	-0.904	0.309
SRL3_2	3.452	1.224	-0.369	-0.770

Exploratory Factor Analysis

Sample adequacy for conducting Exploratory Factor Analysis (EFA) was assessed using the Kaiser Meyer Olkin (KMO) measure and Bartlett's Test of Sphericity. The results showed that the overall KMO value was 0.916, which exceeds the recommended threshold of 0.50, indicating that the data have excellent sampling adequacy for factor analysis. In addition, the Measure of Sampling Adequacy (MSA) values for each item were all above 0.50, ranging from 0.876 to 0.946, indicating that all items met the criteria for further analysis in factor analysis. Furthermore, Bartlett's Test of Sphericity yielded a value of $\chi^2 = 3003.464$ with $df = 105$ and $p < 0.001$, indicating that the correlation matrix among variables is significantly different from an identity matrix. This suggests that there are sufficient correlations among variables to form latent factors. The results of the exploratory factor analysis were further examined using Promax rotation to obtain a clearer factor structure. Based on the rotated factor solution, four main factors were identified, namely feedback awareness, self-regulation, regulation deficit, and adaptive motivation. These four factors consist of 15 items with factor loadings ranging from 0.412 to 0.973, indicating that the indicators have adequate contributions in forming the latent constructs of each factor. Table 3 presents the Promax rotated factor loadings of the retained items, showing their contributions to the four latent factors identified through EFA.

Table 3. Rotated component Matrix

Items	Feedback Awareness	Self-Regulation	Regulation Deficit	Adaptive Motivation
PF1_2	0.973			
AA2_1	0.769			
PF2_1	0.576			
PF1_3	0.506			
PF1_1	0.425			
SRL2_2		0.690		
GA2_3		0.458		
SRL3_1		0.455		
SRL1_2		0.412		
SRL2_1			0.760	
SRL3_2			0.586	
SRL1_1			0.582	
GA1_3				0.803
GA1_1				0.496
AA1_1				0.463

Interpretation and Naming of Factors

The first factor consists of five items, namely PF1_2, AA2_1, PF2_1, PF1_3, and PF1_1, with factor loadings ranging from 0.425 to 0.973. The items in this factor are generally related to students' perceptions of the role, function, and benefits of feedback in supporting the learning process. The presence of items highlighting the

importance of feedback in understanding material and evaluating learning outcomes indicates that this factor represents students' awareness of the strategic value of feedback. Therefore, this factor is interpreted as Feedback Awareness. The second factor consists of four items, namely SRL2_2, GA2_3, SRL3_1, and SRL1_2, with factor loadings ranging from 0.412 to 0.690. The items in this factor reflect students' ability to actively manage their learning processes, including planning, monitoring, and evaluating their learning. In addition, the presence of gradual challenge elements indicates a relationship between self-regulation and adaptive support in learning. Thus, this factor is labeled Self-Regulation.

The third factor consists of three items, namely SRL2_1, SRL3_2, and SRL1_1, with factor loadings ranging from 0.582 to 0.760. The items in this factor indicate a tendency toward suboptimal use of learning strategies, such as not setting goals, insufficiently monitoring learning effectiveness, and not adequately adjusting strategies. These characteristics suggest weaknesses in the self-regulation aspect, and therefore, this factor is interpreted as Regulation Deficit. The fourth factor consists of three items, namely GA1_3, GA1_1, and AA1_1, with factor loadings ranging from 0.463 to 0.803. The items in this factor are related to the adjustment of learning difficulty levels and challenges according to students' abilities, as well as the role of gamification elements in enhancing learning motivation. This indicates that adaptivity in learning contributes to students' engagement and motivation. Therefore, this factor is interpreted as Adaptive Motivation.

Confirmatory Factor Analysis

The factor structure of the model was verified through Confirmatory Factor Analysis (CFA). In the initial stage, the measurement model consisted of indicators representing the four theoretical constructs of adaptive assessment, adaptive gamification, personalized feedback, and self-regulated learning. The results indicated that nine items (AA1_2, AA1_3, AA2_2, AA2_3, GA1_2, GA2_1, GA2_2, PF2_2, and PF2_3) had standardized factor loadings below the recommended threshold of 0.40 and were therefore excluded from the model. Statistically, low factor loadings indicate that these items contributed weakly to the latent constructs and did not adequately explain the shared variance among indicators.

From a conceptual perspective, the eliminated items appeared to capture learners' general beliefs about the usefulness of adaptive assessment, gamification, and feedback rather than their direct perceptions of adaptive learning experiences. Several adaptive assessment items (AA1_2, AA1_3, AA2_2, and AA2_3) emphasized the perceived benefits of assessment adjustment and learning monitoring, which may reflect broad educational beliefs rather than distinct dimensions of adaptive learning. Similarly, the removed adaptive gamification items (GA1_2, GA2_1, and GA2_2) focused primarily on reactions to specific game elements and mechanics, such as points, levels, and gamified activities. These items may not have been sufficiently connected to the broader motivational and self-regulatory processes that emerged from the empirical data. The EFA results indicated that students tended to perceive adaptive learning through integrated

psychological dimensions, namely feedback awareness, self-regulation, regulation deficit, and adaptive motivation, rather than through the original theoretical categories.

A similar pattern was observed for the personalized feedback items PF2_2 and PF2_3. Although these items were theoretically associated with feedback, they emphasized guidance for improvement and reflective learning processes, both of which are conceptually closely related to self-regulated learning. Consequently, students may have interpreted these items as part of their self-regulation activities rather than as distinct feedback experiences. This conceptual overlap may explain their weak contribution to the final factor structure. Overall, the elimination of the nine items suggests that students perceive adaptive learning as an integrated self-regulatory process in which feedback, motivation, and learning regulation operate simultaneously. Therefore, removing these items improved both the conceptual coherence and parsimony of the measurement model while maintaining stronger alignment with the empirically derived dimensions.

Subsequently, model fit evaluation was conducted using several goodness-of-fit indices. The results showed that the model demonstrated a good level of fit, as presented in Table 4. The value of $\chi^2 = 163.212$ with degrees of freedom (df) = 71 resulted in $\chi^2/df = 2.29$, which is below the recommended threshold of 3, indicating good model fit. In addition, the values of CFI = 0.981 and TLI = 0.976 exceed the threshold of 0.90, indicating an excellent model fit. The SRMR value of 0.038 is below the threshold of 0.08, while the RMSEA value of 0.051 is below the recommended threshold of 0.07. Based on these results, it can be concluded that the four-factor measurement model demonstrates a good model fit and can therefore be used to represent the constructs measured in this study.

Table 4. Model Fit Indices

Model	χ^2	df	χ^2/df	CFI	TLI	SRMR	RMSEA
4 Factors (9 Items deleted)	163.212	71	2.29	0.981	0.976	0.038	0.051

Validity and Reliability Scale

Convergent validity was analyzed based on the Average Variance Extracted (AVE) values for each construct. The results of the validity and reliability assessment are presented in Table 5. The AVE values range from 0.349 to 0.583, indicating that some constructs meet the recommended threshold (≥ 0.50), while others fall slightly below this criterion. In addition, the Composite Reliability (CR) values for most constructs exceed 0.60, indicating acceptable internal consistency. However, the Adaptive Motivation construct shows a CR value of 0.561 and an AVE value of 0.349, suggesting that although the construct demonstrates moderate reliability, further refinement of its indicators may improve its measurement quality. Although Adaptive Motivation demonstrated lower CR and AVE values, the construct was retained because it remained theoretically meaningful and contributed to the overall conceptual model. Overall, these findings indicate that the instrument demonstrates

an acceptable level of validity and reliability for measuring adaptive learning constructs.

Table 5. CFA report for every construct model

Construct	Items	Factor Loading	CR	AVE
Feedback Awareness	PF1_2	0.695	0.826	0.583
	AA2_1	0.820		
	PF2_1	0.746		
	PF1_3	0.786		
	PF1_1	0.695		
Self-Regulation	SRL2_2	0.446	0.634	0.368
	GA2_3	0.663		
	SRL3_1	0.697		
	SRL1_2	0.588		
Regulation Deficit	SRL2_1	0.669	0.707	0.487
	SRL3_2	0.696		
	SRL1_1	0.728		
Adaptive Motivation	GA1_3	0.657	0.561	0.349
	GA1_1	0.554		
	AA1_1	0.557		

Based on the results of Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA), this study shows that the developed instrument has a relatively stable factor structure and is able to empirically represent the constructs of adaptive learning. Although the instrument was initially developed based on four theoretical constructs adaptive assessment (AA), adaptive gamification (AG), personalized feedback (PF), and self-regulated learning (SRL). The results of the EFA indicate a different empirical structure. The EFA results identified four main factors, namely feedback awareness, self-regulation, regulation deficit, and adaptive motivation, which were subsequently confirmed through CFA with good model fit indices. These findings indicate that the constructs of adaptive assessment (AA), adaptive gamification (AG), personalized feedback (PF), and self-regulated learning (SRL) do not fully operate as separate variables, but rather interact and form new, more integrated latent structures. To provide a clearer overview of the composition of the validated instrument, the details of items in each factor are presented in Table 6.

Table 6. Final Measurement Items

No	Item Code	Items Statements
1	AA1_1	The questions will be more effective for me if the level of difficulty is adjusted to my ability.
2	AA2_1	I do not feel the need to know the development of my abilities through assessment results.
3	GA1_1	Challenges that are adjusted to my ability can increase my learning motivation.
4	GA1_3	Game elements will be more motivating if they are tailored to my ability.
5	GA2_3	Gradual challenges can encourage me to complete tasks thoroughly.
6	PF1_1	Feedback that explains why an answer is correct or incorrect will help me understand the material.
7	PF1_2	I do not need specific feedback on my mistakes.

8	PF1_3	Feedback that aligns with my performance will support my learning process.
9	PF2_1	Feedback does not influence how I evaluate my learning process.
10	SRL1_1	I usually study without setting goals in advance.
11	SRL1_2	Planning my learning helps me complete tasks more effectively.
12	SRL2_1	I rarely monitor whether my learning strategies are effective.
13	SRL2_2	I am aware when my understanding of the material decreases.
14	SRL3_1	I consider it important to evaluate my learning outcomes after completing tasks.
15	SRL3_2	I rarely change my learning strategies even when the results are not satisfactory.

These findings are consistent with previous literature indicating that, in digital learning practices, the integration of adaptive assessment (AA), adaptive gamification (AG), and personalized feedback (PF) often results in interconnected adaptive mechanisms that support students' learning processes (Villegas-Ch et al., 2025; Yang et al., 2022). However, in contrast to most prior studies that tend to position these components separately, the results of this study show that these aspects can empirically converge into a more concise and contextual factor structure. This suggests that students' perceptions of adaptive learning systems are more holistic compared to the conceptual distinctions commonly found in the literature.

The first factor, namely feedback awareness, indicates that feedback plays a central role in shaping students' perceptions of learning effectiveness. The combination of items derived from the dimensions of personalized feedback and adaptive assessment within a single factor suggests that students do not strictly distinguish between the processes of evaluation and feedback provision rather, they perceive both as an integrated mechanism that supports learning comprehension. This finding reinforces previous research emphasizing that specific and timely feedback is a key component in enhancing learning quality and helping students independently identify their mistakes (Kinder et al., 2025; Weidlich et al., 2025).

The second factor, namely self-regulation, represents students' ability to plan, monitor, and evaluate their learning processes. Effective self-regulated learning involves the ability to manage learning goals, monitor progress, and reflect on learning outcomes. Planning, monitoring, and reflection are considered essential processes for achieving successful learning outcomes and are closely aligned with the self-regulation dimension identified in the present study (Vici et al., 2025). The structure of this factor indicates that SRL elements do not function in isolation but are also influenced by adaptive mechanisms such as gradual and contextual gamification. This aligns with findings suggesting that well designed adaptive systems can support self-regulation cycles by providing appropriate challenges and continuous performance-related information (Leung et al., 2023; Mejeh et al., 2024). Therefore, the integration of cognitive and motivational aspects becomes essential in supporting students' self-regulation.

In contrast, the third factor identified as regulation deficit reflects a negative dimension of SRL, where some students still demonstrate limitations in setting

goals, monitoring learning strategies, and engaging in reflection. The emergence of this factor as a distinct dimension indicates that self-regulation does not always develop optimally, even when supported by adaptive technologies. This finding is consistent with literature suggesting that the effectiveness of adaptive systems largely depends on individual characteristics, including students' self-regulation readiness and digital literacy (Oliveira et al., 2022; Yaseen et al., 2025). Such limitations may explain why some learners are unable to fully benefit from adaptive learning environments, as successful engagement with technology-based systems requires not only access to technology but also adequate digital readiness and learning preparedness (Insani & Irvan, 2026). In other words, the presence of adaptive technology does not automatically guarantee improvements in self-regulation without sufficient user readiness.

The fourth factor, namely adaptive motivation, integrates elements of adaptive gamification and adaptive assessment related to the adjustment of difficulty levels and learning challenges. This finding indicates that students' learning motivation is strongly influenced by the alignment between their ability levels and the level of challenge provided. This is in line with the concept of flow in learning, where the balance between skill and challenge is a key factor in maintaining engagement (Oliveira et al., 2022; Zhang & Huang, 2024). Previous studies have also shown that adaptive gamification can enhance student engagement and support higher order thinking by providing challenges that are adjusted to learners performance levels, reinforcing the importance of balancing challenge and ability in adaptive learning environments (Herlinda et al., 2026). Thus, adaptivity functions not only in the cognitive domain but also plays a significant role in the motivational aspect. The importance of adaptive motivation also aligns with the principles of personalized learning, where learning experiences are tailored to students' needs, interests, and abilities. When learning activities are adjusted to learners' readiness levels, students are more likely to remain motivated and actively engaged throughout the learning process. This supports the interpretation that adaptive learning mechanisms can foster sustained participation by providing appropriate levels of challenge and support (Lusiana et al., 2026).

Furthermore, the results of this study not only confirm the factor structure but also provide an empirical basis for the development of an SRL-based adaptive learning conceptual model, as illustrated in Figure 2. The model shows that the four identified factors (feedback awareness, adaptive motivation, self-regulation, and regulation deficit) are present simultaneously in each phase of the SRL cycle, namely goal setting, monitoring, and reflection. This indicates that self-regulation processes in adaptive learning are neither linear nor isolated, but rather involve dynamic interactions among cognitive, metacognitive, and motivational aspects at each stage of learning.

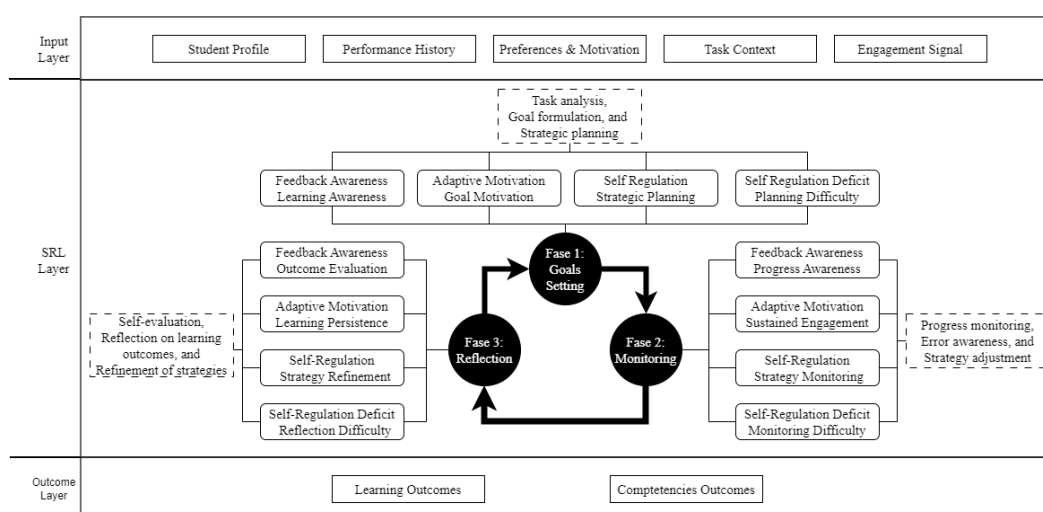


Figure 2. SRL-Based Adaptive Learning Conceptual Model

In the goal-setting phase, the four factors play a role in establishing the foundation of the learning process. Feedback awareness helps students understand their learning needs, adaptive motivation encourages the formulation of meaningful goals, self-regulation supports the planning of learning strategies, while regulation deficit may act as a barrier in this process. These findings reinforce the view that goal setting in SRL is influenced not only by cognitive aspects but also by perceptions of feedback and motivational conditions (Pintrich, 2004; Zimmerman, 2002). In the monitoring phase, the four factors interact in the process of tracking learning progress. Feedback awareness enables students to recognize errors and learning progress, adaptive motivation sustains engagement, self-regulation supports strategy adjustment, while regulation deficit reflects limitations in the monitoring process. This is consistent with studies indicating that effective monitoring requires the integration of feedback, motivation, and learning strategies (Weidlich et al., 2025; Xiao & Hew, 2024). Furthermore, in the reflection phase, the four factors again play roles in evaluating and improving the learning process. Feedback awareness supports the evaluation of learning outcomes, adaptive motivation maintains learning continuity, self-regulation enables strategy improvement, while regulation deficit indicates difficulties in conducting effective reflection. These findings emphasize that reflection is a complex process involving the interaction of multiple components within SRL (Hemmler & Ifenthaler, 2024).

Overall, the resulting model indicates that the effectiveness of adaptive learning is not solely determined by the presence of technology, but by how such technology is able to support the self-regulation cycle in a comprehensive and sustainable manner. The effectiveness of technology-supported learning environments is reflected not only in their technological sophistication but also in their capacity to enhance learning autonomy and student engagement, suggesting that adaptive technologies are most effective when they actively support learners' self-regulation processes (Yozaga et al., 2026). Therefore, the development of adaptive learning systems in vocational education needs to integrate assessment, motivation, and feedback within a holistic SRL framework (Mejeh et al., 2024; Yaseen et al., 2025).

Furthermore, this study not only contributes to the development of a valid and reliable instrument but also enriches the conceptual understanding of how adaptive learning components interact within the context of vocational education. The resulting factor structure demonstrates an integration of assessment, motivation, and feedback in supporting students' self-regulation processes. These findings open opportunities for the development of structural models to examine causal relationships among factors, as well as further exploration of the mediating role of SRL in enhancing the effectiveness of technology-based adaptive learning.

However, from a methodological perspective, this study still has limitations related to the sample size used in the instrument validation process. Although the number of respondents in this study meets the minimum requirements for factor analysis, several recent studies emphasize the importance of using larger sample sizes to improve the stability of factor structures and the accuracy of model estimation, particularly in EFA and CFA combinations. Recent studies indicate that sample sizes exceeding 500 respondents tend to produce more stable models and more consistent goodness of fit in confirmatory factor analysis (Goretzko et al., 2021; Hair Jr. et al., 2019). Therefore, to obtain stronger evidence regarding the resulting construct structure, future studies are strongly recommended to involve larger and more diverse samples. This step will not only enhance the generalizability of the findings but also strengthen external validity and the robustness of the measurement model across different contexts.

4. Conclusion

The present study aimed to develop and validate an instrument for measuring adaptive learning dimensions based on adaptive assessment, adaptive gamification, personalized feedback, and self-regulated learning within vocational education. The findings indicate that the proposed measurement model successfully captures students' perceptions of adaptive learning through four empirically derived factors, namely feedback awareness, self-regulation, regulation deficit, and adaptive motivation. The factor structure identified through Exploratory Factor Analysis was subsequently confirmed through Confirmatory Factor Analysis, demonstrating that the resulting model provides a coherent representation of adaptive learning dimensions.

The findings further suggest that adaptive learning is perceived by students as an integrated process in which feedback, motivation, and self-regulation interact to support learning experiences. Rather than functioning as separate dimensions, these elements collectively contribute to learners' ability to monitor progress, respond to feedback, and regulate their learning activities. This result highlights the importance of designing adaptive learning environments that not only personalize content and assessment but also actively foster students' self-regulatory capacities. The validated instrument contributes to the growing body of research on adaptive learning by providing a practical tool for evaluating adaptive learning implementation in educational settings. Future studies are encouraged to apply the instrument across different educational contexts and populations to further examine

its applicability and support the development of more effective adaptive learning systems.

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