Validation of an Adaptive Decision Support System Framework for Outcome-Based Blended Learning

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***Abstract*—The Adaptive Decision Support System Learning Framework (A-DSS-LF) was developed to address diverse learner needs in blended learning environments by integrating learning styles, cognitive levels, practical skills, and value practices. This study validates the framework using the Fuzzy Delphi Method (FDM), a consensus-building tool that synthesizes expert opinions and addresses uncertainties in subjective judgments. A panel of 15 experts evaluated the framework's constructs: Learning Process, Learning Assessment, Decision Support System, and Adaptive Learning Profile. All constructs met the FDM's consensus criterion, achieving threshold values between 0.087 and 0.118 (≤0.2), indicating high consistency and low variability. The defuzzification process confirmed values exceeding 0.5, with scores ranging from 0.873 to 0.922 and expert agreement surpassing 75 percent for all elements. These findings confirm the robustness and applicability of the A-DSS-LF, validating its role in enhancing personalized learning outcomes and supporting teachers in tailoring adaptive learning resources. The framework is scalable and can be implemented in secondary school computer science education and online learning platforms to create personalized learning paths, improve engagement, and bridge the gap between online and offline learning. This study reinforces the significance of expert validation in adaptive learning frameworks, ensuring their scalability and adaptability for future applications in diverse educational settings.**

Keywords—Learner needs; adaptive learning; blended learning; fuzzy delphi method; decision support system

I. Introduction

In modern education, learners exhibit diverse needs, preferences, and abilities, requiring tailored educational approaches to enhance engagement and improve learning outcomes. According to study [1] and study [2], adaptive learning frameworks have emerged as a promising solution by leveraging computerized algorithms and data-driven methodologies to personalize learning experiences based on individual learner characteristics. Unlike traditional one-size-fits-all teaching methods, these frameworks dynamically adjust content and instructional strategies, allowing learners to receive materials tailored to their cognitive and behavioral profiles [3] [4]. This adaptability enhances student engagement and optimizes learning outcomes by ensuring that instructional content aligns with individual learning needs.

Particularly in blended learning environments, adaptive learning plays a crucial role in bridging online and offline learning components. As highlighted by study [5] and study [6], these frameworks create a more flexible and structured learning approach, allowing seamless integration between traditional and technology-enhanced learning experiences. This integration ensures that adaptive learning is not only personalized but also scalable and adaptable to different educational settings.

Several adaptive learning frameworks have been developed to facilitate personalized learning experiences, with many operating within Learning Management Systems (LMS). For instance, the study in [7] proposed a three-stage implementation model designed to scale adaptive learning in fully online education, focusing on faculty training and infrastructure development. Similarly, the study in [8] introduced a knowledge-based adaptive model that aligns instructional content with students' proficiency levels, while [9] developed an Adaptive Virtual Learning Environment (AVLE) structured around content, student, and adaptation models to provide personalized learning paths. The Adaptive Learning System-Knowledge Level (ALS-KL) by study [10] utilized pre-test and post-test assessments to classify learners and deliver content suited to their knowledge levels.

Despite their potential, existing adaptive learning frameworks face significant limitations that hinder their effectiveness in diverse educational settings. The studies in[5] and [9] highlight that many models rely heavily on Learning Management Systems (LMS), making them less adaptable for classroom-based learning environments that require seamless integration between online and offline instruction. Additionally, the studies in [11] and [12] emphasize that most frameworks primarily focus on cognitive aspects while neglecting other critical learner attributes, such as practical skills and value-based learning, which are essential for holistic education. The absence of these elements limits the ability of adaptive learning to fully support diverse learner needs.

Furthermore, the studies in [13] and [1] argue that many adaptive learning frameworks lack rigorous validation mechanisms, raising concerns about their effectiveness, scalability, and generalizability in different educational settings. Without systematic validation, these frameworks may fail to achieve consistent learning improvements across varied instructional contexts. Addressing these challenges requires a comprehensive and validated framework that integrates multiple learner characteristics while ensuring practical implementation in blended learning environments.

To bridge these gaps, this study introduces the Adaptive Decision Support System Learning Framework (A-DSS-LF), designed to provide a more holistic and data-driven adaptive

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learning experience. A-DSS-LF differs from existing frameworks in several ways. Unlike traditional models that focus solely on cognitive skills, A-DSS-LF integrates learning styles, cognitive levels, practical skills, and value practices to offer a well-rounded personalized learning experience. Additionally, while many adaptive learning models are designed primarily for LMS-based environments, A-DSS-LF is structured to seamlessly integrate both online and offline learning environments, making it more suitable for blended learning. Another key feature of A-DSS-LF is its inclusion of a Decision Support System (DSS), which enables educators to make data-driven instructional decisions and adapt learning interventions based on students' needs, a capability often missing in many existing adaptive learning frameworks. To ensure its effectiveness, adaptability, and scalability, A-DSS-LF is rigorously validated using the Fuzzy Delphi Method (FDM), allowing expert consensus to confirm its applicability in real-world educational settings. These features position A-DSS-LF as a scalable and personalized approach to adaptive learning, supporting both student-centered learning and teacher-driven instructional strategies in blended learning environments.

The objective of this study is to present the validation process and findings of the A-DSS-LF using the Fuzzy Delphi Method (FDM). This study aims to establish expert consensus on the framework's constructs and components, ensuring its robustness, scalability, and applicability in blended learning environments. By detailing the validation process, this study examines how expert feedback informs the refinement and validation of A-DSS-LF to align with modern educational needs. Additionally, it evaluates the findings of the analysis, confirming the framework's effectiveness in supporting personalized learning pathways and educator-driven decision-making. Through this validation, the study contributes to the development of rigorously tested adaptive learning frameworks, ensuring their practical implementation in real-world educational settings to enhance adaptive learning experiences and improve instructional decision-making.

The remainder of this article is structured as follows. Section II reviews related work on the FDM, highlighting its significance in expert-based validation. Section III details the FDM validation methodology, including expert selection and analysis procedures. Section IV presents the key findings, followed by a discussion in Section V. Finally, Section VI concludes with implications and future research directions.

II. Related Work

To ensure the robustness and applicability of A-DSS-LF, a rigorous validation method is required. Traditional validation approaches may lack precision in expert-driven refinements, making them less suitable for validating adaptive learning frameworks. To address this challenge, this study employs the Fuzzy Delphi Method (FDM), a structured approach that systematically refines framework components through expert consensus. The following section explores FDM, its significance in validation research, and its applications in education.

A. *Fuzzy Delphi Method (FDM)*

Given the complexity of adaptive learning frameworks, robust validation measures are essential to ensure their effectiveness. The Fuzzy Delphi Method (FDM) was selected in this study for its ability to address uncertainty and systematically establish expert consensus. Originally introduced by [14] and later refined by study [15], FDM enhances the traditional Delphi Method by integrating fuzzy logic principles, allowing for quantitative evaluation of expert judgments. The study in [16] demonstrated FDM's extensive applications in education, technology, and policy-making, where iterative refinement of theoretical models is necessary.

Unlike conventional validation approaches, FDM refines framework components iteratively, ensuring expert consensus is achieved through multiple evaluation rounds. This process systematically reduces ambiguity and enhances precision in decision-making [17]. By incorporating expert-driven refinements, FDM ensures A-DSS-LF aligns with best practices in adaptive learning, strengthening its adaptability to blended learning environments.

Several validation methods exist for refining adaptive learning frameworks, yet each has notable limitations. Traditional expert review methods, as described by study [18], rely heavily on qualitative assessments and descriptive feedback, often introducing bias and inconsistencies. FDM, by contrast, provides a structured and quantifiable approach, ensuring expert evaluations are numerically analyzed rather than solely based on subjective agreement. Structural Equation Modeling (SEM), commonly used for model validation [19], requires large datasets and strong statistical assumptions, making it unsuitable for early-stage validation where expert input is prioritized. Similarly, Design-Based Research (DBR) emphasizes real-world implementation through iterative testing [20], but its time-intensive nature makes it less practical for preliminary validation stages.

In contrast, Analytic Hierarchy Process (AHP), as proposed by study [21], is widely used for ranking framework components based on weighted criteria. However, it lacks iterative expert feedback loops, making it less effective for dynamically evolving frameworks such as A-DSS-LF. Pilot testing with end-users, though essential for usability validation, is more beneficial in later stages once a framework has been theoretically refined [22]. Given these comparisons, FDM emerges as the most suitable validation method for A-DSS-LF, as it ensures a balance between theoretical validation and expert-driven iterative refinement.

The effectiveness of FDM has been widely demonstrated in prior research. The studies in [17] and [23] applied FDM to validate STEM teaching modules and immersive learning innovations, ensuring that expert recommendations were systematically incorporated into framework refinements. Similarly, the study in [24] demonstrated FDM's utility in validating hybrid learning strategies, synthesizing diverse expert opinions while maintaining theoretical and practical relevance. [25] and [16] confirm that FDM's consensus thresholds—such as a defuzzification coefficient ($d \leq 0.2$) and expert agreement exceeding 75%—enhance reliability and consistency in validation outcomes. These findings reinforce FDM's reliability as a consensus-driven method, confirming its adaptability to various educational settings.

While FDM serves as the primary validation method, complementary approaches such as DBR, AHP, and Pilot Testing contribute to specific aspects of framework validation. DBR enables iterative real-world refinement [20], AHP prioritizes framework components systematically [21], and pilot testing gathers usability insights for final-stage improvements [22]. Together, these methods contribute to a robust validation process, ensuring both theoretical soundness and practical applicability.

FDM's ability to quantify expert judgments, structure consensus, and support iterative refinements makes it an indispensable validation tool for educational research. Prior studies [17], [23], and [24] confirm its effectiveness in aligning theoretical models with real-world applications. Furthermore, FDM's alignment with contemporary challenges, including hybrid learning environments and emerging educational technologies, reinforces its continued relevance as a critical validation method for adaptive learning frameworks.

III. METHODOLOGY

As previously discussed, this study applies the FDM, introduced by study [15] to validate the proposed A-DSS-LF. The validation process follows a three-phase approach to ensure a systematic and structured evaluation of the framework. The following section provides a detailed explanation of each phase.

A. Expert Selection

To achieve consensus on the developed framework, purposive sampling was employed, a method particularly suited to the FDM, as noted by study [18]. The sample for this study comprised experts in the field of education. According to [26], an expert is an individual with extensive knowledge and skills in a specific domain, which in this context refers to subject matter experts. A panel of 23 experts was selected based on their roles, years of experience, and areas of expertise within the field of education. The number of experts selected aligns with study [18] recommendation that 10 to 50 participants are sufficient when the group is relatively uniform or homogenous. The selection criteria included educators with a minimum of 10 years of relevant experience, familiarity with teaching and learning practices, and holding various roles such as Head of Subject Panel, Chief Subject Assessor, School Improvement Specialist Coaches (SISC+), professors, Assistant Education Officers, and Senior Subject Teacher. This diverse panel ensured a comprehensive and well-rounded evaluation of the framework.

B. A-DSS-LF Expert Validation

The process was implemented in four key stages. The first stage involved the presentation of the A-DSS-LF to the expert panel through an online session. This presentation provided an overview of the framework, detailing its components, objectives, and application within blended learning environments. The session aimed to ensure that experts thoroughly understood the framework, enabling them to offer informed and constructive feedback. Following the presentation, a structured questionnaire was distributed to the experts. The questionnaire gathered insights on the framework's relevance, feasibility, and practicality. It incorporated closed-ended questions, evaluated using a fuzzy Likert scale, and used open-ended items to capture qualitative feedback. This combination ensured a comprehensive assessment of the framework.

The 7-point Likert scale was used in this research to identify the constructs and elements of the A-DSS-LF, similar to the approach taken by study [23] and study [27]. The study in [23] utilized the 7-point Likert scale to develop constructs and elements for a framework, emphasizing its accuracy and ability to reduce ambiguity compared to a 5-point scale. Similarly, the study in [27] employed a 7-point Likert scale in their study to evaluate expert agreement on mobile learning implementation in competency-based education, analysing responses using fuzzy logic techniques. These precedents highlight the scale's suitability for capturing nuanced expert feedback in framework development. The linguistic variables were aligned with fuzzy scales to facilitate expert responses, as shown in Table I. The table illustrates the mapping of linguistic variables (e.g., "Strongly disagree," "Moderately agree") to their corresponding Likert scale values and fuzzy scale representations. This approach ensures that the fuzzy logic analysis is grounded in systematically quantified expert input, enhancing the precision of consensus measurement.

TABLE I. LINGUISTIC VARIABLE SCALE

Linguistic Variables	Likert Scale	Fuzzy Scale
Strongly disagree	1	(0.0,0.0,0.1)
Moderately disagree	2	(0.0,0.1,0.1)
Slightly disagree	3	(0.1,0.3,0.5)
Neutral	4	(0.3,0.5,0.7)
Slightly agree	5	(0.5,0.7,0.9)
Moderately agree	6	(0.7,0.9,1.0)
Strongly agree	7	(0.9,1.0,1.0)

Source: [28]

In the third stage, feedback collection was conducted. Experts submitted responses that included both quantitative and qualitative data. Quantitative feedback measured levels of agreement on various aspects of the framework, while qualitative feedback provided additional insights and actionable suggestions for refinement. Finally, the application of fuzzy logic for analysis was carried out. The collected data was analysed using fuzzy logic principles to measure the degree of expert consensus systematically. This structured approach ensured that the validation of the A-DSS-LF was grounded in expert consensus, enhancing its robustness and practical applicability in addressing diverse learner needs in blended learning environments.

C. Validation of Constructs and Elements Through Fuzzy Delphi Analysis for the A-DSS-LF

The analysis of questionnaire data using the FDM involved three main steps: applying Triangular Fuzzy Numbers, calculating the Expert Consensus Percentage, and performing the Defuzzification Process. These steps systematically assessed the expert responses to validate the constructs and elements of the A-DSS-LF. The linguistic variable data obtained from experts in this study, as shown in Table I, must be converted into Triangular Fuzzy Numbers. The Triangular Fuzzy Number has three values, m_1, m_2, and m_3, indicating the minimum, reasonable, and maximum values, as shown in Fig. 1.

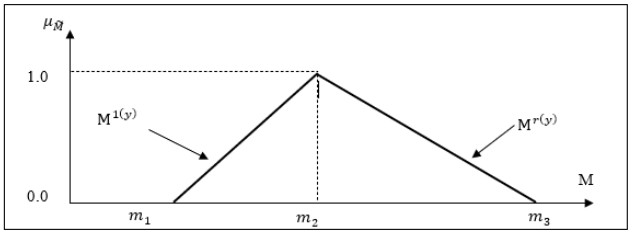

Fig. 1. The Triangular fuzzy number.

Next, the threshold value (*d*) is calculated to measure the dispersion of expert opinions. An element is considered to have achieved expert consensus if $d \leq 0.2$, meaning that every element with a threshold value (*d*) equal to or less than 0.2 is accepted. As shown in Fig. 1, the threshold value (*d*) is calculated using Formula (1).

$$(\tilde{m}\,\tilde{n}) = \sqrt{\frac{1}{3}\left[(m_1 - n_1)^2 + (m_2 - n_2)^2 + (m_3 - n_3)^2\right]} \quad (1)$$

The second step involves calculating the percentage of expert agreement. According to the traditional Delphi technique, an item is accepted if the percentage of agreement among the expert group exceeds 75% [23], [29], [30]. Another requirement in the FDM is the defuzzification process. This step involves analysing the data by averaging fuzzy numbers to calculate the Fuzzy score (A). The Fuzzy score (A) must be greater than or equal to the median value (α-cut value) of 0.5 [19], [31], indicating that the element has achieved expert consensus. The Fuzzy score (A) determines the ranking and identifies acceptable elements based on expert agreement. An item is accepted if the Fuzzy score (A) is equal to or greater than 0.5; otherwise, it is rejected. The fuzzy score (A) is calculated using the formula shown in Formula (2).

$$A = (1/3) * (\mu_1 + \mu_2 + \mu_3) \quad (2)$$

The summary of conditions for the acceptable elements for the A-DSS-LF is shown in Table II.

TABLE II. KEY METRICS FOR FUZZY LOGIC ANALYSIS

Metric	Description	Conditions
Threshold Value (*d*)	Measures the dispersion of expert opinions. Consensus is achieved if $d \leq 0.2$.	$d \leq 0.2$
Percentage Agreement	The proportion of experts agreeing on an element.	> 75%
Defuzzification	Converts fuzzy values into crisp numbers for interpretation.	≥ α-cut value = 0.5

Following the criteria outlined in Table II, the analysis confirmed that elements meeting both the threshold value ($d \leq 0.2$) and achieving a Fuzzy score ($A \geq 0.5$) were accepted. Additionally, elements that achieved an expert consensus percentage of more than 75% were validated. These combined criteria include only elements with strong expert agreement and alignment. The ranked elements provide valuable insights into the framework's relevance and feasibility, reinforcing its robustness in addressing diverse learner needs.

IV. RESULT

This section presents the findings of the FDM analysis conducted to validate the constructs and elements of the A-DSS-LF. The findings include an overview of the expert demographic information and the outcomes of the FDM validation process.

A. Expert Demographic Information

Due to scheduling challenges and time constraints, only 15 experts were available for the final discussion session. This number still falls within the range of 10 to 15 experts suggested by study [32] for achieving a reliable consensus when the expert group is not homogeneous. The expert panel in this study reflects a diverse range of qualifications, expertise, and professional experience, ensuring robust and informed feedback during the validation process. Table III summarises their demographics, categorised into three key areas: Level of Education, Work Experience, and Field of Expertise.

TABLE III. SUMMARY OF EXPERT PANEL

Level of Education	Frequency
PhD	2
Master Degree	4
Bachelor Degree	9
Total	15
Work Experience (Years)	**Frequency**
11 to 15 years	1
16 to 20 years	5
More than 20 years	9
Total	15
Field of Experts	**Frequency**
Information Technology	1
Business Management	2
Education Technology	1
Coaching	1
Science and Mathematics	2
Accounting	1
Multimedia	1
History	1
Computer Science	1
Languages	2
Physical Education	1
Decision Support Systems	1
Total	15

This diversity of backgrounds, spanning fields such as educational technology, decision support systems, computer science, and language studies, adds significant value to the consensus-building process. It ensures a comprehensive evaluation of the A-DSS-LF and its applicability in blended learning environments.

B. Expert Consensus Findings Using the FDM

Data analysis from the closed-ended questionnaire was conducted systematically using a Microsoft Excel data sheet developed by study [33]. This framework has four constructs:

the Learning Process, the Learning Assessment, the Decision Support System, and the Adaptive Learning Profile. Each construct comprises three elements, except for the Learning Assessment, which includes seven

Refer to Table V, which shows th. The elements given to the experts are stated in Table IV.at the threshold value (*d*) for each construct is below the acceptable limit (*d*≤0.2), indicating that all constructs meet the FDM qualification criteria. Specifically, the overall threshold value (*d*) for the Learning Process construct is *d*=0.114, the Learning Assessment construct is *d*=0.094, the Decision Support System construct is d=0.092, and the Adaptive Learning Profile construct is *d*=0.097. These values confirm that all constructs are acceptable based on the Fuzzy Delphi process.

In addition, individual elements within the constructs also meet the Fuzzy qualification requirement, with *d*≤0.2 for each element. The details are below:

- Learning Process elements: E1 (d=0.111), E2 (d=0.112), and E3 (d=0.118) are all acceptable.
- Learning Assessment elements: E4 (d=0.094), E5 (d=0.087), E6 (d=0.094), E7 (d=0.112), E8
- (d=0.089), E9 (d=0.094), and E10 (d=0.094) meet the requirement.
- Decision Support System elements: E11 (d=0.087), E12 (d=0.087), and E13 (d=0.102) are within the threshold.
- Adaptive Learning Profile elements: E14 (d=0.108), E15 (d=0.092), and E16 (d=0.092) are also acceptable.

TABLE IV. ELEMENTS FOR THE A-DSS-LF ACCORDING TO THE CONSTRUCTS

Learning Process	
E1	Apply adaptive learning in the blended learning environment.
E2	Apply student-centred approach
E3	Apply self-regulated learning
Learning Assessment	
E4	Identify students' learning styles.
E5	Apply a learning style model to determine students' learning styles.
E6	Use systematic instruments to assess students' learning styles.
E7	Use systematic instruments to evaluate student's learning status.
E8	Use systematic instruments capable of measuring specific learning objectives.
E9	Use systematic instruments to assess various learning domains, including cognitive skills, practical skills, and value practices.
E10	Use systematic instruments with clear criteria to determine students' mastery levels for various learning domains.
Decision Support System	
E11	Utilise identified student characteristics (student model) to make adaptive decisions.
E12	Use a collection of information (learning object model) to support adaptive decision-making.
E13	Apply criteria to align student characteristics with available information for making adaptive decisions.
Adaptive Learning Profile	
E14	Recommend personalized learning paths based on students' characteristics.
E15	Provide tailored feedback aligned with students' characteristics.
E16	Suggest learning resources that match students' characteristics.

TABLE V. SUMMARY OF THRESHOLD VALUE FOR CONSTRUCTS AND ELEMENTS IN A-DSS-LF

Experts	Learning Process			Learning Assessment							Decision Support System			Adaptive Learning Profile		
	E1	**E2**	**E3**	**E4**	**E5**	**E6**	**E7**	**E8**	**E9**	**E10**	**E11**	**E12**	**E13**	**E14**	**E15**	**E16**
1	0.102	0.092	0.138	0.132	0.107	0.086	0.092	0.096	0.066	0.086	0.107	0.107	0.122	0.112	0.096	0.096
2	0.055	0.065	0.031	0.027	0.047	0.067	0.065	0.057	0.066	0.067	0.047	0.047	0.036	0.045	0.057	0.057
3	0.102	0.092	0.138	0.132	0.107	0.086	0.092	0.096	0.066	0.086	0.107	0.107	0.122	0.112	0.096	0.096
4	0.102	0.092	0.138	0.132	0.107	0.086	0.092	0.096	0.066	0.086	0.047	0.047	0.036	0.045	0.096	0.096
5	0.055	0.092	0.031	0.027	0.047	0.067	0.301	0.057	0.088	0.067	0.047	0.047	0.273	0.282	0.057	0.057
6	0.102	0.301	0.256	0.027	0.047	0.067	0.092	0.096	0.066	0.086	0.047	0.047	0.036	0.112	0.096	0.096
7	0.102	0.092	0.138	0.132	0.107	0.086	0.092	0.096	0.066	0.086	0.107	0.107	0.122	0.112	0.096	0.096
8	0.102	0.092	0.138	0.263	0.047	0.086	0.092	0.096	0.066	0.086	0.107	0.107	0.122	0.112	0.096	0.096
9	0.102	0.092	0.031	0.027	0.047	0.086	0.092	0.057	0.066	0.086	0.047	0.107	0.036	0.112	0.057	0.057
10	0.292	0.065	0.256	0.027	0.289	0.308	0.065	0.057	0.327	0.067	0.047	0.047	0.273	0.045	0.057	0.057
11	0.055	0.065	0.256	0.027	0.047	0.067	0.301	0.299	0.088	0.308	0.047	0.289	0.036	0.282	0.299	0.299
12	0.292	0.301	0.031	0.263	0.047	0.067	0.092	0.057	0.088	0.067	0.047	0.047	0.036	0.045	0.057	0.057
13	0.055	0.092	0.031	0.027	0.107	0.086	0.065	0.057	0.088	0.067	0.107	0.047	0.122	0.045	0.057	0.057
14	0.055	0.065	0.031	0.027	0.047	0.067	0.065	0.057	0.066	0.067	0.289	0.047	0.036	0.045	0.057	0.057
15	0.102	0.092	0.138	0.132	0.107	0.086	0.092	0.096	0.066	0.086	0.107	0.107	0.122	0.112	0.096	0.096
Threshold Value (*d*) for each	**0.111**	**0.112**	**0.118**	**0.094**	**0.087**	**0.094**	**0.112**	**0.092**	**0.089**	**0.094**	**0.087**	**0.087**	**0.102**	**0.108**	**0.092**	**0.092**
Value (*d*) Construct	**0.114**			**0.094**							**0.092**			**0.097**		

Furthermore, the Fuzzy qualification requirement includes the percentage of expert consensus, which must exceed more than 75% for each element. The results demonstrate that all items meet this additional criterion, ensuring strong expert agreement for all elements and constructs. The threshold value (*d*), expert consensus percentage, defuzzification, and item position for the above elements are shown in Table VI.

Table V summarises the defuzzification process for the four constructs: Learning Process, Learning Assessment, Decision Support System, and Adaptive Learning Profile. The findings provide insight into the priority and significance of each element, as detailed below:

1) Learning process: The Learning Process construct comprises three elements, with Fuzzy scores (A) ranging from 0.873 to 0.904. All elements exceeded the FDM's α-cut value of A≥0.5 and met the expert consensus benchmark of more than 75%, confirming their acceptability and inclusion in the framework. The highest-ranked element, E2 (A=0.904, Rank1), demonstrates the most substantial expert agreement. E1 (A=0.898, Rank2) follows closely, reflecting its prioritization within the construct. Although ranked lowest, E3 (A=0.873, Rank3) still satisfies the Fuzzy Delphi criteria, validating its inclusion.

2) Learning assessment: The Learning Assessment construct comprises seven elements, with Fuzzy scores (A) ranging from 0.878 to 0.922. All elements exceeded the FDM's α-cut value of A≥0. and met the expert consensus benchmark of more than 75%, confirming their acceptability and inclusion in the framework. The highest-ranked element, E9 (A=0.922, Rank1), reflects the most substantial expert agreement, likely due to its alignment with the primary objectives of the construct. E6 (A=0.909, Rank2) and E10 (A=0.909, Rank2) share the second rank, highlighting their equal importance. E7 (A=0.904, Rank4) and E8 (A=0.902, Rank5) follow closely, demonstrating high levels of expert agreement. Although ranked lower, E5 (A=0.896, Rank6) and E4 (A=0.878, Rank7) remain valid, contributing to the construct's comprehensiveness.

3) Decision support system: The Decision Support System construct consists of three elements, with Fuzzy scores (A) ranging from 0.884 to 0.896. All elements exceeded the FDM's α-cut value of A≥0.5 and met the expert consensus benchmark of more than 75%, validating their inclusion in the framework. The highest-ranked element, E11 (A=0.896, Rank1), reflects strong expert prioritization. E12 (A=0.884, Rank2) and E13 (A=0.884, Rank2) share the second rank, indicating equal agreement and relevance within the construct.

4) Adaptive learning profile: The Adaptive Learning Profile construct comprises three elements, with Fuzzy scores (A) ranging from 0.891 to 0.902. All elements exceeded the FDM's α-cut value of A≥0.5 and met the expert consensus benchmark of more than 75%, confirming their acceptability. E15 (A=0.902, Rank1) and E16 (A=0.902, Rank1) share the top rank, reflecting the most substantial expert agreement and prioritization. Although ranked lower, E14 (A=0.891, Rank3) remains valid and aligned with the Fuzzy Delphi criteria, validating its inclusion in the construct.

TABLE VI. SUMMARY OF THE DEFUZZIFICATION PROCESS FOR CONSTRUCTS AND ELEMENTS IN A-DSS-LF

Elements	**Triangular Fuzzy Numbers**		**Defuzzification Process**				**Expert Consensus**	**Acceptable Element**	**Ranking**
	Threshold, *d*, value	**% Expert Consensus**	m_1	m_2	m_3	**Fuzzy Score (A)**			
Learning Process									
1	0.111	87%	0.780	0.927	0.987	0.898	Accepted	0.898	2
2	0.112	87%	0.793	0.933	0.987	0.904	Accepted	0.904	1
3	0.118	80%	0.740	0.900	0.980	0.873	Accepted	0.873	3
Learning Assessment									
4	0.094	87%	0.740	0.907	0.987	0.878	Accepted	0.878	7
5	0.087	93%	0.767	0.927	0.993	0.896	Accepted	0.896	6
6	0.094	93%	0.793	0.940	0.993	0.909	Accepted	0.909	2
7	0.112	87%	0.793	0.933	0.987	0.904	Accepted	0.904	4
8	0.092	93%	0.780	0.933	0.993	0.902	Accepted	0.902	5
9	0.089	93%	0.820	0.953	0.993	0.922	Accepted	0.922	1
10	0.094	93%	0.793	0.940	0.993	0.909	Accepted	0.909	2
Decision Support System									
11	0.087	93%	0.767	0.927	0.993	0.896	Accepted	0.896	2
12	0.087	93%	0.767	0.927	0.993	0.896	Accepted	0.896	1
13	0.102	87%	0.753	0.913	0.987	0.884	Accepted	0.884	3
Adaptive Learning Profile									
14	0.108	87%	0.767	0.920	0.987	0.891	Accepted	0.891	3
15	0.092	93%	0.780	0.933	0.993	0.902	Accepted	0.902	1
16	0.092	93%	0.780	0.933	0.993	0.902	Accepted	0.902	1

All elements' Fuzzy scores (A) range from 0.873 to 0.922, exceeding the FDM's α-cut value of A≥0.5 and the more than 75% expert consensus benchmark, confirming their validity. The findings highlight the prioritization of significant elements, such as E2 in the Learning Process, E9 in the Learning Assessment, E11 in the Decision Support System, and E15/E16 in the Adaptive Learning Profile. These results provide a robust foundation for the A-DSS-LF, ensuring its alignment with expert consensus and relevance in addressing diverse learner needs.

Table VII presents the summary ranking of all elements. According to Table VII, experts reached the highest agreement on E9 (A=0.922), emphasizing the importance of using systematic instruments to assess various learning domains. This element is the most essential component in the proposed A-DSS-LF framework.

TABLE VII. SUMMARY RANKING OF ALL A-DSS-LF ELEMENTS

Ranking	Acceptable Element	Elements
1	0.922	E9
2	0.909	E6
2	0.909	E10
4	0.904	E2
4	0.904	E7
6	0.902	E8
6	0.902	E15
6	0.902	E16
9	0.898	E1
10	0.896	E12
11	0.896	E5
11	0.896	E11
13	0.891	E14
14	0.884	E13
15	0.878	E4
16	0.873	E3

V. DISCUSSION

This section discusses the implications of the findings from the FDM analysis in validating the A-DSS-LF. It interprets the results, highlighting how the validated constructs and elements align with the study's objectives and contribute to a robust framework. Furthermore, the discussion explores the relevance of these findings in supporting personalized learning pathways within blended learning environments. Lastly, it identifies limitations and suggests directions for future research to enhance the framework's applicability and impact.

A. *Expert Panel and Its Role in FDM Validation*

In this study, the number of experts on the panel, 15, for the FDM process was deemed acceptable, although it did not fully meet the desired target. Prior research supports this approach, as studies such as [27], [23], [29], and [17] have employed expert panels ranging from 11 to 17 participants to achieve consensus on educational frameworks. Selecting an appropriate number of experts is critical to ensuring diverse perspectives, reliable consensus, and statistical robustness. This study's selection of 15 experts aligns with established FDM practices, thereby enhancing the credibility of the findings.

B. *FDM Validation of A-DSS-LF*

This section discusses the findings from the FDM validation, confirming the relevance of the A-DSS-LF. The results demonstrate that all elements across the four key constructs—Learning Process, Learning Assessment, Decision Support System, and Adaptive Learning Profile—achieved strong expert consensus. Each element successfully fulfilled the three essential criteria for FDM analysis:

- Meeting the required threshold value ($d \leq 0.2$).
- Achieving an expert agreement of >75%.
- Exceeding the α-cut defuzzification score ($A \geq 0.5$).

These findings validate the A-DSS-LF framework's ability to support adaptive learning in blended environments, reinforcing its role in enhancing engagement, personalization, and data-driven decision-making. The interactions between the four constructs—Learning Process, Learning Assessment, Decision Support System, and Adaptive Learning Profile—are illustrated in Fig. 2, showing how these components collectively enable adaptive learning experiences.

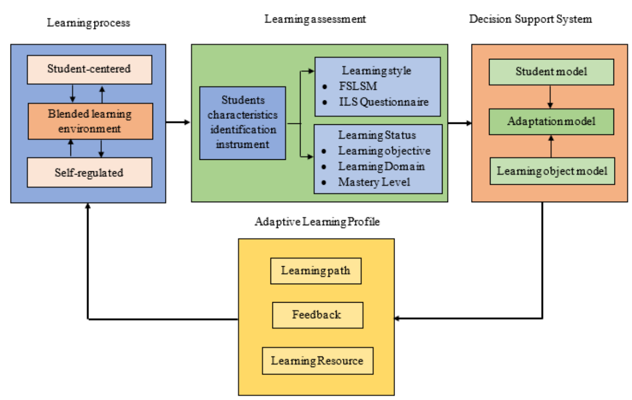

Fig. 2. Adaptive-decision support system-learning framework.

The following subsections provide a detailed discussion of the research findings, focusing on expert validation for each construct and the significance of the validated elements in supporting adaptive learning within the A-DSS-LF framework.

1) Learning process: The effectiveness of a structured learning process within a blended learning environment depends on its ability to adapt to individual learner needs, promote student-centered learning, and encourage self-regulation. Expert validation conducted in this study confirms the importance of these three key elements—blended learning environment, student-centered approaches, and self-regulated learning—as fundamental components in the learning process within the A-DSS-LF. All elements surpassed the α-cut threshold ($A \geq 0.5$) and the 75% consensus benchmark, confirming their necessity in the A-DSS-LF framework. Experts agreed that integrating these elements enhances learner engagement and autonomy while aligning with best practices in adaptive learning and blended education models.

Among these, applying a student-centered approach (A = 0.904, Rank 1) received the highest expert consensus, emphasizing its role in fostering learner autonomy, engagement, and decision-making. The findings indicate that placing students at the center of the learning process improves motivation and enhances participation, reinforcing the importance of active learning strategies. This aligns with prior research, which highlights that student-centered learning fosters self-directed learning and critical thinking [34][35][36]. Applying adaptive learning in the blended learning environment (A = 0.898, Rank 2) was also strongly supported, as experts acknowledged that personalized learning paths, tailored feedback, and flexible progression help accommodate diverse learning needs. Previous studies similarly emphasize that adaptive learning improves instructional effectiveness by allowing students to advance at their own pace while receiving personalized support [7][37].

Although applying self-regulated learning (A = 0.873, Rank 3) ranked lowest, experts agreed on its significance in fostering learner independence, metacognitive skills, and academic performance. The findings suggest that students who engage in self-regulated learning demonstrate greater persistence and improved learning outcomes, particularly when they receive structured feedback and tracking tools. This is consistent with [38], who found that students with strong self-regulation skills achieve higher engagement and academic success in digital learning environments. Additionally, [39] emphasize that goal setting, adaptive scaffolding, and self-monitoring mechanisms are crucial in supporting self-regulation, reinforcing the importance of incorporating these strategies into the A-DSS-LF framework.

2) Learning assessment: A practical learning assessment is crucial for understanding student progress, identifying learning gaps, and personalizing instructional strategies. In Malaysian secondary education, the National Philosophy of Education emphasizes balancing cognitive, practical, and value-based domains. The FDM validation in this study confirms the importance of systematic learning assessments, with all elements surpassing the α-cut threshold ($A \geq 0.5$) and the 75% consensus benchmark, validating their inclusion in the A-DSS-LF.

Among these elements, systematic instruments with clear criteria to determine students' mastery levels (A = 0.922, Rank 1) received the most substantial expert consensus, highlighting the need for structured assessment frameworks. This aligns with [40], who demonstrated the effectiveness of DSS in behavioral modeling for personalized learning assessments. Similarly, [41] emphasizes that clear mastery criteria in formative assessments enhance student motivation and outcomes.

Assessing various learning domains (A = 0.909, Rank 2) also gained strong support, reinforcing the need for comprehensive, multidimensional assessments beyond cognitive evaluation to practical skills and value-based learning. The study in [1] validated this approach, showing that adaptive learning paths based on learner profiles improve engagement and achievement, a perspective supported by study [42], who highlight that digital assessment tools enhance data-driven instructional adjustments.

Identifying students' learning styles (A = 0.904, Rank 4) and applying a learning style model (A = 0.902, Rank 5) were also validated, reinforcing the importance of personalized education. The Felder-Silverman Learning Style Model (FSLSM) is a core component of the A-DSS-LF framework, aligning with studies that emphasize tailored instructional strategies [37] [43]. [44] further supports these findings, demonstrating that systematic learning style classification enhances adaptive learning effectiveness, ensuring that students receive personalized support, leading to better engagement and learning outcomes.

3) Decision support system: The DSS is a pivotal component of the A-DSS-LF, enabling adaptive learning decisions based on structured data analysis. The FDM validation confirms the DSS's importance, with all elements surpassing the α-cut threshold ($A \geq 0.5$) and the 75% consensus benchmark, validating its critical role in the framework.

Among these elements, utilizing identified student characteristics (A = 0.896, Rank 1) received the most substantial expert consensus, emphasizing the need for tailoring learning experiences based on student profiles. This aligns with [45], who highlighted the potential of ontology-based DSS for predictive learning and [46], who demonstrated that tailored educational technologies enhance engagement and satisfaction.

Experts also validated using a collection of information (A = 0.884, Rank 2) and applying criteria to align student characteristics with learning resources (A = 0.884, Rank 2), receiving equal expert consensus. These findings reinforce the importance of structured decision-making in adaptive learning, ensuring that DSS-driven systems effectively match learner needs with relevant instructional content. [47] emphasized that DSS enhances personalized learning by leveraging student models and learning resources and optimizing adaptive learning pathways. Similarly, the study in [9] highlighted that student models, content adaptation, and structured decision-making criteria are crucial in delivering tailored learning experiences, ensuring student profiles align with instructional content in adaptive systems.

Additionally, the study in [48] demonstrated that fuzzy weight-based rule systems dynamically adjust content complexity and volume based on cognitive-level analysis, reinforcing the importance of structured alignment between learner characteristics and learning resources. By integrating decision-making criteria with student profiles and learning objects, DSS ensures that personalized learning paths evolve dynamically, improving instructional effectiveness and learner engagement.

4) Adaptive learning profile: The Adaptive Learning Profile received unanimous expert agreement, reinforcing its critical role in enhancing personalized learning for both students and teachers. This construct focuses on three key elements: personalized learning paths, tailored feedback, and adaptive learning resources, ensuring data-driven, individualized learning experiences. The FDM validation confirms the importance of these elements, with all components exceeding the α-cut threshold (A ≥ 0.5) and the 75% expert consensus benchmark, validating their essential role in the A-DSS-LF framework.

Among these elements, providing tailored feedback aligned with students' characteristics (A = 0.902, Rank 1) and suggesting learning resources that match students' characteristics (A = 0.902, Rank 1) received the highest expert consensus, reflecting their strong prioritization in adaptive learning environments. The findings emphasize that actionable feedback improves engagement and instructional strategies, ensuring that students receive personalized insights into their learning progress [9] [48]. Additionally, adaptive learning resources enhance accessibility and relevance by offering content aligned with students' cognitive levels and learning styles, reinforcing the importance of adaptive content curation [43].

Although recommending personalized learning paths based on students' characteristics (A = 0.891, Rank 3) was ranked slightly lower, it remains a fundamental component of adaptive learning. Personalized learning paths allow students to progress at their own pace, addressing knowledge gaps and supporting competency-based progression [2] [49]. The expert validation results confirm that while learning path recommendations are essential, they are most effective when paired with tailored feedback and adaptive learning resources, ensuring holistic and personalized educational outcomes.

VI. Conclusion

This study aimed to validate the A-DSS-LF using the FDM. Through the involvement of expert consensus, the findings confirmed the credibility and applicability of the proposed framework in supporting personalized adaptive learning within the blended learning environment. The FDM approach ensured robust validation of the constructs and elements, as evidenced in similar educational contexts where it effectively built consensus and established framework reliability.

The FDM results demonstrated a high level of agreement among experts, particularly regarding the essential components of the framework: the learner model, adaptation model, and learning object model. These findings align with studies emphasizing the significance of adaptive learning frameworks tailored to individual learner profiles. The validated A-DSS-LF provides a structured approach to integrating adaptive learning in blended settings, emphasizing personalized learning paths tailored to individual learner characteristics. Furthermore, this framework contributes to the ongoing dialogue on adaptive educational systems by incorporating unique elements such as value practices and practical skills, extending beyond traditional cognitive assessments.

The results of this study contribute significantly to the field by offering a validated framework tailored to the Malaysian education context, addressing theoretical and practical gaps. It sets a foundation for implementing the A-DSS-LF prototype and testing its impact in real-world education. Future work should refine the framework based on further qualitative feedback and usability testing. Additionally, implementing and evaluating the A-DSS-LF prototype in secondary school settings will provide valuable insights into its practical effectiveness and scalability. This study aims to enhance personalized education and optimize learning outcomes in blended learning environments by advancing adaptive learning frameworks.

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