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Research article

Enhancing Online Learning: Integrating the Social Interaction Dimension into the Felder Silverman Learning Styles Model

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ABSTRACT

The Felder-Silverman Learning Style Model (FSLSM) is widely used in adaptive online learning, but its four dimensions mainly describe how learners process and receive learning materials. They do not explicitly represent peer interaction, feedback-seeking, or collaborative knowledge exchange, although these activities are essential to learning management systems. This study proposes an enhanced FSLSM by integrating the sociological dimension of the Dunn and Dunn model, represented by solitary deep-reflective and social feedback learning preferences, to improve personalization in online learning. A mixed-methods design was applied to 400 undergraduate students using ELITAG, the learning management system (LMS) of Universitas 17 Agustus 1945 Surabaya. The integration was conducted by mapping FSLSM indicators and social interaction indicators into learner profiles and learning object recommendations. The research instrument was evaluated through expert judgment using Aiken's V, while the empirical model was tested using Confirmatory Factor Analysis (CFA) and partial least squares structural equation modeling (PLS-SEM). Learning performance was assessed through a before-and-after comparison using midterm examination scores before implementation and final examination scores after implementation. The results showed that social interaction significantly affected learning performance (path coefficient = 0.315; p = 0.001). The average examination score increased from 85 to 88, equivalent to a 3.5% improvement. These findings indicate that extending the FSLSM with social interaction provides a more complete learner profile and supports more personalized online learning experiences.

1. Introduction

Online learning has become an important infrastructure in higher education because it enables learning activities to continue without being limited by place and time. Before the COVID-19 pandemic, e-learning was commonly used as a supporting medium for face-to-face instruction. However, the rapid development of information technology and the growing need for distance learning have made e-learning and learning management systems (LMSs) more central to delivering learning materials, assignments, communication, and assessment [1], [2], [3]. Recent studies also show that adaptive and personalized learning has become increasingly important because conventional e-learning environments often apply a one-size-fits-all approach that may reduce engagement and learning performance when learner characteristics are ignored [4], [5], [6], [7], [8].

One approach used to improve online learning is personalization. A personalized LMS can provide learning objects that are more suitable for student characteristics, such as videos, reading materials, quizzes, examples, exercises, and discussion activities. To support this process, learning objects require metadata that describes their type, format, teaching strategy, and interaction patterns

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[9], [10], [11]. This metadata allows the system to recommend learning materials and activities that are better aligned with student preferences. Therefore, adaptive online learning requires a learner model that can describe how students receive, process, and interact with learning content. Recent research on adaptive e-learning further emphasizes that learner data, learning analytics, and behavioral traces can be used to support more personalized learning paths and enhance student engagement and performance [7], [8], [12].

The Felder-Silverman Learning Style Model (FSLSM) is one of the most widely used models for adaptive learning because it provides clear dimensions for classifying student learning preferences [10]. FSLSM classifies learners into four dimensions: processing, which consists of active and reflective learning styles; perception, which consists of sensing and intuitive learning styles; input, which consists of visual and verbal learning styles; and understanding, which consists of sequential and global learning styles [6]. These dimensions are useful for mapping learning objects to students' preferred ways of receiving and processing information. Recent behavioral data research also confirms that FSLSM remains relevant for adaptive e-learning because its dimensions can be aligned with behavioral data, system traces and learner engagement patterns in digital learning environments [13].

Although FSLSM is useful for personalizing learning objects, its original dimensions are not sufficient to represent the complexity of online learning. The model mainly focuses on how students receive and process instructional content, while current LMS environments are not limited to content delivery. Online learning also involves discussion forums, peer responses, collaborative activities, knowledge sharing, and feedback from both lecturers and students. Previous studies on adaptive learning and learning style detection have shown that learning styles can be identified and used to support instructional adaptation [14], [15], [16], [17]. However, FSLSM-based adaptation still provides an incomplete learner profile because it does not explicitly include students' preferences for social interaction as a formal dimension. This limitation is important because recent studies show that online collaboration and the quality of digital interaction are closely related to learning gains, satisfaction, engagement, and performance in higher education [18], [19].

Recent reviews distinguish learning styles from broader learning preferences and strategies and continue to discuss models that incorporate contextual and social elements [20]. Among models that address social aspects, the Dunn and Dunn Learning Style Model is relevant because its sociological dimension concerns how learners engage independently or with others [21]. In online learning, this distinction is reflected in the complementary roles of self-regulation, learner interaction, and social presence [22]. In this study, the sociological dimension of the Dunn and Dunn model was selected because it directly addresses the main limitation of FSLSM: the absence of a dimension that represents students' interaction preferences in online learning. Other Dunn and Dunn dimensions were not selected as the main extension because several aspects are already partially represented in FSLSM, such as perception and information processing, while the sociological dimension provides a distinct contribution that is highly relevant to LMS-based learning. This argument is supported by recent studies showing that collaborative online learning depends on interaction quality, communication, participation, and group relational processes [18], [19].

The sociological dimension can be operationalized in online learning through solitary deep reflective and social feedback learning preferences. Solitary deep reflective learners tend to learn independently, conduct self-analysis, and focus on personal learning tasks. In contrast, social feedback learners prefer discussion, communication, response, and collaborative interaction. These preferences can be observed in LMS activities such as forum visits, posts, replies, views, homework activities, and feedback interactions [17]. Therefore, integrating the social interaction dimension into FSLSM can provide a more comprehensive learner profile because it combines cognitive learning preferences with social learning preferences. This integration is expected to improve the ability of an LMS to recommend not only suitable learning materials, but also suitable learning activities. Recent studies using LMS log analytics also show that persistent and consistent engagement behavior in LMS environments is positively related to learning performance [12].

In addition to social interaction, motivation is also discussed in this study because it is related to learning effectiveness. Prior research shows that intrinsic and extrinsic motivation may influence how students engage with learning activities [23], [24]. However, other studies have reported mixed findings

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regarding the relationship between motivation and learning styles [25]. Therefore, motivation is included in this study as an antecedent factor that may influence learning style dimensions, rather than as the main dimension used to extend FSLSM. This distinction is important because the novelty of this research focuses on enhancing FSLSM through the integration of social interaction, while motivation is used to support the explanation of student learning behavior.

Based on the above discussion, the research gap is that existing FSLSM-based adaptive learning approaches can personalize learning objects according to cognitive preferences, but they do not sufficiently represent social interaction preferences that are essential in online learning. This study addresses this gap by integrating the social interaction dimension from the Dunn and Dunn Learning Style Model into FSLSM. The objective of this study is to investigate the impact of the enhanced FSLSM on student learning performance in an LMS environment. The study was conducted in ELITAG, the LMS used by Universitas 17 Agustus 1945 Surabaya, by comparing student learning performance before and after the integration of the social interaction dimension. The contribution of this study is threefold: first, it proposes an enhanced FSLSM that includes social interaction; second, it explains the rationale for selecting the sociological dimension as the extension; and third, it provides empirical evidence on whether the enhanced model improves student learning performance in online learning. This contribution is relevant to recent adaptive and personalized learning research, which emphasizes the need for learner data, behavioral interaction, and dynamic personalization to improve online learning outcomes [7], [12], [13].

2. Materials and Methods

This study used a quasi-experimental mixed-methods design to evaluate the impact of enhancing the Felder-Silverman Learning Style Model (FSLSM) with a social interaction dimension in an online learning environment. The method combined a literature-based construct development, expert judgment, questionnaire data, learning management system (LMS) log data, and a before-and-after comparison of student learning performance. This approach was appropriate because recent learning-style and LMS studies emphasize learner profiling, LMS behavioral traces, learning analytics, and performance-based evaluation to support adaptive and personalized online learning [12], [13], [26], [27], [28]. The stages used to develop and evaluate the enhanced FSLSM are summarized in Fig. 1.

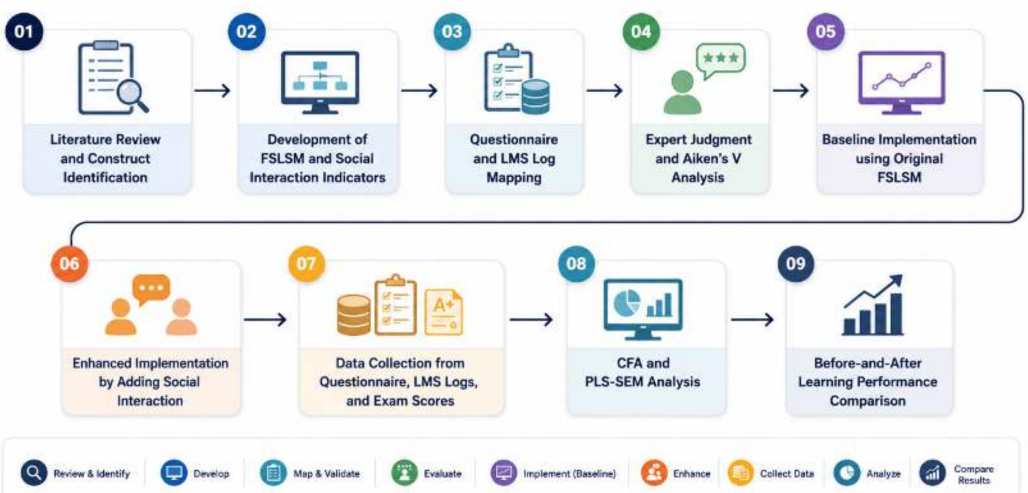

Fig. 1. Research procedure of the enhanced FSLSM study [12], [27], [28], [29], [30], [31]

2.1. Research Context and Participants

The study was conducted in ELITAG between October 2021 and December 2021. ELITAG provides online courses, learning materials, assignments, discussion activities, and assessment features for undergraduate students. The sample consisted of 400 undergraduate students who actively used ELITAG. The respondents were drawn from several study programs and semester levels. The inclusion criteria were active undergraduate students who followed the regular curriculum and used ELITAG during the research period. Students who were unable to participate in regular LMS activities were

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excluded from the analysis because LMS log-based studies require consistent activity records to represent learner behavior, engagement persistence, and performance-related learning patterns [12], [32], [33].

This study did not use two separate groups of students. Instead, the same 400 students were observed under two conditions. The first condition was the original FSLSM-based LMS before the integration of the social interaction dimension. The second condition was the enhanced FSLSM-based LMS after the social interaction dimension was integrated into the learner profile and recommendation mechanism. Therefore, the number of students in the FSLSM-alone condition and the enhanced-FSLSM condition was the same. This before-and-after design was used to reduce bias caused by comparing different student groups and to observe performance changes within the same learning population [33].

2.2. Research Instrument and Data Sources

The research instrument was developed from previous studies on learning styles, motivation, online learning behavior, and learning performance [34], [35], [36], [37], [38]. The questionnaire consisted of 61 items using a five-point Likert scale. The questionnaire was first developed in English based on the reviewed literature. Because the respondents were Indonesian students, the instrument was translated into Indonesian and verified through back-translation to ensure that the meaning of the items remained consistent. The demographic section collected information about participants' study program, semester, age, gender, and duration of ELITAG use. The use of expert-validated questionnaire items is consistent with recent LMS instrument-validation studies using Aiken's V [29].

The questionnaire asked students about the following construct groups and purposes. These constructs were selected because learning-style identification and LMS-based personalization require data on motivation, learning preferences, interaction behavior, and learning performance [26], [27]. The corresponding constructs, question focus, and measurement purpose are summarized in Table 1.

Table 1. Questionnaire constructs, question focus, and measurement purpose

Construct	Question Focus	Measurement Purpose
Intrinsic motivation	Interest, enjoyment, and perceived usefulness of using e-learning	To identify internal motivation that may influence learning behavior
Extrinsic motivation	Grade-related benefits, institutional requirements, and external encouragement to use e-learning	To identify external motivation that may affect student engagement
Processing	Preference for active participation or reflective learning	To identify the active or reflective learning style in FSLSM
Perception	Preference for practical, concrete, or abstract learning resources	To identify the sensing or intuitive learning style in FSLSM
Input	Preference for visual or verbal learning materials	To identify the visual or verbal learning style in FSLSM
Understanding	Preference for step-by-step or holistic learning navigation	To identify the sequential or global learning style in FSLSM
Social interaction	Preference for independent learning, discussion, peer feedback, and communication	To identify the solitary deep reflective or social feedback learning preference
Learning performance	Perceived learning achievement and examination score data	To evaluate the effect of the enhanced model on learning outcomes

In addition to questionnaire data, this study used LMS log data and ELITAG database records. LMS log data were used to observe student activities, such as forum access, posts, replies, wiki activities, homework submission, video views, textbook access, outline access, K-map access, and navigation behavior. ELITAG database records were used to obtain demographic information, course enrollment, and examination scores. These data sources allowed the study to examine both self-reported learning preferences and observed LMS behavior, which is recommended in learning analytics research because activity logs can represent student engagement and learning behavior in online environments [32], [33].

2.3. Integration of FSLSM and Social Interaction

The original FSLSM identifies student learning styles using four dimensions: processing, perception, input, and understanding [6]. In ELITAG, these dimensions were used to create student learner profiles and recommend learning objects that matched student's learning styles. However, the original FSLSM does not explicitly represent social interaction preferences, even though online learning involves discussion, communication, feedback, and knowledge exchange. Therefore, this study enhanced FSLSM

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by adding a social interaction dimension derived from the sociological dimension of the Dunn and Dunn Learning Style Model. Recent studies also show that FSLSM remains relevant for adaptive e-learning because its dimensions can be validated through behavioral data, LMS traces, and learner profiles generated by the system [13], [26], [27].

The integration process was conducted by extending the learner profile from four FSLSM dimensions to five dimensions. The added dimension classified students into solitary-deep reflective and social feedback preferences. Solitary deep-reflective learners were identified as students who tended to focus on individual learning activities, homework, and self-directed exploration. Social feedback learners were identified as students who frequently interacted through forum visits, posts, post views, replies, chat activities, and feedback-related activities. The enhanced learner profile was then used by ELITAG to recommend not only learning materials but also learning activities that matched student's interaction preferences [22], [27], [39]. The operational differences between the original and enhanced models are summarized in Table 2.

Table 2. Operational comparison between FSLSM alone and enhanced FSLSM

Component	Original FSLSM Condition	Enhanced FSLSM Condition
Learner profile	Processing, perception, input, and understanding	Processing, perception, input, understanding, and social interaction
Main purpose	Matching learning objects to cognitive learning preferences	Matching learning objects and learning activities to cognitive and social learning preferences
Data source	Questionnaire and LMS behavior related to material use	Questionnaire, LMS behavior, and social interaction logs
Social interaction representation	Not explicitly represented as a formal learner-profile dimension	Represented through solitary deep reflective and social feedback preferences
LMS recommendation	Materials such as readings, videos, quizzes, examples, and exercises	Materials plus interaction-based activities such as discussion, feedback, and collaborative learning support
Performance assessment	Midterm score before social interaction integration	Final-semester score after social interaction integration
Number of students	400 students	The same 400 students

2.4. LMS Behavior Mapping

The mapping between LMS behavior and learning style dimensions was adapted from previous learning-style detection studies [17], [26], [39]. For the processing dimension, active learners were identified through participation activities, such as forum posts, replies, wiki edits, and early homework submission. Reflective learners were identified through reading and observation behavior, such as viewing forum posts and accessing wiki entries. For the perception dimension, sensing learners were identified through activities related to practical resources, homework review, videos, textbooks, and K-maps, while intuitive learners were identified through activities related to abstract resources, outlines, and course introductions. This mapping is strengthened by recent evidence that FSLSM dimensions can be aligned with behavioral traces and learning analytics indicators in online learning environments [13], [17], [39].

For the input dimension, visual learners were identified through the frequency and duration of video views, figures, graphs, tables, and K-map access. Verbal learners were identified through their access to textual materials such as textbooks, course introductions, wiki views, and written learning resources. For the understanding dimension, sequential learners were identified through detailed navigation behavior, such as views of the table of contents and button clicks, while global learners were identified through access to general information such as course outlines and introductions. This mapping follows recent LMS-based learning-style studies that use online activity indicators, behavioral clustering, and system-traceable learner dimensions to detect FSLSM-based learner profiles [13], [26], [27].

For the added social interaction dimension, students were classified based on activities that represented their level of interaction intensity. Social feedback learners were identified through a higher frequency of forum visits, posts, replies, post views, chat views, and chat replies. Solitary deep-reflective learners were identified through stronger individual learning behavior, such as homework access and lower levels of posting, replying, and chatting. This mapping allowed ELITAG to distinguish students

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who preferred independent learning from those who preferred socially supported learning, while LMS log studies show that activity traces can be used to understand student engagement and learning behavior in online courses [27], [32].

2.5. Expert Judgment and Content Validity

Expert judgment was conducted to evaluate the content validity of the questionnaire before it was used for data collection. Four expert raters with expertise in e-learning, learning styles, and educational psychology evaluated the instrument. The experts were asked to assess whether each item was relevant to its construct, clearly worded, suitable for undergraduate LMS users, and representative of the intended learning style dimension. They also provided revision notes when an item was unclear or did not sufficiently represent the construct. Expert consensus and item relevance evaluation are commonly used in instrument development studies employing Aiken's V [29].

The rating method used a five-point relevance scale, where 1 represented irrelevant and 5 represented highly relevant. The expert ratings were analyzed using Aiken's V to measure the degree of agreement among the experts. Recent LMS instrument-validation research also applies Aiken's V to quantify expert agreement and determine whether questionnaire items should be retained, revised, or removed [29].

Aiken's V was calculated using Equations 1 and 2 [29].

$$V = \frac{\sum \quad s}{[n(c-1)]} \quad (1)$$

$$s = r - I_0 \quad (2)$$

where V is the content validity coefficient, r is the score given by an expert, I_0 is the lowest score in the rating scale, c is the highest score in the rating scale, and n is the number of experts. An item or dimension was considered valid when the coefficient reached the accepted validity threshold. Items that received low relevance scores or required revisions were reviewed and improved before the final data collection [29].

2.6. Reliability, Validity, and Structural Model Analysis

After the questionnaire data were collected, the measurement model was evaluated using Confirmatory Factor Analysis (CFA). CFA was used to examine whether the collected data consistently represented the intended constructs. Convergent validity was evaluated through factor loadings, composite reliability (CR), average variance extracted (AVE), and Cronbach's alpha. Discriminant validity was evaluated using the Fornell-Larcker criterion by comparing the square root of the AVE with the correlation values among constructs [40]. Recent educational technology research also supports the use of PLS-SEM for examining complex relationships among latent constructs in technology-enhanced learning studies [30], [31], [40].

The structural model was tested using Partial Least Squares Structural Equation Modeling (PLS-SEM). PLS-SEM was used to examine the relationships between intrinsic motivation, extrinsic motivation, FSLSM dimensions, social interaction, and learning performance. Motivation was included as an antecedent factor that may influence the learning style dimensions, while the main enhancement of the model was the integration of the social interaction dimension into FSLSM. The significance of each relationship was evaluated using path coefficients, t-values, p-values, and R-square values, following recent PLS-SEM guidelines and educational technology review findings [30], [31].

2.7. Learning Performance Evaluation

Student learning performance was evaluated using examination scores because academic performance data are commonly used to evaluate learning achievement and the effectiveness of online learning interventions [41], [42], [43], [44], [45]. The baseline performance was represented by the midterm examination scores, which reflected student performance before the social interaction dimension was integrated into FSLSM. The post-implementation performance was represented by the final examination scores, which reflected student performance after the enhanced FSLSM was implemented in ELITAG. Recent LMS log analytics and student performance prediction studies also support the use

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of learning activity data, LMS traces, and assessment scores to evaluate online learning outcomes [32], [12], [13], [33].

To ensure a fairer comparison, the analysis was conducted using the same cohort of 400 students and the data were grouped by semester level before calculating the overall average. This approach reduced the risk of comparing different student populations or combining students from different semester levels without control. Both midterm and final-semester scores were recorded using the same 0-100 scoring scale. The improvement percentage was calculated using Equation 3 [12], [13], [33].

$$Improvement\ (\%) = \left[\frac{(Final\ Exam\ Score - Midterm\ Exam\ Score)}{Midterm\ Exam\ Score}\right] \times 100 \quad (3)$$

The comparison was used to determine whether the enhanced FSLSM condition produced higher learning performance than the original FSLSM condition. Therefore, the method directly assessed the difference between the original FSLSM and the enhanced FSLSM with social interaction integration [33].

3. Results and Discussion

This study involved 400 undergraduate students from Universitas 17 Agustus 1945 Surabaya who actively used ELITAG. The same students were observed in two learning conditions: the original FSLSM-based condition before the integration of social interaction and the enhanced FSLSM-based condition after social interaction was integrated into the learner profile. Therefore, the comparison did not involve two different groups but rather a before-and-after observation of the same cohort to reduce bias caused by differences in student characteristics [47]. The demographic characteristics of the participants are presented in Table 3.

Table 3. Demographic characteristics of respondents

Segmentation	Demographics	N	%
Program study	State Administration	23	5.75%
	Commerce Administration	18	4.5%
	Communication Science	34	8.5%
	Economic Management	31	7.75%
	Economic Accounting	22	5.5%
	Economic Development	28	7%
	Industrial Engineering	27	6.75%
	Civil Engineering	24	6%
	Mechanical Engineering	16	4%
	Architectural Engineering	16	4%
	Electrical Engineering	21	5.25%
	Informatics Engineering	29	7.25%
	English Literature	26	6.5%
	Japanese Literature	20	5%
	Law	30	7.5%
	Psychology	21	5.25%
	Vocational	14	3.5%
Semester	1	88	22%
	3	128	32%
	5	72	18%
	7	112	28%
Age	17-18	77	19.25%
	19-20	245	61.25%
	21-22	78	19.5%
Gender	Male	188	47%
	Female	212	53%
Duration of Using ELITAG	< 1 Year	88	22%
	1 – 2 Years	128	32%
	2 – 3 Years	72	18%
	> 3 Years	112	28%

The demographic data show that the respondents represented several study programs, semester levels, age groups, and durations of LMS use. This distribution is important because LMS-based learning behavior can be influenced by the duration of LMS use, academic level, and exposure to online activities. In learning analytics research, a sufficiently varied sample helps to explain how students interact with LMS activities and how those activities relate to learning outcomes [32], [33].

Content validity was assessed through expert judgment before the questionnaire was used in the main data collection. Four experts evaluated whether each item was relevant, clear, representative of the construct, and suitable for undergraduate LMS users. Aiken's V was used to quantify the level of expert agreement because it is appropriate for validating questionnaire instruments based on expert relevance ratings [29]. The results of the content validity assessment are shown in Table 4.

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Table 4. Content validity results

Dimension	Average Coefficient V
Processing	0.96
Perception	0.97
Input	0.94
Understanding	0.94
Social Interaction	0.92
Motivation	0.92

The Aiken's V results indicate that all dimensions achieved coefficients between 0.92 and 0.97. These values show that the experts considered the questionnaire items valid and suitable for measuring the FSLSM dimensions, social interaction, motivation, and learning performance. The results support the use of the instrument in the next analysis stage because recent LMS instrument-validation studies also use Aiken's V to determine whether items should be retained or revised before empirical testing [29].

Descriptive analysis was conducted to identify the general tendency of students' responses to each construct. The mean values ranged from 3.841 to 3.924, indicating that students generally responded positively to ELITAG, learning style personalization, social interaction, and learning performance. The standard deviation values were relatively small, indicating that the responses were not extremely dispersed across respondents [26], [27]. The descriptive statistics are presented in Table 5.

Table 5. Descriptive analysis

Construct	Variable	Item	Mean	SD
Intrinsic motivation	X1	Interesting use of e-learning	3.883	0.548
	X2	Fun use of e-learning	3.860	0.563
	X3	Useful use of e-learning	3.924	0.579
Extrinsic motivation	X4	The use of e-learning in the ease of value	3.864	0.561
	X5	The use of e-learning to make it easier to recognize characteristics	3.875	0.553
	X6	Use of e-learning due to institutional	3.879	0.551
	Y1	Processing	3.883	0.482
	Y2	Perception	3.902	0.535
	Y3	Input	3.860	0.492
	Y4	Understanding	3.841	0.527
	Y5	Social interaction	3.871	0.499
Learning performance	Z	Learning performance	3.898	0.516

The descriptive results suggest that students perceived both the original FSLSM dimensions and the added social interaction dimension as relevant to their online learning experience. The mean value of the social interaction construct was 3.871, which indicates that communication, discussion, feedback, and peer-related activities were meaningful components of ELITAG use. This result is consistent with recent online collaboration studies showing that LMS-based collaboration, discussion boards, communication, and feedback support learning, relationship building, and engagement in online courses [18], [46].

The measurement model was evaluated using factor loadings, composite reliability, and average variance extracted. The factor loadings ranged from 0.945 to 0.984, composite reliability ranged from 0.935 to 0.983, and the AVE ranged from 0.841 to 0.966. These values exceeded the commonly accepted minimum criteria for convergent validity and reliability in PLS-SEM, indicating that the constructs were measured consistently [30]. The results are presented in Table 6.

Table 6. Reliability and convergent validity

Construct	Variable	Factor Loading	CR	AVE
Intrinsic motivation	X1	0.983	0.982	0.948
	X2	0.980		
	X3	0.957		
Extrinsic motivation	X4	0.971	0.982	0.948
	X5	0.981		
	X6	0.970		
	Y1	0.983	0.970	0.880
	Y2	0.969	0.957	0.881
	Y3	0.958	0.956	0.914
	Y4	0.953	0.941	0.841
	Y5	0.984	0.983	0.966
Learning performance	Z	0.945	0.935	0.906

The reliability and convergent validity results indicate that the questionnaire items were able to represent their intended constructs. Social interaction produced the highest AVE value, indicating that

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the added dimension demonstrated strong explanatory consistency in the enhanced FSLSM model. This supports the argument that social interaction can be integrated as an additional learner profile dimension because LMS-based learning style studies have shown that online activities can be mapped to learning style characteristics and used for learner modeling [26], [27].

Discriminant validity was evaluated using the square root of the AVE and the correlation matrix. The square root of the AVE values ranged from 0.84 to 0.97. The results show that the constructs had strong internal consistency; however, several correlations were also high. This condition indicates conceptual closeness among motivation, FSLSM dimensions, social interaction, and learning performance. Therefore, the findings should be interpreted as an integrated learner profile model rather than as completely isolated constructs. Future studies should complement the Fornell-Larcker criterion with additional tests such as the HTMT criterion to strengthen discriminant validity assessment [30]. The discriminant validity results and correlation matrix are reported in Table 7.

Table 7. Discriminant validity and correlation matrix

Variable	Construct	AVE	A	B	C	D	E	F	G	H
A	Extrinsic Motivation	0.95	1.00							
B	Input	0.91	0.91	1.00						
C	Intrinsic Motivation	0.95	0.96	0.91	1.00					
D	Learning Performance	0.91	0.88	0.90	0.88	1.00				
E	Perception	0.88	0.86	0.88	0.86	0.84	1.00			
F	Social Interaction	0.97	0.91	0.92	0.92	0.89	0.86	1.00		
G	Processing	0.88	0.94	0.95	0.94	0.93	0.90	0.93	1.00	
H	Understanding	0.84	0.87	0.91	0.88	0.85	0.83	0.87	0.90	1.00

The structural model was tested using PLS-SEM to examine the relationships among motivation, FSLSM dimensions, social interaction, and learning performance. The results show that intrinsic and extrinsic motivation significantly affected the processing, perception, input, understanding, and social interaction dimensions. The FSLSM dimensions and social interaction also significantly affected learning performance, as indicated by p-values below 0.05 [30]. The structural model results are presented in Table 8.

Table 8. Structural model result

Relationship	β	t-value	p-value	R^2
Intrinsic Motivation → Processing	0.354	4.560	0.000	0.932
Extrinsic Motivation → Processing	0.246	2.964	0.003	
Intrinsic Motivation → Perception	0.317	3.236	0.001	0.776
Extrinsic Motivation → Perception	0.253	2.484	0.013	
Intrinsic Motivation → Input	0.359	4.728	0.000	0.877
Extrinsic Motivation → Input	0.219	2.697	0.007	
Intrinsic Motivation → Understanding	0.450	5.729	0.000	0.804
Extrinsic Motivation → Understanding	0.205	2.162	0.031	
Intrinsic Motivation → Social Interaction	0.435	4.353	0.000	0.883
Extrinsic Motivation → Social Interaction	0.219	2.044	0.041	
Processing → Learning Performance	0.398	3.918	0.000	0.793
Perception → Learning Performance	0.341	3.530	0.000	
Input → Learning Performance	0.390	4.055	0.000	
Understanding → Learning Performance	0.269	3.385	0.001	
Social Interaction → Learning Performance	0.315	3.396	0.001	

The model explains 79.3% of the variance in learning performance, indicating that the combination of FSLSM dimensions and social interaction has strong explanatory power. Among the predictors of learning performance, the processing dimension had the highest coefficient, followed by the input, perception, social interaction, and understanding dimensions. The significant path from social interaction to learning performance ($\beta = 0.315$; $p = 0.001$) provides empirical evidence that the added dimension contributes to the enhanced FSLSM model, not merely as an additional theoretical component but also as a significant predictor of learning outcomes [27], [30].

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The estimated path coefficients of the enhanced FSLSM are visualized in Fig. 2.

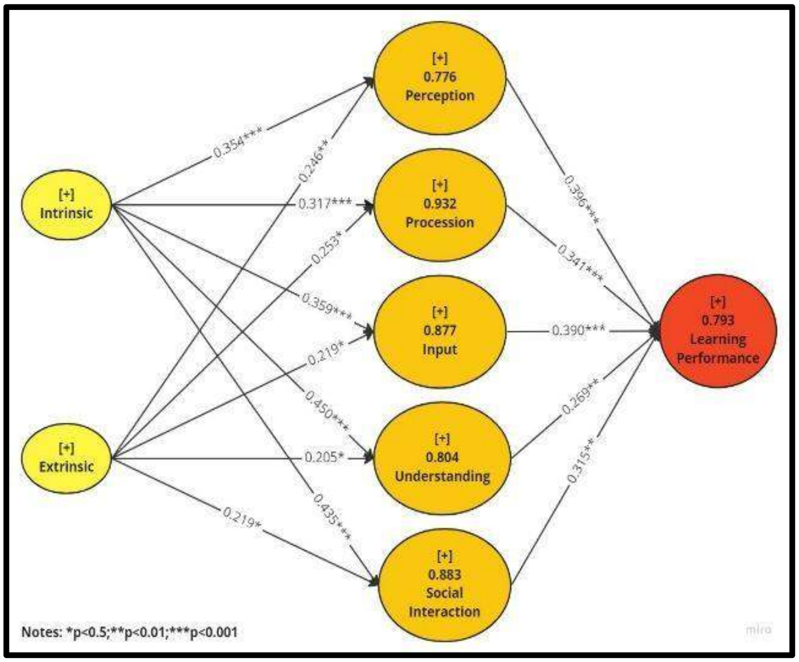

Fig. 2. Path coefficient model of enhanced FSLSM

The significance of social interaction supports the argument that online learning should not be personalized only through content format and cognitive preferences. Online learners also engage through discussion, feedback, peer communication, and collaborative activities. Recent online collaboration research shows that online learner collaboration supports knowledge construction, communication skills, collaboration skills, and relationship building. Therefore, the present findings strengthen previous studies by showing that social interaction can be effectively integrated into an FSLSM-based LMS and can significantly affect learning performance [18], [47].

The before-and-after comparison was conducted to directly answer whether learning performance improved after social interaction was integrated into FSLSM. The same 400 students were observed in both conditions. The midterm examination score represented the FSLSM-alone condition before implementation, while the final examination score represented the enhanced FSLSM condition after implementation. To avoid an unfair comparison across different academic levels, the results were grouped by semester before calculating the overall average [33]. The comparison is shown in Table 9.

Table 9. Student examination scores before and after enhanced FSLSM implementation

Semester	Midterm Score (Before Implementation)	Final Exam (After Implementation)	Difference
1	84	88	4.8%
3	82	85	3.7%
5	86	89	3.5%
7	88	90	2.3%
Average	**85**	**88**	**3.5%**

Table 9 shows that the average score increased from 85 in the FSLSM-alone condition to 88 in the enhanced FSLSM condition. The overall improvement was 3.5%, with improvements observed across all semester groups. The largest increase occurred in semester 1, while the smallest increase occurred in semester 7. This pattern suggests that the enhanced FSLSM may provide greater benefits for students in earlier semesters, who may still require more structured LMS guidance and social support to adapt to online learning [33], [47].

The result indicates that the integration of social interaction into FSLSM improved the learner profile used by ELITAG. In the original FSLSM condition, personalization mainly focused on how students processed, perceived, received, and understood learning materials. After the enhancement, ELITAG could also represent whether students preferred independent learning or socially interactive

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learning. This broader learner profile made it possible to recommend not only learning objects, but also learning activities such as discussion, feedback, and collaborative learning [18], [27].

The findings also show that motivation significantly affected the FSLSM dimensions and social interaction. This indicates that students' internal and external reasons for using e-learning may influence how they engage with learning content and online activities. However, motivation was not used as the main extension of FSLSM in this study because the novelty of the study focused on the social interaction dimension. Motivation was positioned as an antecedent factor to explain student learning behavior, while social interaction was integrated as an additional learner profile dimension [30], [46].

The main strength of this study is that it combines questionnaire data, expert judgment, LMS activity data, CFA, PLS-SEM, and examination scores to evaluate the enhanced FSLSM. This combination provides a stronger basis for evaluation than using self-reported learning style data alone. The study also used the same cohort of 400 students in the FSLSM-alone and enhanced FSLSM conditions, which reduced the potential for bias associated with comparing different student groups [32], [33].

Nevertheless, this study has several limitations. First, the before-and-after design did not use a randomized control group, so other learning factors during the semester may also have influenced the final score. Second, the comparison used midterm and final exam scores, which may not have had identical content difficulty even though they were measured on the same 0-100 scoring scale. Third, several construct correlations were high, indicating that future studies should apply additional discriminant validity tests and compare the model with other learner profile models. These limitations should be addressed in future research through a randomized experimental design, HTMT analysis, larger multi-institutional samples, and more detailed LMS log-based learning analytics [30], [33].

4. Conclusion

This study confirms that integrating the social interaction dimension into the Felder-Silverman Learning Style Model (FSLSM) provides a more comprehensive learner profile for adaptive online learning. The original FSLSM condition represented students through the processing, perception, input, and understanding dimensions, while the enhanced FSLSM added social interaction through solitary deep reflective and social feedback preferences. Based on the same 400 students observed before and after implementation in ELITAG, the enhanced model showed a positive effect on learning performance. Social interaction significantly influenced learning performance, and the average examination score increased from 85 before implementation to 88 after implementation, representing a 3.5% improvement. These findings indicate that online learning personalization should not only match students with suitable learning materials, but also consider how students interact, communicate, and receive feedback in the learning environment. The main contribution of this study is the extension of FSLSM by incorporating a social interaction dimension that is relevant to LMS-based learning, especially for designing personalized and collaborative online learning systems. Practically, the enhanced FSLSM can help educators, instructional designers, and LMS developers provide more suitable learning objects and interaction-based learning activities. However, this study was conducted in a single institutional context and used a before-and-after design; therefore, future research should validate the enhanced model using a randomized experimental design, multiple institutions, broader learner populations, and more detailed LMS log-based learning analytics.

Author Contributions

Supangat: Conceptualization, data curation, formal analysis, funding acquisition, investigation, methodology, project administration, resources, software, supervision, validation, visualization, writing – original draft, and writing – review & editing.

Declaration of Competing Interest

We declare that we have no conflict of interest.

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