

DistilBERT-based Text Classification for Learning Style Identification Based on the Felder-Silverman Model

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Received: June 13, 2025; Revised: January 10, 2026; Accepted: February 4, 2026; Published: June 8, 2026

Abstract: Identifying students' learning styles is an important step in supporting adaptive and personalized learning environments, particularly in higher education contexts. This study investigates the use of a transformer-based language model, DistilBERT, for automated learning style identification based on the Felder–Silverman Learning Style Model (FSLSM). Binary responses from the 44-item Index of Learning Styles (ILS) questionnaire were systematically transformed into descriptive textual representations, preserving the underlying FSLSM decision logic while enabling semantic modeling. Separate DistilBERT classifiers were fine-tuned for the four FSLSM dimensions—Active/Reflective, Sensing/Intuitive, Visual/Verbal, and Sequential/Global. Model training was conducted using three epochs within a stratified five-fold cross-validation framework, with the primary objective of assessing optimization stability and representational consistency rather than predictive superiority. Across all dimensions, training loss decreased monotonically, with the most substantial reductions occurring between the first and second epochs, indicating rapid adaptation of pre-trained representations to the structured learning style descriptions. Differences in convergence behavior across dimensions were observed, reflecting variation in class distributions and response patterns. Near-perfect classification metrics were obtained across multiple folds; however, these results are interpreted as evidence of deterministic consistency between the textual inputs and FSLSM-derived labels rather than independent generalization performance. To examine alignment with human judgment, model predictions were further compared with expert assessments conducted independently using standard FSLSM interpretation guidelines. The resulting Cohen's Kappa coefficient of 1.0 indicates perfect agreement, confirming that the model faithfully reproduces expert-consistent FSLSM categorizations under controlled conditions. Overall, the findings demonstrate that transformer-based models can reliably encode and recover rule-based learning style constructs from descriptive questionnaire data, supporting their use as computational tools for scalable, consistent learning style analysis, while acknowledging the task's deterministic and framework-dependent nature.

Keywords: Learning Style Identification, Felder-Silverman Learning Style Model, Transformer-Based Text Classification, DistilBERT, Deterministic Questionnaire Modeling

1. Introduction

In modern education, personalization of learning has become a central theme in improving student engagement, learning efficiency, and academic outcomes. The traditional “one-size-fits-all” instructional model is increasingly insufficient for addressing learners’ diverse cognitive preferences. As a result, the ability to identify and adapt to individual learning styles has emerged as a critical component of educational innovation, particularly within technology-enhanced learning (TEL) environments.

Numerous studies in educational technology, psychology, and teaching methodology have explored how to recognize and accommodate different learning styles to support this innovation. Learning styles refer to the distinct ways individuals acquire, process, and retain knowledge. Keefe defines them as the cognitive, emotional, and psychological traits that influence how a person learns[1], while Felder and Silverman emphasize that these styles are highly individual and vary from one learner to another[2].

Understanding and accounting for these differences is essential, as students vary widely in how they engage with content. Some prefer working with ideas, theories, facts, and experiments, while others enjoy problem-solving and reading texts. A standardized teaching approach often fails to meet these diverse needs, especially in terms of providing effective feedback and maintaining motivation[3].

Recognizing individual learning preferences helps tailor instructional strategies and plays a key role in enhancing academic performance. When educators are aware of how their students learn best, they can adjust their teaching methods to foster more effective and inclusive learning environments[4]. Taking these preferences into account can also help reduce student frustration and disengagement[5], and the risk of academic failure[6].

Among the various models developed to classify learning preferences, the Felder-Silverman Learning Style Model (FSLSM) is one of the most widely recognized and applied frameworks. Due to its precise categorization and ease of implementation, FSLSM has been extensively adopted in higher education and e-learning settings. It categorizes learners along four key dimensions: Active–Reflective, Sensing–Intuitive, Visual–Verbal, and Sequential–Global. Each dimension reflects a spectrum of how students process information, perceive content, receive input, and organize knowledge[2].

The Index of Learning Styles (ILS) questionnaire is commonly used to measure these dimensions. Traditionally, identifying learning styles through the ILS has involved manual scoring or basic statistical analysis. While useful, these methods are often limited in their ability to extract deeper semantic understanding from students’ responses. As a result, there has been growing interest in employing automated techniques, particularly those powered by artificial intelligence (AI), to enhance the identification process.

Among AI technologies, machine learning (ML) has gained substantial attention for its capacity to classify learning styles automatically. Techniques such as Support Vector Machines (SVM) have shown promising results in detecting learning preferences based on FSLSM, often yielding high accuracy[7, 8]. Beyond classification, regression analysis has also been proposed as a probabilistic method to infer learning styles, particularly effective when students exhibit hybrid characteristics across different dimensions[9]. Furthermore, integrating prior knowledge assessments with behavioral data has been shown to enhance model performance, especially when combining data-driven approaches with insights from educational theory[10].

Despite their advantages, conventional machine learning approaches have several limitations. These include dependency on large amounts of labeled data, sensitivity to noise or irrelevant features, high computational demands, and difficulty in addressing complex or non-standard patterns [11]. These challenges highlight the need for more sophisticated and adaptive models that can effectively capture learning styles’ dynamic and contextual nature of learning styles.

In response to these limitations, deep learning—particularly Transformer-based models—offers a flexible representational framework for modeling structured educational data in textual form. Originally developed for natural language processing, Transformer architectures have demonstrated strong capability in learning contextual relationships within sequential text [12]. Their successful application in related domains, including emotion classification [13], depression detection [14], and mental health text analysis [15], indicates potential for educational modeling tasks that rely on structured yet semantically expressed inputs.

Building on this premise, this study develops and evaluates a DistilBERT-based approach for learning style identification grounded in the Felder–Silverman Learning Style Model (FSLSM). Binary responses from the Index of Learning Styles (ILS) questionnaire are systematically transformed into descriptive textual representations that preserve the original FSLSM decision logic. Rather than aiming to infer latent behavioral traits, this work examines the feasibility of using a Transformer-based model to encode and consistently reproduce rule-based learning style mappings from text. The primary contribution lies in assessing representational consistency, optimization stability, and alignment with FSLSM-defined constructs, thereby informing the methodological integration of NLP models within deterministic educational assessment frameworks.

2. Literature Review

Various learning style theories have been developed and are widely recognized in educational theory and learning strategies. These theories categorize individuals based on distinct characteristics that shape their learning preferences[10]. Several well-established models are frequently referenced in the literature, including the VARK model (Visual, Auditory, Reading/Writing, and Kinesthetic) proposed by Fleming and Mills[16]. Kolb's Learning Style Inventory (LSI) was introduced by D.A. Kolb[17]. The Felder-Silverman Learning Style Model (FSLSM) developed by Felder and Silverman [2]. The Honey and Mumford Learning Style Model is explained by Honey and Mumford[18].

Each model includes a specific instrument that uses a structured questionnaire to identify an individual's preferred learning style. For instance, the VARK model categorizes learners into four types: visual, auditory, reading/writing, and kinesthetic[16]. Similarly, Kolb's LSI, one of the most widely used frameworks, defines four learning styles based on experiential learning theory[17]. The FSLSM utilizes the Index of Learning Styles (ILS) questionnaire to classify learners across four dimensions: perception, input, processing, and understanding[2]. In comparison, the Honey and Mumford model identifies four learner types: activists, reflectors, theorists, and pragmatists[19].

Learning styles can be identified using three primary approaches: traditional, automated, and hybrid methods. In recent years, increasing attention has been given to automatic learning style detection. Many studies have explored applying various machine learning techniques, both supervised and unsupervised.

Hasibuan et al. [6] proposed several machine learning algorithms—Decision Tree (DT), K-Nearest Neighbor (K-NN), Naïve Bayes, Random Forest, and Neural Networks—to detect learning styles based on the Felder-Silverman Learning Style Model (FSLSM). Their experiments on a dataset of 138 students demonstrated that the Naïve Bayes algorithm (average accuracy of 97.343%) and the Neural Network algorithm (average accuracy of 97.344%) outperformed K-NN, DT, and RF classifiers.

In a related study, Hasibuan and Aziz[20] compared the performance of three classifiers—Support Vector Machine (SVM), Naïve Bayes, and K-NN—for learning style detection. The Naïve Bayes classifier yielded the highest accuracy of 91.48%, supported by a standard deviation of ± 5.90 and a kappa value of 0.7, indicating reliable results. K-NN and SVM followed with accuracy values of 89.39% and 87.31%, respectively. The study also compared three detection strategies: prior knowledge-based, literature-based, and data-driven. Results revealed that prior knowledge provided the most accurate representation of students' learning styles, outperforming the other two methods, with accuracy scores below 87.31%.

Waladi et al. [8] introduced an intelligent and dynamic model for adaptive learning that encompasses the entire learning cycle, from diagnostic assessment to knowledge assimilation. The model uses k-means clustering to group learners based on similar traits defined by the Kolb Learning Style Model. To enhance prediction accuracy, neural networks were integrated for learning style classification, and a decision tree was employed to generate personalized pedagogical content.

Azzi et al. [21] proposed an approach to learning style detection in online platforms using FSLSM and the fuzzy C-means clustering algorithm. Their method facilitates the automatic selection of learning objects (LOs) in intelligent e-learning environments based on learners' styles. Given the ambiguous nature of LOs, a fuzzy classification technique was applied to align LOs, compliant with the IEEE Learning Object Metadata (LOM) standard, with the appropriate FSLSM categories. Experimental results confirmed the approach's effectiveness.

Muhammad et al. [22] presented a method that utilizes students' learning behaviors to detect their styles. Initially, behaviors were modeled using a bipartite graph and reduced via graph embedding to create a lower-dimensional representation. These embeddings were then used for clustering via the Fuzzy C-Means algorithm based on FSLSM dimensions. The method was evaluated using the 2015 KDD Cup dataset and outperformed previous approaches, achieving a precision of 0.8737 and an accuracy of 0.9182.

Mehenaoui et al. [9] applied the SVM algorithm to automatically detect learning styles in online courses using FSLSM. The study involved 73 students from a higher education institution, and the model achieved an average accuracy of 88%. These findings indicate the method's potential to enhance academic achievement and learner satisfaction.

Nguyen et al. [23] combined SVM and Extreme Gradient Boosting (XGBoost) to classify learning styles among 546 university students in Vietnam. The hybrid approach improved content personalization and provided students with a more tailored learning experience.

Hussain et al. [24] proposed a framework integrating multi-layer topic modeling with FSLSM to identify learning styles within intelligent educational systems. The study involved 126 students who responded to learning-related questions and demographic information. Fuzzy logic was used for weighting input, and web usage mining and sentiment analysis (via latent Dirichlet allocation) were applied to refine the classification process. Their approach outperformed traditional models in accuracy.

Finally, Altamimi et al. [10] evaluated five machine learning algorithms: Neural Network (NN), SVM, DT, RF, and K-NN, as regression models to estimate learning style probabilities. Data from 72 students were gathered using the VARK questionnaire. Among the algorithms tested, Random Forest achieved the highest prediction accuracy across all learning style categories.

After reviewing the literature, it is evident that numerous studies have investigated learning style identification using conventional supervised and unsupervised machine learning techniques. However, relatively limited attention has been given to examining how transformer-based language models can be integrated into structured, questionnaire-driven learning style frameworks. In particular, prior work has seldom explored the use of deep learning models to encode and represent learning style information derived from deterministic instruments such as the Index of Learning Styles (ILS).

Against this background, the present study contributes by examining the feasibility of operationalizing the Felder–Silverman Learning Style Model (FSLSM) through a DistilBERT-based representational approach. By transforming binary ILS responses into descriptive textual inputs, this work does not aim to replace or surpass rule-based FSLSM scoring, but rather to evaluate whether a transformer-based model can consistently encode and reproduce FSLSM-defined learning style mappings under controlled conditions.

3. Methodology

3.1. Proposed Model

This study proposes a transformer-based classification framework using the DistilBERT model to identify students' learning styles according to the Felder–Silverman Learning Style Model (FSLSM). Unlike approaches that rely on naturally occurring learner-generated text, the proposed method operates on structured textual representations deterministically derived from questionnaire-based responses. The primary objective is to examine the feasibility and robustness of lightweight transformer models when applied to constrained and semi-structured textual inputs generated from educational assessment data.

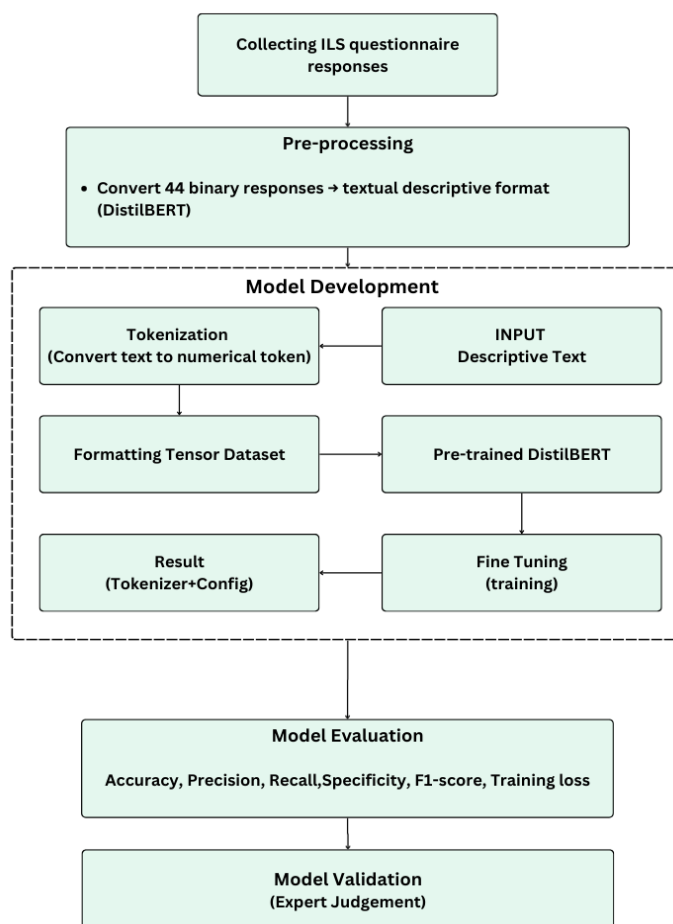


Fig. 1. Flow Diagram of Proposed Model.

The overall research methodology is illustrated in Fig. 1. The first stage involves data collection using the Index of Learning Styles (ILS) questionnaire, which is grounded in the FSLSM framework. The questionnaire was administered online via Google Forms and distributed to students from multiple universities across Indonesia.

Following data collection, a data preprocessing stage is conducted. In this stage, the binary responses corresponding to each FLSM dimension are converted into rule-based descriptive text sequences to meet the input requirements of the DistilBERT model. These textual representations are generated through a fixed encoding scheme, where each questionnaire response is mapped to a predefined descriptive sentence.

Subsequently, a transformer-based classification model is developed using the DistilBERT architecture. Four independent classifiers are fine-tuned, each corresponding to one FLSM dimension, to preserve the conceptual independence of learning style dimensions. To ensure robust evaluation, k-fold cross-validation is employed, in which the dataset is divided into k folds, and each fold is used once as a validation set while the remaining folds are used for training.

Finally, the fine-tuned models are validated using previously unseen respondent data through an expert-based evaluation process. In this stage, learning style profiles generated by the proposed models are compared against independent assessments conducted by an educational psychology expert. This validation strategy enables an empirical comparison between model predictions and expert judgments within the FLSM framework. The evaluation results are interpreted in light of the structured, deterministically generated textual inputs, emphasizing the model's representation-learning capability rather than natural-language understanding.

3.2. Data Collection

The dataset used in this study was collected from 1,095 undergraduate students enrolled at multiple universities across Indonesia, representing diverse academic disciplines, including education, engineering, computer science, and social sciences. Participants were drawn from several regions, including Sumatra and Java, to ensure variability in academic backgrounds and learning contexts.

Data were collected using the Index of Learning Styles (ILS) questionnaire developed by Felder and Soloman and grounded in the Felder–Silverman Learning Style Model (FLSM). The ILS comprises 44 forced-choice items equally distributed across four bipolar dimensions: Processing (Active–Reflective), Perception (Sensing–Intuitive), Input (Visual–Verbal), and Understanding (Sequential–Global). Each item presents two predefined alternative statements, enabling responses to be consistently encoded in a binary format.

The questionnaire was administered online via Google Forms and distributed through digital communication platforms. Participants were instructed to complete the questionnaire honestly based on their typical study habits and learning experiences. They were informed that there were no correct or incorrect answers, as the objective of the questionnaire was to identify individual learning style tendencies rather than to assess academic performance.

To enhance data validity and response reliability, the survey was supervised by lecturers during scheduled class sessions. The questionnaire was administered approximately 15 minutes before the end of lectures to ensure participation by active, enrolled students in a controlled academic environment, thereby reducing response bias and improving data quality.

Following data collection, a data cleaning and validation process was conducted to remove incomplete and inconsistent responses. This process resulted in a final dataset of 1,081 valid samples. Each participant's response was represented as a structured 44-bit binary vector corresponding to the ILS questionnaire items, forming the basis for subsequent analysis and model development.

3.3. Data Preprocessing

This stage consisted of three main steps. First, the 44 binary response items from the ILS questionnaire were grouped into four FLSM dimensions, with each dimension represented by 11 item-level responses. Second, a learning style label for each dimension was determined based on the dominant binary response within the corresponding group of 11 items, following the ILS's standard scoring procedure. This labeling process was performed independently of the text construction stage and was used solely for supervised model training and evaluation. Third, the binary responses within each dimension were converted into structured descriptive text by mapping each item-level response to its corresponding original questionnaire statement. The resulting input text for each dimension consisted of a concatenation of 11 short, predefined statements reflecting the participant's selected options. This transformation was designed to preserve the original semantic content of the questionnaire items while adapting the structured responses to a text-based format compatible with the DistilBERT architecture.

Importantly, the generated textual inputs do not explicitly encode the target learning style label but instead represent aggregated item-level preferences within each dimension. As a result, the model learns patterns from structured textual representations rather than directly inferring labels from deterministic text cues.

3.4. Model Development

The processed dataset was modeled using a Transformer-based architecture, specifically DistilBERT, to perform supervised classification of learning styles based on structured textual representations derived from the ILS questionnaire. Rather than targeting free-form natural language understanding, the model is employed to learn discriminative representations from consistent, item-level textual inputs associated with students' learning preferences.

Transformer architectures utilize self-attention mechanisms to aggregate information across token sequences in a

position-aware manner. In this study, self-attention primarily functions as a feature aggregation mechanism, enabling the model to integrate multiple short statements corresponding to questionnaire items within each FLSM dimension. This property makes Transformer-based encoders well-suited for modeling structured text composed of repeated, semantically related statements.

Transformer models can be broadly categorized into encoder-only, decoder-only, and encoder-decoder architectures. Given that the task focuses on classification rather than text generation, an encoder-only architecture was selected. DistilBERT was chosen for its reduced computational complexity while retaining most of the original BERT model's representational capacity. With approximately 66 million parameters, DistilBERT provides an effective balance between predictive performance and computational efficiency, making it suitable for scalable educational applications.

3.4.1. Model Architecture

This study employs DistilBERT as the core classification architecture for identifying students' learning styles according to the FLSM framework. The model input consists of structured textual representations generated from students' ILS responses for each learning style dimension.

The input text is first processed using the DistilBERT tokenizer, which applies WordPiece tokenization to segment text into subword units. These tokens are converted into token IDs and attention masks, allowing the model to process variable-length inputs while ignoring padding tokens during training.

Token embeddings and positional embeddings are combined and passed through the DistilBERT encoder, which consists of six stacked Transformer layers. Each layer applies multi-head self-attention and position-wise feed-forward networks to aggregate information across the sequence of questionnaire-derived statements. Given the structured and repetitive nature of the input text, the encoder primarily learns weighted representations of item-level preferences rather than complex linguistic dependencies.

For classification, the contextualized representation associated with the special classification token is extracted from the final encoder layer and passed to a task-specific classification head, which consists of a fully connected linear layer followed by a softmax activation. The model produces a binary prediction for each pole of each FLSM dimension.

To maintain modularity and interpretability, the model is fine-tuned independently for each FLSM dimension, resulting in four separate binary classifiers. This design allows each classifier to focus on dimension-specific response patterns and accommodates differences in class distributions across dimensions. Fig. 2. illustrates the overall architecture of the proposed DistilBERT-based learning style classification model.

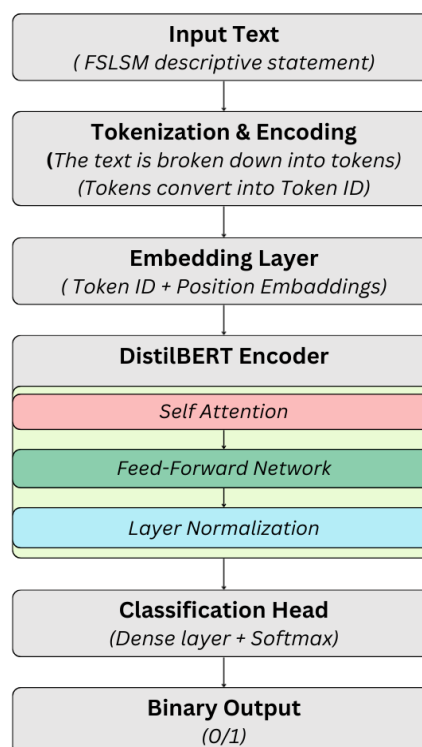


Fig. 2. DistilBERT architecture for learning style classification.

a. Tokenization and Encoding

Tokenization and encoding convert the structured textual representations derived from the ILS questionnaire into numerical inputs compatible with the DistilBERT architecture. The DistilBERT WordPiece tokenizer is used to segment each input sequence into subword units and map them to corresponding token IDs based on the model's predefined vocabulary [25]. Special tokens, including [CLS] and [SEP], are automatically appended to indicate sequence boundaries.

To ensure uniform input length across samples, sequences are standardized through padding and truncation based on a predefined maximum length. Shorter sequences are padded using [PAD] tokens, while longer sequences are truncated to retain the core questionnaire-derived content. This standardization enhances computational efficiency and ensures stable training behavior.

The tokenization process produces two primary inputs: input IDs, representing numerical token encodings, and attention masks, which distinguish valid tokens from padding. These encoded representations enable DistilBERT to process structured learning style descriptions in a consistent manner, supporting reliable feature extraction rather than free-form linguistic interpretation.

b. Embedding Layer

The embedding layer in DistilBERT maps token IDs into dense vector representations that serve as input to the Transformer encoder. Each token is represented by a fixed-dimensional embedding vector that captures lexical information derived from the pre-trained model.

DistilBERT combines token embeddings with positional embeddings to encode the relative positions of tokens within the sequence. Since Transformer architectures do not inherently process input sequentially, positional embeddings provide structural information that allows the model to distinguish the order of questionnaire-derived statements within each learning style dimension.

In this study, the embedding layer supports the representation of ordered item-level responses rather than complex linguistic semantics, enabling the model to learn consistent patterns across structured textual inputs corresponding to FSLSM dimensions.

c. Transformer Layer

The Transformer layers form the core of the DistilBERT encoder and are responsible for aggregating information across the input token sequence. Each layer consists of a multi-head self-attention mechanism followed by a position-wise feed-forward network, with residual connections and layer normalization applied to ensure stable optimization [26].

In the context of this study, the self-attention mechanism functions primarily as a weighting and aggregation mechanism, allowing the model to integrate multiple questionnaire-derived statements within a single learning style dimension. Rather than modeling complex discourse-level dependencies, the Transformer layers learn to emphasize informative item-level tokens and suppress less discriminative patterns. The feed-forward sublayers refine these representations through non-linear transformations, while residual connections and layer normalization facilitate effective gradient flow and convergence during fine-tuning [27].

d. Classification Head

The classification head is placed on top of the DistilBERT encoder to perform learning style prediction. The contextualized representation associated with the [CLS] token from the final encoder layer is extracted as a compact summary of the aggregated input sequence.

This representation is passed through a fully connected linear layer followed by a softmax activation function to produce class probabilities. In this study, the classification head is configured for binary classification, corresponding to each bipolar FSLSM dimension.

The DistilBERT encoder and classification head are jointly fine-tuned end-to-end. This training strategy enables the model to learn discriminative representations from structured questionnaire-based text and align them with FSLSM learning-style labels, without relying on explicit linguistic cues or generative language understanding.

3.4.2. Fine-Tuning Strategy

Fine-tuning was conducted using a supervised learning strategy, with separate models trained for each bipolar FSLSM dimension. This dimension-wise approach ensures focused optimization and prevents interference across learning style dimensions.

To address class imbalance, a class-weighted cross-entropy loss function was employed, assigning higher penalty weights to minority classes. The loss function is defined as:

$$\mathcal{L} = - \sum_{i=1}^C w_i y_i \log(\hat{y}_i) \quad (1)$$

where C denotes the number of classes, y_i is the ground-truth label, $\hat{y}_i$ is the predicted probability for the class i , and w_i

represents the class weight computed inversely proportional to class frequency. Model optimization was performed using the Adam optimizer with a fixed learning rate of 2×10^{-5} . The Adam optimizer [28] updates the neural network's weights using the following formulas:

$$m_t = \beta_1 (m_{t-1}) + (1 - \beta_1) \cdot g_t \quad (2)$$

$$v_t = \beta_2 (v_{t-1}) + (1 - \beta_2) \cdot g_t^2 \quad (3)$$

$$\hat{m}_t = \frac{m_t}{1 - \beta_1^t} \quad (4)$$

$$\hat{v}_t = \frac{v_t}{1 - \beta_2^t} \quad (5)$$

$$\theta_{t+1} = \theta_t - \frac{\eta}{\sqrt{\hat{v}_t + \epsilon}} (\hat{m}_t) \quad (6)$$

Each model was trained for three epochs. This choice was guided by preliminary convergence observations, which showed that performance metrics stabilized early during training. Additional epochs did not consistently improve validation performance and increased the risk of overfitting due to the structured and repetitive nature of the input text. Model robustness was further supported through stratified k-fold cross-validation.

During fine-tuning, both the DistilBERT encoder and the classification head were updated jointly, enabling the model to adapt its representations to questionnaire-based textual inputs in an end-to-end manner.

3.5. Model Evaluation

Model performance was evaluated using a stratified k-fold cross-validation strategy to ensure robustness and reduce potential bias arising from class imbalance across FSLSM dimensions. In this approach, the dataset was partitioned into k folds while preserving class distribution, with each fold used once as the test set and the remaining k-1 folds used for training. This procedure enables more reliable estimation of model generalization across different data splits.

Classification performance was assessed using standard evaluation metrics, including accuracy, precision, recall, and F1-score, which together provide a balanced view of overall correctness and class-specific prediction quality. These metrics are particularly relevant to learning style classification tasks, where class imbalance can affect predictive performance. In addition, confusion matrices were analyzed to examine misclassification patterns and to identify systematic prediction tendencies across learning style categories.

Given that the input text is derived from structured questionnaire responses rather than free-form natural language, the evaluation focuses on the model's ability to consistently discriminate between learning style categories based on aggregated item-level preferences. Accordingly, performance results are interpreted in terms of the effectiveness of representation learning rather than natural language understanding capability.

To further assess the practical validity of the proposed approach, model predictions on unseen student data were compared with independent assessments conducted by an educational psychology expert. This expert-based evaluation provides an external validation layer beyond statistical metrics, enabling an examination of the alignment between model predictions and human expert judgment within the FSLSM framework.

3.6. Model Validation

In addition to conventional classification metrics, model validity was further examined through an expert-based validation process, using Cohen's Kappa coefficient to assess agreement between model predictions and human expert assessments beyond chance.

An educational psychology expert with experience in learning style assessment independently evaluated a set of previously unseen student responses using the standard FSLSM interpretation procedure. The expert conducted the assessment without access to the model's predictions to ensure objectivity. The resulting expert labels were then compared with the predictions generated by the fine-tuned DistilBERT models for each learning style dimension.

Cohen's Kappa coefficient was employed to quantify inter-rater agreement between the model and the expert evaluator. Unlike accuracy-based measures, Cohen's Kappa accounts for agreement occurring by chance, providing a more reliable indicator of alignment between automated predictions and expert judgment. The strength of agreement was interpreted using commonly accepted benchmarks, ranging from slight to almost perfect agreement.

This expert-based validation serves as an external reliability check, complementing cross-validation results and providing additional evidence of the model's practical validity in identifying learning styles within the FSLSM framework.

Cohen's Kappa coefficients were measured using the following Equation 7:

$$K = \frac{P_o - P_e}{1 - P_e} \quad (7)$$

$P(o)$ is the proportion of observed agreements. $P(e)$ is the proportion of agreement expected by chance. Interpretations based on the agreement interpretation level using the following guidelines[29], as shown in Table 1.

Table 1. Interpretation of Cohen's Kappa Coefficient.

Cohen's Kappa Coefficient	Category
$K < 0.00$	Poor / Bad
$0.00 \leq K \leq 0.20$	Slight / Modest
$0.20 < K \leq 0.40$	Fair
$0.40 < K \leq 0.60$	Moderate
$0.60 < K \leq 0.80$	Substantial / Significant
$0.80 < K \leq 0.99$	Almost perfect
$K = 1$	Perfect agreement

4. Results and Discussion

4.1. Dataset Characteristic and Class Distribution

The dataset used in this study was derived from the Index of Learning Styles (ILS) questionnaire, which consists of 44 forced-choice items designed according to the Felder–Silverman Learning Style Model (FSLSM). The questionnaire was administered online to undergraduate students, resulting in 1,095 initial responses. After removing incomplete or invalid submissions, a total of 1,081 responses were retained for analysis.

Each ILS item requires respondents to select one of two alternatives, reflecting contrasting learning preferences. Accordingly, all responses were encoded in a binary format (0 or 1). Following the standard FSLSM scoring procedure, the dominant response pattern within each of the four FSLSM dimensions—Processing, Perception, Input, and Understanding—was used to assign a binary learning style label to each respondent (e.g., Active vs. Reflective, Sensing vs. Intuitive). Table 2 summarizes the structure of the raw dataset prior to further transformation.

Table 2. Result of the raw dataset.

ID	Question								Learning Style Dimension			
	Q1	Q2	Q3	Q4	Q5	Q6	...	Q44	Active / Reflective	Sensing / Intuitive	Visual / Verbal	Sequential / Global
0001	0	1	1	0	1	0	...	0	0	0	0	0
0002	0	1	0	0	1	1	...	1	0	1	1	0
0003	0	0	0	1	1	0	...	1	1	0	0	1
0004	1	1	1	0	1	0	...	0	0	0	1	0
0005	1	1	0	1	1	1	...	0	1	1	0	0
...	...	...	...	...	...	...	...	...	...	...	...	...
1081	1	0	1	1	1	0	...	0	1	1	1	1

To enable transformer-based modeling, the binary response patterns were systematically converted into descriptive textual representations. Each binary response was mapped to a predefined phrase describing the corresponding learning behavior, and dimension-specific conversion rules were applied consistently across all 44 questionnaire items. As illustrated in Table 3, this transformation preserved the underlying FSLSM decision logic while expressing learners' preferences in natural language form suitable for semantic modeling.

Table 3. The descriptive text conversion for each dimension.

Learning Style Dimension	Binary response	Text Conversion
Active / Reflective	0	I prefer to learn by doing and discussing
	1	I prefer to think things through quietly first
Sensing / Intuitive	0	I focus on concrete facts and practical details
	1	I focus on theories and underlying meanings
Visual / Verbal	0	I remember best what I see
	1	I remember best what I hear or read
Sequential / Global	0	I learn in linear steps
	1	I learn in big jumps and make intuitive leaps

As a result, each respondent's binary response vector was converted into a coherent textual paragraph summarizing learning tendencies across all FLSM dimensions. The final dataset comprised these generated textual descriptions alongside their corresponding binary labels for each learning style dimension, stored in CSV format for reproducibility and downstream analysis.

Table 4 presents the distribution of learners across the four FLSM dimensions based on the 1,081 valid samples. The table reports both the absolute frequencies and proportional distributions of each learning style category. This overview highlights the structured and imbalanced nature of the dataset, which reflects the deterministic characteristics of the ILS questionnaire and has important implications for model training and evaluation.

Table 4. Summary of the dataset by learning style categories.

FLSM Dimension	Learning Style Category	Number of learners
Processing	Active	688 (63.65%)
	Reflective	393 (36.35%)
Perception	Sensing	930 (88.03%)
	Intuitive	151 (13.97%)
Input	Visual	862 (79.74%)
	Verbal	219 (20.26%)
Understanding	Sequential	589 (54.49%)
	Global	492 (45.51%)

4.2. Cross-Validation Performance Across FLSM Dimensions

The training behavior of the DistilBERT model across the four FLSM dimensions was examined using a 5-fold stratified cross-validation framework, with the primary objective of assessing optimization stability and reproducibility rather than demonstrating predictive superiority. For each fold, the model was fine-tuned for three epochs, and training loss was monitored to analyze convergence behavior across folds and learning style dimensions.

Model optimization was guided by the cross-entropy loss function, which measures the divergence between predicted class probabilities and ground-truth labels. This loss was computed on the training data for each batch and is hereafter referred to as training loss. The AdamW optimizer was employed with a fixed learning rate of 2×10^{-5} to ensure stable gradient updates during fine-tuning. Table 5 summarizes the training loss values observed across epochs and folds for each FLSM dimension.

Table 5. Training loss per epoch for each learning style dimension.

Learning Style Dimension	Epoch	Training Loss					% Decrease loss (Epoch 1 → 2) (Average)	% Decrease Loss (Epoch 2 → 3) (Average)
		Fold 1	Fold 2	Fold 3	Fold 4	Fold 5		
Active / Reflective	1	0.317	0.296	0.272	0.258	0.172	0.858	0.861
	2	0.008	0.084	0.011	0.075	0.009		
	3	0.003	0.012	0.004	0.004	0.003		
Sensing / Intuitive	1	0.209	0.176	0.202	0.360	0.139	0.565	0.939
	2	0.073	0.237	0.016	0.097	0.049		
	3	0.007	0.005	0.004	0.009	0.004		
Visual / Verbal	1	0.342	0.291	0.393	0.227	0.417	0.735	0.907
	2	0.041	0.150	0.042	0.155	0.054		
	3	0.007	0.008	0.008	0.011	0.007		
Sequential / Global	1	0.396	0.321	0.120	0.376	0.281	0.953	0.729
	2	0.011	0.027	0.005	0.014	0.013		
	3	0.004	0.004	0.003	0.004	0.004		

Across all four dimensions, a consistent and monotonic reduction in training loss was observed from Epoch 1 to Epoch 3. The most substantial decrease occurred between the first and second epochs, with average loss reductions ranging from 56.5% to 95.3% across learning style dimensions. This pronounced early-stage reduction indicates rapid adaptation of the pre-trained DistilBERT representations to the task-specific learning style descriptions. The comparatively smaller reduction from Epoch 2 to Epoch 3 suggests that the model approached a stable optimization region after the second epoch.

Convergence patterns were highly consistent across folds, despite minor variations in initial loss values. This behavior reflects the structured, deterministic nature of the input data, which were derived from rule-based

transformations of ILS questionnaire responses. As the textual representations preserve the underlying FLSM decision logic, the learning task primarily involves aligning semantic token patterns with predefined binary labels rather than discovering latent or noisy behavioral signals. Fig. 3 illustrates the comparison of training loss values across epochs and folds for each learning style dimension.

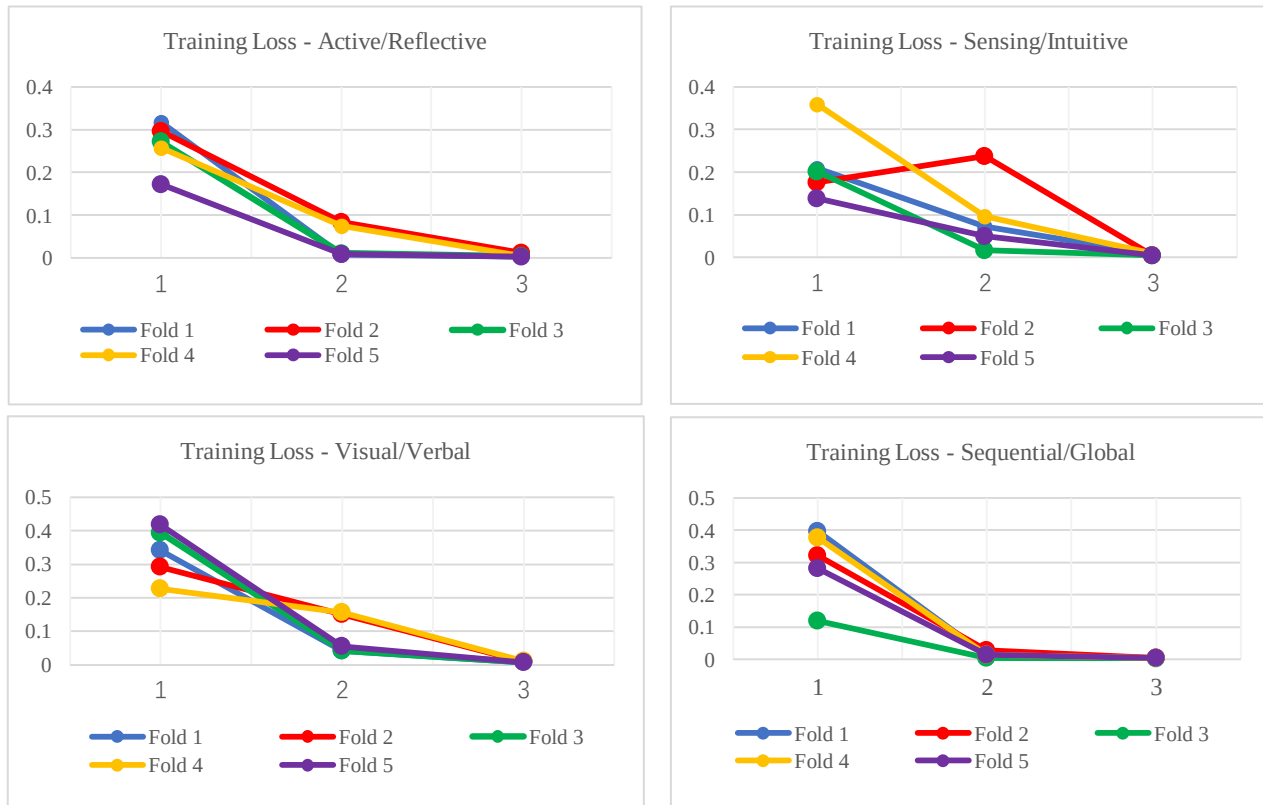


Fig. 3. Training loss for all dimensions.

To mitigate the effects of class imbalance observed in several FLSM dimensions, particularly in the Sensing–Intuitive and Visual–Verbal categories, class-weighted cross-entropy loss was employed during training to ensure proportional contribution from minority classes. In addition, stratified k-fold cross-validation was applied independently for each learning style dimension to preserve class distributions across folds. Given the deterministic and rule-based nature of the label generation process, robustness analyses such as noise injection or perturbation-based sensitivity testing were not conducted, as such analyses are more appropriate for datasets containing inherently noisy or subjective annotations.

The cross-validation results for each FLSM dimension are summarized in Table 6, reporting accuracy, precision, recall, F1-score, and confusion matrix statistics across five folds and three training epochs. These metrics were computed to examine internal consistency and training stability under repeated training–validation splits rather than to assess generalization performance to independent behavioral data.

Across multiple folds and epochs, the model achieved near-perfect or perfect classification scores for several learning style dimensions. This outcome reflects the highly structured nature of the input–label relationship, in which learning style labels are deterministically derived from binary ILS response patterns following FLSM rules. Consequently, the classification task evaluates the model’s ability to faithfully reproduce rule-based learning style mappings from descriptive textual representations under controlled conditions.

The confusion matrices further indicate minimal false positives and false negatives in most folds, confirming rapid and consistent convergence across dimensions. These results should not be interpreted as evidence of overfitting or real-world predictive dominance, but rather as indicators of training stability and representational consistency. External validity and educational interpretability are therefore addressed separately through expert-based validation, as discussed in the following subsection.

Table 6. Evaluation Metrics for Each Learning Style Dimension.

Dimensions	Fold	Epoch	Performance metrics				Confusion Matrix			
			Accuracy	Precision	Recall	F-1	TP	FP	FN	TN
Active / Reflective	1	1	0.9862	1	0.962	0.9806	76	0	3	138
		2	1	1	1	1	79	0	0	138
		3	1	1	1	1	79	0	0	138
	2	1	0.8333	1	0.5385	0.7	42	0	36	138
		2	0.8611	1	0.6154	0.7619	48	0	30	138
		3	1	1	1	1	78	0	0	138
	3	1	1	1	1	1	78	0	0	138
		2	1	1	1	1	78	0	0	138
		3	1	1	1	1	78	0	0	138
	4	1	0.9722	0.9294	1	0.9634	79	6	0	131
		2	1	1	1	1	79	0	0	137
		3	1	1	1	1	79	0	0	137
	5	1	1	1	1	1	79	0	0	137
		2	1	1	1	1	79	0	0	137
		3	1	1	1	1	79	0	0	137
Sensing / Intuitive	1	1	0.9908	0.9394	1	0.9688	31	2	0	184
		2	1	1	1	1	31	0	0	186
		3	1	1	1	1	31	0	0	186
	2	1	1	1	1	1	30	0	0	186
		2	0.9815	1	0.8667	0.9286	26	0	4	186
		3	1	1	1	1	30	0	0	186
	3	1	0.9444	0.7143	1	0.8333	30	12	0	174
		2	0.9861	1	0.9	0.9474	27	0	3	186
		3	1	1	1	1	30	0	0	186
	4	1	0.9907	1	0.9333	0.9655	28	0	2	186
		2	1	1	1	1	30	0	0	186
		3	1	1	1	1	30	0	0	186
	5	1	1	1	1	1	30	0	0	186
		2	1	1	1	1	30	0	0	186
		3	1	1	1	1	30	0	0	186
Visual / Verbal	1	1	1	1	1	1	44	0	0	173
		2	0.9724	0.88	1	0.9362	44	6	0	167
		3	1	1	1	1	44	0	0	173
	2	1	0.9861	0.9348	1	0.9663	43	3	0	170
		2	1	1	1	1	43	0	0	173
		3	1	1	1	1	43	0	0	173
	3	1	0.8241	0.5366	1	0.6984	44	38	0	134
		2	1	1	1	1	44	0	0	172
		3	1	1	1	1	44	0	0	172
	4	1	0.8056	0.5116	1	0.6769	44	42	0	130
		2	1	1	1	1	44	0	0	172
		3	1	1	1	1	44	0	0	172
	5	1	0.9722	0.88	1	0.9362	44	6	0	166
		2	1	1	1	1	44	0	0	172
		3	1	1	1	1	44	0	0	172
Sequential / Global	1	1	1	1	1	1	99	0	0	118
		2	1	1	1	1	99	0	0	118
		3	1	1	1	1	99	0	0	118
	2	1	1	1	1	1	98	0	0	118
		2	1	1	1	1	98	0	0	118
		3	1	1	1	1	98	0	0	118
	3	1	1	1	1	1	98	0	0	118
		2	1	1	1	1	98	0	0	118
		3	1	1	1	1	98	0	0	118
	4	1	0.7824	1	0.5204	0.6846	51	0	47	118
		2	1	1	1	1	98	0	0	118
		3	1	1	1	1	98	0	0	118
	5	1	1	1	1	1	99	0	0	117
		2	1	1	1	1	99	0	0	117
		3	1	1	1	1	99	0	0	117

4.3. Analysis of Deterministic Consistency and Error Patterns

The evaluation results presented in the previous subsection reveal near-perfect classification performance across multiple FSLSM dimensions and cross-validation folds. While such results may appear unusually high for educational and behavioral data, they must be interpreted in light of the deterministic structure underlying both the input representations and the target labels.

In this study, the descriptive textual inputs were generated through systematic, rule-based transformations of binary ILS questionnaire responses. Likewise, the learning style labels were assigned using the standard FSLSM scoring mechanism, which aggregates the same binary responses within each dimension. As a result, both the input texts and the corresponding labels originate from the same questionnaire logic and reflect the same underlying decision rules. This creates a highly structured input-label relationship with minimal ambiguity or stochastic variation.

Under these conditions, the classification task does not constitute a general natural language understanding problem in which models must infer latent behavioral traits from noisy, open-ended text. Instead, it represents a constrained semantic alignment task, where the model learns to associate consistent and repetitive linguistic patterns with deterministically derived labels. The near-perfect performance scores should therefore be interpreted as evidence of deterministic consistency rather than independent predictive superiority.

Analysis of the confusion matrices further supports this interpretation. Across most folds and dimensions, misclassification rates were negligible, with false positives and false negatives occurring rarely or not at all. This pattern reflects the internal coherence of the dataset rather than exceptional generalization capability. Once convergence is achieved, the model reliably reproduces FSLSM-defined mappings embedded within the descriptive textual representations.

Importantly, the absence of substantial error patterns does not imply that the model has learned nuanced or context-sensitive representations of learners' cognitive behaviors beyond the FSLSM framework. Instead, it indicates that the transformer-based architecture is capable of faithfully encoding and recovering rule-based learning style constructs expressed in natural language form. Consequently, claims regarding robustness to noise, sensitivity to ambiguous responses, or transferability to alternative learning style frameworks fall outside the scope of the present results.

This analysis clarifies that the primary contribution of the proposed approach lies in demonstrating the feasibility of operationalizing established learning style theories within modern NLP architectures, rather than in outperforming rule-based methods or uncovering new behavioral insights. External validity and interpretative alignment with human judgment are therefore examined separately through expert-based agreement analysis, as presented in the following subsection.

4.4. Expert Agreement Analysis

To complement the quantitative cross-validation analysis, an expert agreement assessment was conducted to examine the conceptual alignment between the DistilBERT model outputs and human interpretation of FSLSM-based learning styles. This evaluation involved a subset of 36 students whose ILS questionnaire responses were independently assessed by an educational psychology expert with domain knowledge in learning style theory.

In this process, the expert conducted an independent, respondent-level assessment by assigning learning style categories for each FSLSM dimension to every student, following the standard FSLSM interpretation guidelines. This assessment was performed individually for each respondent based on their complete ILS questionnaire responses. Following the initial classification, the expert reviewed the corresponding student responses to ensure internal consistency with the FSLSM decision rules.

These expert-derived classifications were then compared with the corresponding predictions produced by the fine-tuned DistilBERT models. The level of agreement between the two assessments was quantified using Cohen's Kappa coefficient, which measures inter-rater agreement while accounting for chance.

Table 8 presents the confusion matrices for each FSLSM dimension, illustrating the alignment between expert judgments (Rater A) and DistilBERT predictions (Rater B). Across all four dimensions—Processing, Perception, Input, and Understanding—no discrepancies were observed between the expert assessments and model outputs.

Table 7. Confusion Matrix Across FSLSM Dimensions.

Dimension	Expert (Rater A)	DistilBERT Model (Rater B)	
		Action1	Action2
Active/Reflective	Action1	TP 20	FN 0
	Action2	FP 0	TN 16
Sensing/intuitive	Action1	TP 30	FN 0
	Action2	FP 0	TN 6
Visual/Verbal	Action1	TP 32	FN 0
	Action2	FP 0	TN 4
Sequential/Global	Action1	TP 10	FN 0
	Action2	FP 0	TN 26

This resulted in a Cohen's Kappa value of 1.0 for each dimension, indicating perfect agreement under the given evaluation setting. It is important to emphasize that this expert agreement analysis does not constitute an independent ground-truth validation in the traditional predictive sense. Both the expert judgments and the model predictions are derived from interpretations of the same ILS questionnaire responses, following the FSLSM theoretical framework. Therefore, the observed perfect agreement should be interpreted as evidence of strong conceptual consistency between

the transformer-based model and expert-level FSLSM interpretation, rather than as proof of independent predictive superiority.

From a methodological perspective, these findings demonstrate that the proposed DistilBERT-based approach is capable of faithfully operationalizing FSLSM constructs in a manner that aligns with human expert reasoning when applied to structured questionnaire data. This alignment supports the validity of the model as an automated representation and interpretation tool for FSLSM-based learning style analysis, while acknowledging that broader generalization to alternative instruments or open-ended behavioral data remains outside the scope of the present study.

5. Discussion and Conclusion

This study investigated the feasibility of applying a transformer-based language model (DistilBERT) to the identification of learning styles based on the Felder–Silverman Learning Style Model (FSLSM) using text representations derived from the Index of Learning Styles (ILS) questionnaire. By systematically converting binary ILS responses into structured descriptive text, the proposed framework enables FSLSM-based learning style categorization to be modeled within a modern natural language processing pipeline.

The experimental results demonstrate that DistilBERT can consistently and stably reproduce FSLSM learning style labels across all four dimensions under a cross-validation setting. The observed convergence behavior and near-perfect evaluation metrics reflect the deterministic relationship between the transformed textual inputs and the rule-based FSLSM labels, rather than uncontrolled generalization to unseen behavioral patterns. Accordingly, the reported performance should be interpreted as evidence of representational fidelity and optimization stability, not as superiority over traditional FSLSM scoring procedures.

Expert-based agreement analysis further confirms that the model’s predictions remain pedagogically interpretable and aligned with established FSLSM concepts when assessed by human evaluators. This validation indicates that transformer-based models can serve as reliable semantic intermediaries that preserve theoretical learning style constructs while facilitating automated processing and downstream integration.

Overall, the contribution of this work lies in demonstrating a transparent and theoretically grounded integration of psychometric learning style instruments with transformer-based NLP models. The proposed approach provides a foundation for future research exploring adaptive learning systems, hybrid rule–learning architectures, and the extension of learning style representations beyond fixed questionnaire formats, while maintaining alignment with established educational theory.

All the Declarations and Statements

Author Contributions Statement

Nesi Syafitri – Conceptualization, Methodology: Proposed research ideas, Constructed the overall framework, Data analysis, Model training, Validation, Performance evaluation, Formal analysis, Visualization, and writing.
Suzani Mohamad Samuri – Supervision, Validation, Performance Evaluation, Review, and Project Management.
Yudhi Arta – Research Design and Data Collection: Coordinated the quasi-experimental study, organized participant involvement, and managed data collection procedures.

All authors have read and agreed to the published version of the manuscript.

Conflict of Interest Statement

The authors declare no conflicts of interest.

Funding Declaration

This research received no external funding.

Data Availability Statement

Data sharing is not applicable to this article.

Ethical Declarations

This study involving human participants was conducted in accordance with established institutional and national ethical standards. Ethical approval for this research was obtained from the relevant institutional review board. Prior to participation, informed consent was obtained from the participants’ legal guardians, and participation was entirely voluntary. Participants were informed of their right to withdraw from the study at any time without any consequences. All data collected were handled with strict confidentiality. Personal identifiers were removed, and all data were fully anonymized to ensure the privacy and protection of participants throughout the research process.

Acknowledgment

The authors express deepest gratitude to the Universiti Pendidikan Sultan Idris and Universitas Islam Riau for their continuous support and valuable facilities throughout this research. The institutional encouragement and academic environment have been instrumental in completing this study.

Declaration of Generative AI in Scholarly Writing

During the preparation of this manuscript, generative AI tools were used solely to enhance language clarity, grammar, and overall readability. The technology was applied under full human oversight and control, and all generated text was carefully reviewed, edited, and verified by the authors to ensure accuracy, completeness, and academic integrity. No AI tools were used to generate research data, conduct statistical analyses, or draw scientific conclusions. Generative AI technologies are not listed as authors or co-authors. The authors take full responsibility for the content and integrity of this manuscript.

Abbreviations

The following abbreviations are used in this manuscript:

AI – Artificial Intelligence
FSLSM – Felder Silverman Learning Style Model
ILS – Index of Learning Style
ML – Machine Learning
NLP – Natural Language Processing

Appendix

None.

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How to cite this paper

Nesi Syafitri, Suzani Mohamad Samuri, Yudhi Arta, "DistilBERT-based Text Classification for Learning Style Identification Based on the Felder-Silverman Model", International Journal of Modern Education and Computer Science(IJMECS), Vol.18, No.3, pp. 135-151, 2026. DOI:10.5815/ijmecs.2026.03.09